The Development of a Gridded Weather Typing Classification Scheme

This dissertation is submitted to the Department of Geography and the College of Arts and Sciences at Kent State University in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

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May, 2014

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ACKNOWLEDGEMENTS

While in some ways it seems like it was just a couple of years ago that I was writing something similar for my master's thesis, in many ways it also seems like a lifetime ago, as so much has changed since then. Indeed, time is an enigma. Somewhere between endless home improvement projects (deck, carpet, roof, siding, painting, fixing, plumbing, mulching, trimming, mowing, digging, fencing, etc.), trips of a lifetime, emerging gray hairs and milestone birthdays; I took classes, read, wrote, researched, published, presented, traveled, taught, and among a litany of additional things, put together – and defended – this dissertation.

First and most of all, I want to thank Amanda, my wife, who despite my gray hairs, has supported me in every way a person can be supported. The Ph.D. years are challenging not only for the student, but possibly even more so for the spouse. I cannot thank her enough for being by my side, supporting me (and showing me endless patience) throughout all of the aforementioned experiences, and all others. Thank you. I could not have completed this without you.

An important thank you goes out to my family as well. In addition to their encouragement to go back to graduate school in the first place, my parents especially have always provided me with sound advice and guidance, and are always interested in how my studies are going. I would also like to thank my friends (especially the TNC). Without occasional social outings to break-up bouts of frustration and writer's block, this process would have been overwhelming.

I would like to thank my advisor, Scott Sheridan, not only for his guidance throughout my master's and doctoral years at Kent State, but also for the knowledge gained, skills learned, travels experienced, publications co-authored, and support received through research grants he obtained. Through his advisory role on this dissertation, I was able to advance my knowledge of synoptic climatology to a level that will hopefully serve me well in the future. Additionally, I would like to thank my committee members for their thoughtful suggestions and comments throughout the past couple of years that have helped me hone my research, and have undoubtedly improved this dissertation.

I have spent nearly a third of my life at Kent State University; my time here has been more than just life-changing, it literally has been a good chunk of my life. So finally, I would like to thank the students, staff, and faculty in the department and in the wider university, both past and present, for their support and friendship throughout all of these years. Thank you for making my experience here such a positive one.

CHAPTER 1

INTRODUCTION

Classifications of typical meteorological patterns, air masses, and weather types have long been utilized by synoptic climatologists to examine the day-to-day relationship between the weather and a host of different surface phenomena (Yarnal, 1993; Barry and Perry, 2001). Synoptic classifications have successfully partitioned out different categories of weather that are associated with phenomena ranging from atmospheric events such as tornadoes (Lee, 2012), heat waves (Sheridan et al., 2012a), teleconnections (Sheridan and Lee, 2012) or derechos (Coniglio et al., 2004), to topics as diverse as the transport of airborne pathogens (Frank et al., 2008), air quality (Davis et al., 2010), human health (Jamason et al., 1997; Sheridan et al., 2012b) and many others (Yarnal, 2001; Huth et al., 2008; Sheridan and Lee, 2010; 2011). Additionally, synoptic classifications have also grown markedly more popular in climate change research in recent years due to their ability to take the wealth of meteorological data available from global climate models (GCMs) and partition out intuitive categories of weather that may

have important regional to local-scale impacts on future surface environments (Sheridan and Lee, 2010; Lee and Sheridan, 2011).

Much recent literature has been dedicated to the development, evaluation, and application of map pattern classifications (e.g. the COST733 project; Huth, 2010) – a categorization of ‘typical’ atmospheric circulation patterns over a broad spatial domain. The advent of gridded climatological reanalysis data, with improved spatial resolution (in both the horizontal and vertical) along with the aforementioned rise in synoptic-based climate change research has certainly warranted this attention. However, weather-type classifications – a categorization of typical daily weather situations at individual locations – have received much less attention with regard to development and assessment since the advent of such data. Thus, the primary goal of this dissertation will be to develop a new synoptic weather-typing classification scheme that takes advantage of these gridded reanalysis data sets. The technique outlined will be applied to derive daily weather types for locations within the continental United States, with the partitioning ability of the methodology also being evaluated.

CHAPTER 2

BACKGROUND

Yarnal (1993) describes a number of different types of synoptic classifications: map-pattern classification, weather-typing classification, and regionalization. While all three of these types of synoptic methods have their utility, most recent research has focused on the first two. Map-pattern classifications are often interested in the atmospheric flow over a broad spatial scale, usually examining one or two variables – often sea-level pressure, temperature or geopotential height – and how each changes through space on a daily basis. Weather typing (sometimes referred to as air mass classification), on the other hand, is most often focused on classifying the daily ‘meteorological situation’ at individual locations – in essence, examining a multitude of meteorological variables at a particular weather station in order to classify each day into one of a number of different weather types. Such classifications are particularly useful in human health and other biometeorological applications (Kalkstein et al., 1996), though can also be applied to a wide range of other uses as well.

Each of these methods of synoptic classification can also be undertaken with either a circulation-to-environment approach (where the atmospheric data are classified independently of the application for which it was meant) or with an environment-to-circulation approach (when the event/application itself plays a role in determining which cases of atmospheric data will be classified; Yarnal, 1993). While taking the latter approach is considerably more focused on a particular research question, synoptic climatologists utilizing the former approach often find their climatologies are useful for a much broader range of applications – even after the completion of the research for which the classification was originally intended. The most useful of these classifications can be turned into catalogs or calendars – a data set consisting of the patterns (or types) by day, rather than all researchers having to go through the labor of creating the classification for themselves. Due to the intuitiveness of map-pattern classifications in applying the same classification over a broad spatial scale or at a single point, the vast majority of circulation-to-environment classifications are map-pattern classifications rather than weather typing classifications. This is also due largely to the fact that most usages of weather types are to examine a specific phenomenon at a specific location, requiring the use of a classification with a particular set of variables. However, the few weather-type classifications that have been developed with consistent typing over a broad spatial scale have been particularly useful.

2.1 – Notable Weather-Type Classifications

The Temporal Synoptic Index (TSI; Kalkstein and Corrigan, 1986) represented an important shift in the synoptic climatological paradigm, as, when it was first introduced, it was the first point-based air mass / weather type classification of its kind. The TSI utilized techniques still common in many synoptic classifications today, including principal components analysis (PCA) and cluster analysis (CA). The first application of the TSI was successful at partitioning out poor air quality days (sulfur dioxide concentrations) in winter near Wilmington, Delaware (Kalkstein and Corrigan, 1986), proving more useful than multiple regression in the analysis. After its original introduction, the TSI underwent a modification, utilizing average-linkage cluster analysis in place of Ward's algorithm in the prototype (Kalkstein et al., 1987). Further, the success and relative ease of use of the method led to myriad applications, from air quality in a number of US cities (Davis, 1991; Greene et al., 1999), to asthma-related hospital admissions (Jamason et al., 1997) and a variety of other applications (see Kalkstein et al., 1996; Davis and Rogers, 1992).

The fundamental nature of the TSI procedure, however, does have two major drawbacks regarding the inconsistency of the weather types across space: both the number and the nature of the weather types at each location are often different (Sheridan, 2000). This decreases the intuitiveness of the classification, as weather type X at one location may be completely different in character than weather type X at another location. After its introduction, subsequent uses of the TSI were mostly for the

methodology rather than a daily catalog of weather types at the locations classified.

Today, the PCA/CA-based TSI methodology is still often used as a classification procedure, though it is not always referred to as the TSI.

The TSI methodology was later redeveloped by Davis and Kalkstein (1990) into the Spatial Synoptic Index (SSI) in an attempt to improve compatibility between stations. In this evolution of the weather typing methodology, the researchers first utilized a PCA/CA technique to perform a day-by-day regionalization for a single year (1984) that categorized each of the 141 stations in their domain into a region, based upon 24 meteorological variables. Each of these regions represented an area of relatively homogeneous weather – an air mass. Once completed, the 2400 regions (365 days with multiple air masses across the continent on each day) were clustered into 90 final weather types, with a subsequent manual classification of the most frequently occurring types done to aid interpretation. The maps produced from the SSI were quite useful in visualizing the progression of cyclonic systems across the continent, however, the methodology was limited in future usage due to the need to repeat the regionalization for each day in a time series.

After the development of the TSI and the SSI, Schwartz (1991) developed a weather type classification at the 850mb level for 15 stations in the north central United States based upon a unique ‘hybrid’ approach involving the combination of both a manual/subjective

trajectory analysis and an objective utilization of the partial collectives technique for the frequency distributions of each weather type. This methodology has been used little since, however, likely due to its relatively time-consuming procedure (in comparison to the TSI, and especially considering the ability of contemporary statistical software to complete a quick PCA and cluster analysis), and the necessity of topographically homogeneous regions for classification.

The major circulation-to-environment weather typing classification that has been particularly useful for a broad range of applications over the past decade (and on a broad spatial scale) is the Spatial Synoptic Classification (SSC; Kalkstein et al., 1996; Sheridan, 2002). Originally created by Kalkstein et al. (1996) for first-order weather stations east of the Rockies, the SSC also utilized a hybrid classification technique that manually identified weather type ‘seed days’ at each location and then used an automated procedure to classify all days in the winter season. Although quite useful in a number of applications (Greene and Kalkstein, 1996; Kalkstein and Greene, 1997; Kalkstein et al., 1998), the original SSC suffered from two important limitations. In its original form, the SSC was only available for the winter and (eventually) summer seasons, and the match percentage between neighboring stations was less than desirable (Sheridan, 2000). Both of these shortcomings were overcome by Sheridan’s redevelopment of the SSC in the early 2000s (Sheridan, 2002). ‘Sliding seed days’ were formulated to allow the SSC to classify days in the transitional seasons (spring and

autumn), and the transfer of actual seed days to neighboring stations improved the spatial match percentage considerably.

The redeveloped SSC utilizes observations of temperature, dew point, pressure, wind speed, wind direction and cloud cover, taken at a four-times daily temporal resolution, in order to classify a daily surface weather type for a particular location. Each day's classification is most heavily influenced by its temperature and humidity characteristics, and is thusly named (dry polar, dry moderate, dry tropical, moist polar, moist moderate, and moist tropical). When one weather type yields to another within a day, the day gets classified as a transitional type. These weather types are also relative to the time of the year and to the station's location; in that, a dry tropical type is going to represent higher temperatures for a location in a relatively warm climate compared to one in a cooler climate. Similarly, a tropical type is going to have higher average temperatures in summer than it would in winter for the same location. This relativity of the weather type to time of year and location is exhibited for all 24 variables considered in the classification. It has been used to classify millions of days at hundreds of stations, throughout a broad spatial domain, both in the United States and internationally (Bower et al., 2007; Hondula and Davis, 2011). The catalog of daily weather types for every station is updated yearly and easily accessed for free on-line (at <http://sheridan.geog.kent.edu/ssc.html>) – a key benefit of the classification.

As mentioned above, similar synoptic climatologies, most notably the TSI (Kalkstein and Corrigan, 1986) suffered from having to do separate classifications for different times of year, or for different locations – each of which yielded either a different number of weather types, or types with varying character (and varying names or descriptions) from season to season and place to place. When applying these classifications to study a particular event, this can hamper the interpretation of the results by complicating comparisons between results from various locations and different seasons. Because of this, perhaps the most important attribute of the SSC is the universality of the resultant categories. That is, as one moves from station to station, the complete set of weather types (mentioned above) and the names of the types remain constant. Thus, a moist polar (MP) weather type represents a relatively cool and humid set of conditions for a particular location – which are always cooler than moist moderate (MM) and always more humid than dry polar (DP) – wherever on the planet it may be. Thus, while the *methodology* of the TSI has been used for a number of synoptic-based analyses, the SSC is often employed as a *data set* (i.e. a calendar of daily weather types) and is therefore much easier to utilize by researchers from a variety of different backgrounds. The availability of the redeveloped SSC (as a calendar of daily weather types – rather than just a method, and for free on-line, updated annually) and its intuitive nature have led to its extension to Europe (Bower et al., 1997) and to its usage in a wide variety of applications (Ashley et al., 2011; Hanna et al., 2011; Lee et al., 2012), especially in researching heat waves and heat-related mortality (Sheridan and Dolney, 2003; Knight

et al., 2008; Sheridan and Kalkstein, 2009). Hondula et al. (2013) provide an extended overview of the SSC, along with a review of the applications of the SSC to human health and potential future directions.

2.2 – Aims of the Dissertation

Like any science, the field of climatology has grown considerably over the last decade. Most notably, the widespread acceptance and usage of gridded historical reanalysis data has become an increasingly important mainstay in the climatological literature. While a variety of new synoptic classification techniques have emerged over this time to take advantage of such data sets, the only types to spread across more than a local scale have all been map pattern classifications (MPCs) as opposed to weather type classifications (WTCs). Many MPCs with a European focus are thoroughly discussed and evaluated in the COST733 project (Beck and Philipp, 2010; Huth, 2010; Philipp et al., 2010). Therefore, it seems reasonable that a natural progression in the field of synoptic climatology would be to take advantage of the structured nature and enhanced spatial resolution of these gridded data sets to create a catalog of daily surface weather types for grid points across a broad spatial domain.

Thus, this research details the development of a gridded weather typing classification (GWTC) scheme for the continental United States. The classification is designed to integrate some of the more successful components of previous WTCs (mainly the

redeveloped SSC), while also overcoming some of their limitations. Further, the classification will incorporate a number of new advancements, novel to weather-type classifications. The GWTC was developed with the following goals guiding the research:

- Create a structured, gridded weather typing classification.
- Create a classification that improves upon the spatial resolution of existing classifications.
- Create a more automated classification *methodology* that eliminates the time consuming task of creating *a priori* definitions of the different weather types experienced at a location, and is therefore easily repeatable by other researchers.
- Create a classification that is relative to the time of year and location
- Create a classification that identifies the nature of transitional weather types.
- Create a classification that has an adequate frequency of each core weather type at all locations and times of year (i.e. ensuring that the core weather types do occur in each calendar month in all locations).

With these goals in mind the following chapter will detail the development of the GWTC, including the data used, the discussion of key decisions in the process of development, the finalized methodology, and the metrics by which its success is evaluated. In Chapter 4, the weather types are used to perform a regionalization which

aids in the interpretation of the results. The resulting character of the weather types in different regions, along with weather type climatologies, and classification evaluation statistics are presented and discussed in Chapters 5-7. The classification is then framed within the context of existing synoptic climatological literature in Chapter 8, with direct comparisons with the SSC. Finally, the limitations and key benefits of the classification are discussed along with a summary of the work done, final conclusions, potential future uses of the classification, and potential future updates.

CHAPTER 3

DATA AND METHODOLOGY

3.1 – Data

All climatological data for the classification were obtained from the National Centers for Environmental Prediction (NCEP) North American Regional Reanalysis (NARR) project (Mesinger et al., 2006). As the potential of a spatial resolution much finer than current WTCs is one of the primary goals of the GWTC, NARR data were selected over other reanalysis data sets mainly because of substantially greater spatial resolution. Though not without its own biases, especially in regards to precipitation (Knight and Davis, 2009; Mesinger et al., 2006), the NARR project is considered a major improvement from previous reanalysis products from NCEP (such as the NNR; Kalnay et al., 1996) in both resolution and accuracy (Mesinger et al., 2006). The NARR is comprised of a gridded set of meteorological data incorporated from a number of actual observation sources (e.g. surface weather stations, rawinsondes, dropsondes, buoy data, satellites, and many others), and assimilated into a model in order to output data on a gridded basis for all of North America and about a quarter of the Northern Hemisphere. These data are

available for free on-line for the years 1979 through the present and are updated annually.

It is important to note, however, that the NARR data set consists of *model* variables rather than actual *observations*. While it is beyond the scope of the research to detail representativeness of the NARR data, it is assumed for this research that these data are accurate representations of the actual surface weather. In the case of both 2m temperatures (a variable not directly assimilated into the model, but derived from land-surface temperatures and the lowest mid-level temperature) and 10m winds, Mesinger et al. (2006) show that spatially averaged biases are quite small compared to surface station-based observations and previous reanalyses.

The data selected for use in the classification are the 8-times daily representations of the following six variables: temperature at 2m (in °C), dew-point temperature at 2m (°C), pressure at mean sea level (in millibars; mb), u-component of the wind (in m/s), v-component of the wind (in m/s), and cloud cover (in percentage of total cloud cover). The data are “snapshots” of the conditions at the same time across the entire domain, and are available at the times indicated in Table 1. These data were selected for their importance with many biometeorological applications (especially those involving human health and air quality) and due to their usage in previous weather typing climatologies, especially the current SSC.

Using ArcMap 10 GIS software, a mask of the lower 48 United States is used to select only the grid points that fall within the continental United States and just offshore (i.e. within 10 miles, 16 km). The spatial resolution of the NARR data set used herein is set at roughly 32km ($0.3^\circ \times 0.3^\circ$) for most of the domain of interest. At this domain and resolution, weather types could be derived at over 17,000 grid points. However, due to perfect correlations noticed in the temperature and dew point records of some neighboring grid points of the NARR data set, for the research herein, every second grid point (for both latitude and longitude) is obtained from the data set. This results in 2,070 US grid points/locations (Figure 1) available for weather typing which are obtained for each day, from 1 January 1979 to 30 December 2010 (due to the starting time of each annual data set at 00z, data for 31 December 2010 are incomplete in the 2010 data sets, and can therefore only be typed when 2011 data are later integrated into the classification).

Table 1 – Local time by time zone for each of the 8 daily observations (1-8) of each of the six variables (x).

Standard Time	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
Eastern	4am	7am	10am	1pm	4pm	7pm	10pm	1am (Tomorrow)
Central	3am	6am	9am	Noon	3pm	6pm	9pm	Midnight
Mountain	2am	5am	8am	11am	2pm	5pm	8pm	11pm
Pacific	1am	4am	7am	10am	1pm	4pm	7pm	10pm

Figure 1 – Map of the locations in the continental US (and within 10 miles) of the 2,070 grid points that are weather typed in this research.

3.2 – Methodology

One of the aims of the classification is to intuitively categorize ‘spatially universal’ weather types that are fully relative to time of the year and to the specific location.

Thus, one of the major differences between the GWTC and other weather typing

schemes is that the frequency of each core weather type is more balanced, at each location and at all times of the year. This definition of a weather type differs significantly from that of the classical Bergeron-based air masses. While likely still relatable to source regions and sectors of a mid-latitude cyclone, the *weather types* created here are not meant to be thought of necessarily as *air masses*. To underscore this desired disconnect, the resultant weather type names avoid geographical inferences (such as continental, maritime, tropical and polar) and instead are strictly temperature and humidity based, and therefore always reference the relative weather for that location and that time of year (for all locations, and for all times of year). These aims were key to the development of the classification methodology outlined below.

Another major goal of the classification is for the methodology to be as automated as possible. However, as in all classifications there are a number of subjective decisions that depend on the expertise of the climatologist undertaking the research (Kalkstein et al., 1996; Yarnal, 1993), and therefore all classifications are inherently subjective and there is no “perfect classification.” Therefore, the aim of the methodology section herein is to be as candid as possible with those subjective decisions, and when necessary, justify at least qualitatively (if not also quantitatively) why the chosen methodology was selected.

The development of the final classification methodology underwent numerous trial and error periods at various stages of the methodology where the scheme was continually honed and updated. The steps outlined below represent the final chosen methodology derived from multiple attempts. The steps through section 3.2.4 below outline the typing procedure completed for a single location (grid point), which is then iterated for each of the 2,070 locations before subsequent steps (in section 3.2.5) incorporate a spatial component into the final classification. Each location's data are set up in their own file, with days as cases (rows) and each individual observation (8-times daily observations) of each variable (6 variables) as its own column (i.e. 48 columns of data). The complete methodology is shown in Figure 2.

Figure 2 – Flow chart depicting weather typing methodology

3.2.1 – Data Preparation

Prior to standardization, a *data preparation* step is completed for each location. A preliminary evaluation of the data showed that in some locations, on a small fraction of days, for one of the 8-times daily observations, dew point temperatures were a few tenths of a degree higher than air temperatures. These situations were determined to be of little consequence to the classification itself, but were nonetheless rectified by setting the dew point temperature equal to the air temperature. All other data were

unchanged in this regard. Data preparation also included the calculation of means of each of the 6 variables from their 8-times daily observations – creating an additional 6 columns (54 columns total).

Following data preparation, each of the 54 variables is then subjected to a seasonal standardization process. First, a 15-day centered moving average (CMA) is calculated for each variable. This 15-day CMA is then used to calculate a day-of-the-year (DOY) average. This DOY average is then further smoothed using a subsequent 15-day CMA, creating the final seasonal average (SAVG) for each variable. Standard deviations are calculated similarly, though without the inclusion of the initial 15-day CMA: first, the standard deviation of each variable on each day of the year is calculated, then these standard deviation values are smoothed using a 15-day CMA to create the seasonal standard deviation (SSDEV) for each variable. *Deseasonalized z-scores* for each day can then be calculated by:

$$z_{iv} = \frac{x_{iv} - SAVG_{dv}}{SSDEV_{dv}}$$

where z_{iv} is the deseasonalized z-score for variable v on day i of the entire time series, x_{iv} is the raw value of variable v on day i of the entire time series, $SAVG_{dv}$ is the

seasonal average for variable v on day-of-the-year d , and $SSDEV_{dv}$ is the seasonal standard deviation for variable v on day-of-the-year d .

There are a number of different ways to define daily climate normals (averages). Often, the values of a variable for each individual day of the year over a 30-year period are averaged (i.e. $n=30$), though this often results in a very noisy seasonal curve. To correct this, a low pass filter of some length (often about 28-31 days) can be applied to these DOY averages (Arguez and Applequist, 2013). Alternatively, as Arguez et al. (2012) note, historic NCDC climate normals prior to the latest release “were calculated using a simple cubic spline fit” of the *monthly* climatology. However, in the current research, neither of these methods were deemed sufficient, as the former would result in a seasonal curve that was still more noisy than desired, and the latter would be unable to adequately capture sub-monthly variability in the seasonal curve that could prove important when classifying surface weather types (as would the former method, if the filter was of 28-31 days). Thus, the selected methodology outlined above was developed; simply by adding the extra 15-day CMA filtering process to the calculation of SAVG. This resolved each of the aforementioned shortcomings of the alternative methods, resulting in a more robust sample that also still represented the exact 15-day window of interest. This additional step was not included, however, in the calculation of SSDEV above, as a standard deviation of *smoothed* averages would fail to capture the true degree of variability possible for a particular day of the year.

As mentioned above, it was desired to retain important sub-monthly variability when calculating baseline normals (especially for temperature), and thus, multiple permutations of smoothing processes (for SAVGs and SSDEVs) were attempted in order to gauge the effect of these decisions on the classification, with a 31-day (monthly) smoother chosen as the maximum limit. Within this limit, testing on an Ohio-based location revealed minimal impacts of these decisions on the classification. Seven-day, 21-day and 31-day smoothing options resulted in maximum differences of less than 1°C in afternoon temperature or dew points of any initial weather type in any month. Further, day-by-day weather type match percentages with the types obtained from the chosen methodology were greater than 90% with all other smoothing lengths. Further, chi-square tests revealed no significant ($p \leq 0.05$) differences of the monthly frequencies of the resultant weather types in any permutation. From these results, and taking into consideration the 15-day windows chosen for seed day selection in the SSC (Sheridan, 2002), the methodology outlined above was eventually chosen for the calculation of deseasonalized z-scores. These scores are the backbone of the classification, as they give an indication of the relative value of each observation of each variable, at each location, at every time of the year. While some data used in the classification are non-normally distributed, Wilks (2006) notes that this is not a necessary qualification for calculating standardized anomalies. In this case, these z-scores are certainly valid

metrics of the 'spatiotemporal relativity' of a value, and are shown below to be successful indicators of different weather conditions.

3.2.2 – Initial Typing

The next step in the weather typing process is to determine the initial temperature category (TCAT) to which each day belongs. Three temperature categories were chosen based upon the number of different temperature categories in the SSC (Sheridan, 2002) and to represent average, below average and above average temperatures. A number of permutations with varying z-score thresholds for partitioning these categories were evaluated, including a "30/40/30" split of the standard normal curve, a ± 1 standard deviation split, a 'significant' split (i.e. ± 1.96 standard deviations), and a ± 0.5 standard deviation split. Each of these splits resulted in a large number of moderate types and minimal warm or cool types – which would not be useful in many applications. With one of the main aims of the research being to have an adequate number of all weather types occurring throughout the year, standard deviation values representing an even split of the z-distribution into thirds was selected. Thus, each of the eight temperature z-scores and the average temperature z-score for each day were individually partitioned with threshold cutoffs at $z_i < -0.4307$ for cool types; $-0.4307 \leq z_i \leq 0.4307$ for moderate types; and $z_i > 0.4307$ for warm types. Once each of these 9 temperature columns (8-times daily temperature and the daily average) were grouped into their temperature categories based upon these thresholds, the daily mode of the

types was selected as the initial TCAT for that day. On days when cool, moderate and warm types each occurred equally among the nine temperatures (i.e. each occurred three times), the temperature category for the daily average temperature variable was determined to be the initial TCAT for the day (usually moderate). On days when two types each occurred four out of the nine observations, the temperature category (among those two that occurred four times each) that occurred first (earliest) in the day was selected as the initial TCAT for the day.

Once each day's initial TCAT is determined, that day is then classified into initial humidity categories within that TCAT using within-TCAT deseasonalized z-scores (TDZ) for each of the nine dew point temperature observations (8-times daily, and the daily average). Since it is theoretically possible that not every TCAT type occurred on every day of the year (and practically, in order to get an adequate sample size of days within each TCAT), seasonal averages (SAVG) and seasonal standard deviations (SSDEV) of each of the nine dew point temperature observations within each TCAT had to be calculated using *monthly* averages instead of *day-of-the-year* averages (as was outlined above). These monthly averages and standard deviations are then subjected to a 31-day CMA smoother – to remove step-like discontinuities that arise by computing monthly averages – resulting in values that are relative to the day of the year. Each day's TDZ is then calculated using a slightly transformed equation from the one above:

$$TDZ_{iv} = \frac{x_{iv} - SAVG_{dvt}}{SSDEV_{dvt}}$$

where TDZ_{iv} is the within-temperature category deseasonalized z-score for dew point variable v on day i of the entire time series; x_{iv} is the raw value of dew point variable v on day i of the entire time series, $SAVG_{dvt}$ is the seasonal average for dew point variable v on day-of-the-year d within TCAT t ; and $SSDEV_{dvt}$ is the seasonal standard deviation for dew point variable v on day-of-the-year d within TCAT t . Thus, each day's dew point z-score is calculated relative to the seasonal average and seasonal standard deviation of the dew points within only the temperature category into which that day has already been classified.

For the same reasons discussed above regarding temperature classes, humidity categories were also split evenly within their predetermined TCAT using the same threshold z-scores, with cutoffs at $TDZ_{iv} < -0.4307$ for dry types; $-0.4307 \leq TDZ_{iv} \leq 0.4307$ for average types; and $TDZ_{iv} > 0.4307$ for humid types. Similarly, the mode of the nine observations was chosen as the winning humidity classification for that day, with ties in diurnal occurrence of each humidity category being settled in the same way as those with the initial temperature categories. The non-normally distributed nature of TDZ_{iv} in some locations results in slightly more or fewer than 33% of days classified into some humidity categories, however, the inclusion of PCA in the secondary typing

procedure outlined below reduces the importance of this exact threshold (± 0.4307) in the overall classification scheme. When a percentile ranking strategy was examined at the original Ohio-based location to minimize the impacts of this non-normality, the character of some 'extreme' types became less extreme (i.e. dry cool types were warmer and more humid, and humid and warm types were drier and cooler), resulting in poorer variability skill scores (explained below). Although the overall WT frequencies were slightly more equal with this alternate methodology, this benefit was not great enough to warrant the undesirable offset it caused in weather type character.

Multiple permutations of the initial typing procedure were also run without the *a priori* definition of temperature categories when considering the humidity variables. Regular dew point z-scores and dew point depression z-scores, were assessed via trial and error, however, qualitatively, in many locations both of these options resulted in cold and dry weather types dominating in winter and warm and humid types dominating in summer (especially with dew point z-scores not defined within temperature categories) – counterproductive to the goals of the classification. Quantitatively, these alternatives also resulted in poorer variability skill scores (explained below) at most test locations as well. The approach of using within-TCAT dew point z-scores was thus developed, representing a truly multivariate initial classification, rather than the conjoining of two separate univariate classifications.

Days that are classified into a 'middle' category (i.e. they are in the average humidity category and/or the moderate temperature category) are referred to more intuitively as single entities: Average Cool as Cool (C), Average Warm as Warm (W), Humid Moderate as Humid (H), Dry Moderate as Dry (D), and Average Moderate as Seasonal (S) – the last of which represents both humidity and temperature characteristics that are near normal for that location, for that time of year. Days on which neither temperature nor humidity are classified into a 'middle' category are referred to by both qualities, Humid Cool (HC), Humid Warm (HW), Dry Cool (DC) and Dry Warm (DW). These four 'extreme' types (HC, HW, DC, DW) and the five 'middle' types (C, W, H, D, S) together form the nine 'core weather types' of the GWTC (Figure 3).

Figure 3 – The nine core weather types of the GWTC and their representative z-score threshold values of temperature (zTemp) and within temperature category dew point (TDZ) in the initial typing procedure.

3.2.3 – Initial Transitional Typing and Sub-Typing

While ideally each day would fit neatly into one of the nine core weather types, mid-latitude weather is prone to quick changes, especially in conjunction with approaching cyclones. If this change were to happen overnight, between days, the classification may still work well, however, this is not always the case. Thus, on days where the weather is rapidly transitioning, signifying that one weather type is yielding to another, there is a

need for a more appropriate categorization of the surface weather situation that is representative of this change. To accommodate this transitional situation, prior to the initial classification into either a temperature or humidity category, each day is evaluated to determine if it is a transitional day. Previous research has shown that transitional weather on a synoptic scale is characterized by large diurnal dew point and pressure ranges (Sheridan, 2002; Hondula and Davis, 2011), and thus, diurnal ranges of deseasonalized z-scores of each of the 6 variables were also calculated (using the 8-times daily values of each of these six variables). It was desired to maintain the seasonal cycle of the frequency of these transitional sub types (cold front and warm front) because they are named after (and are meant to represent) actual synoptic scale phenomena that are familiar to the climatological community. Thus, this method of determining the ranges was selected over the alternative option of first defining a range of the 8 raw daily values and then subsequently subjecting that range variable to the same deseasonalized z-score standardization processes described above.

Using this calculation of ranges, in the first step of the transitional typing process, transitional days are defined as days on which both the diurnal range of the deseasonalized dew point z-scores (z_{iv} , not TDZ_{iv}) and the pressure z-scores (z_{iv}) were greater than 1.28155. This threshold value was one of many thresholds assessed (originally devised as a representation of the top 10% of the cumulative distribution function when using the alternative method of calculating ranges) and was ultimately

selected due to its proximity to the threshold used for delineating transitions in the SSC (+1.3 standard deviations; Sheridan, 2002). Hondula and Davis (2011) note that transitional situations in the SSC typically occur on about 5-15% of winter days, and thus, it was desired to maintain an average transitional frequency within this range at test locations. Across the domain as a whole, this threshold resulted in an average transitional weather type frequency of 8.3% in the winter, and a 7.1% average frequency year-round.

If a day meets these criteria, it is then evaluated to determine the *nature* of the transition (i.e. it is sub-typed). Previous synoptic research has shown that cold front passages are often accompanied by sharply decreasing dew points and rising pressures, while warm fronts are characterized by increasing dew points and falling pressures as a low pressure system approaches a location (Hondula and Davis, 2011). Thus, a day on which a cold front passes will experience its lowest deseasonalized pressure z-score value of the day (before the front passes) before it experiences its highest deseasonalized pressure z-score value of the day, while concurrently experiencing its lowest TDZ_{iv} of the day (after the front passes) after its highest TDZ_{iv} of the day. The opposite is true for warm fronts. From this logic and based off of the methodology used in Hondula and Davis (2011), days that have been selected as transitions (i.e. that meet the criteria from the paragraph above) and exhibit one of these two trends are then sub-typed either as warm front passage (WFP) days or cold front passage (CFP) days.

This is done by simply finding whether the maximum z_{iv} for each variable (dew point and pressure) occurred before or after the minimum z_{iv} of that same variable on that day.

Since this transitional typing process takes place prior to the classification of a day into a temperature category (and thus, these days do not receive a temperature category designation), it is important to note that the daily values of dew point variables on CFP and WFP days are not included in the calculation of seasonal averages and standard deviations used in the within temperature category dew point z-scores (TDZ_{iv}) equation above when classifying the nine core weather types.

In early prototypes of the classification, transitional days on which pressure and dew point both trended in the same direction (i.e. falling dew points and falling pressures, or rising dew points and rising pressures) were also defined and given their own categories. However, these types were eventually removed from the classification for three reasons: 1) they were extremely rare, occurring less than 0.3% of the time each on average, and not occurring at all in many locations; 2) they appeared to represent different phenomena at different locations, and thus were not distinct ‘spatially universal’ synoptic situations; and 3) they were difficult to conceptualize intuitively as a transitional situation. For these reasons, these days were de-selected as transitions and

treated as 'normal,' going back into the process to be classified into one of the nine core weather types.

Together with the nine core weather types, these two transitional sub-types (CFP and WFP) create a total of 11 weather types for use in the GWTC.

3.2.4 – Secondary Typing

The initial typing procedure described above uses only temperature and humidity (and pressure in the case of CFP and WFP days) to establish the initial weather types.

However, in order to classify more-holistic weather types at each location, other meteorological data need to be incorporated. These data are incorporated into the classification through a secondary typing procedure, utilizing unrotated principal components analysis (PCA) and discriminant function analysis (DFA) in SPSS Statistical Software. Again, through trial and error with dozens of different permutations (with and without PCA, with different variables, with all variables, and with different settings in the DFA), the following methods were ultimately chosen, as they resulted in the best quantitative and qualitative results according to the evaluation metrics discussed in section 3.3 below.

The variables included in the PCA were all 8-times daily deseasonalized z-scores (z_{iv}) for temperature and sea-level pressure, the daily average deseasonalized z-score (z_{iv}) for

temperature, sea level pressure, u-wind, v-wind and cloud cover, the diurnal range of deseasonalized z-scores for all six variables (temperature, dew point, sea-level pressure, u-wind component, v-wind component, and cloud cover), and the 8-times daily and average daily within-temperature category dew point z-scores (TDZ_{iv}). On days that were initially typed as CFP or WFP (transitions), simple deseasonalized dew point z-score values (z_{iv} ; not “within-temperature category”) were substituted in place of the nine within-temperature category deseasonalized dew point z-scores (TDZ_{iv}) in the PCA, as these days do not have temperature categories, and thus TDZ_{iv} cannot be calculated on these days. The impact of this substitution on the classification was examined at a location in the Northern Plains (a region with the most transitional types of any) with an alternative classification strategy (without this substitution), and yielded an 88% daily match to the selected methodology (91% among the nine core WTs), but a poorer variability skill score.

Table 2 – Variables used in the initial and secondary typing procedures. Notes: (1) – used to determine the direction of the diurnal trend of this variable. (2) – used to fill missing TDZ data on days initially typed as CFP or WFP.

Abbr.	Deseasonalized Z-score Variable	Type	Count	Use in Initial Typing (for Core WTs)?	Use in Initial Typing (for TR)?	Use in PCA in Secondary Typing?
T_x	Temperature	8-times daily	8	Yes		Yes
T_avg	Temperature	daily average	1	Yes		Yes
D_x	Dew Point	8-times daily	8		Yes (1)	Yes (2)
D_avg	Dew Point	daily average	1			Yes (2)
TDZ_x	Within Temperature Category Dew Point	8-times daily	8	Yes		Yes
TDZ_avg	Within Temperature Category Dew Point	daily average	1	Yes		Yes
P_x	Sea Level Pressure	8-times daily	8		Yes (1)	Yes
P_avg	Sea Level Pressure	daily average	1			Yes
U_x	U-wind component	8-times daily	8			
U_avg	U-wind component	daily average	1			Yes
V_x	V-wind component	8-times daily	8			
V_avg	V-wind component	daily average	1			Yes
C_x	Cloud Cover	8-times daily	8			
C_avg	Cloud Cover	daily average	1			Yes
T_range	Temperature	diurnal range of z-scores	1			Yes
D_range	Dew Point Temperature	diurnal range of z-scores	1		Yes	Yes
P_range	Sea Level Pressure	diurnal range of z-scores	1		Yes	Yes
U_range	U-wind component	diurnal range of z-scores	1			Yes
V_range	V-wind component	diurnal range of z-scores	1			Yes
C_range	Cloud Cover	diurnal range of z-scores	1			Yes

This set of 36 variables (Table 2) was ultimately selected as it minimized the variability skill score (VSS; described below) for temperature and dew point z-scores at selected test locations in different climatological regions of the domain. All 8-times daily values of temperature, dew point, and sea-level pressure were decided to be paramount to the proper identification of transitional sub-types (as they together would indicate diurnal *trends*), and thus, each of the daily observations of these 3 entities were included in the PCA. Principal components (PCs) with eigenvalues greater than one (suggesting that a

PC accounts for at least as much of the variance in the data as an actual variable it is replacing) were retained as variables for inclusion in the DFA below.

The level to which the partitioning of weather types is dependent upon each of these variables undoubtedly varies throughout the year and varies by location as well.

Because of this, PCA was used here in the classification procedure to better capture the true contribution of each variable to the surface weather situation of a location on a year-round and continent-wide basis, while also eliminating multicollinearity prior to the DFA step of the procedure. Among the locations most representative of each region of the domain (displayed in Figure 4) there were usually 6 to 7 PCs (most often six) that met the above criterion (eigenvalues greater than one), on average accounting for about 83% of the variance of the variables included in the PCA (Table 3). Extraction tables derived from the PCA for these locations reveal that the vast majority of the variance for the 8-times daily observations of the temperature (93% on average, excluding the Great Lakes region), pressure (93%), and within temperature category dew point (88%) variables were accounted for in these PCs, especially the daily averages of these variables (over 98% on average for each). For most locations, cloud cover and wind components are less well-represented.

The next part of this secondary stage of the classification is the use of discriminant function analysis (DFA). A common technique employed in climatological analysis (e.g.

Lee and Sheridan, 2011; Kalkstein et al., 1996), DFA uses a set of rules (or functions) to classify continuous data into predefined categorical groups. The goal of the analysis here is to obtain functions that best partition the data into these groups based upon how each day scores on each PC from the step above. In this manner, DFA here is used as a tool to incorporate all other variables (via PCA) into the classification. In the development of the original SSC, Kalkstein et al. (1996) chose DFA over k-means clustering to run the classification scheme for all days, and over the whole domain. In their research, the grouping of days in the DFA was based upon the parameters of weather-type-defining “seed days” that were manually selected beforehand (i.e. as the grouping variable). Similarly herein, maintaining the integrity of the weather types and the intuitiveness of the classification on a continent-wide basis is paramount, necessitating temperature and humidity (the basis for the weather type names) weighing the heaviest in the classification system. Thus, DFA is utilized in a manner similar to Kalkstein et al. (1996), however, with all days conceptually contributing as pre-defined “seed days” for their representative group.

Table 3 – Retained PCs and percent of variance accounted for by representative location of each region (regional representatives correspond to locations highlighted in Figure 4).

REGION	NAME OF REGION	RETAINED PCs	% VARIANCE
1	Desert SW	6	84.15
2	Southern High Plains	6	83.52
3	Intermontane	7	84.23
4	West Coast	6	83.84
5	Northwest	6	81.70
6	Great Lakes	6	81.42
7	Northeast	7	86.58
8	Southern TX	6	83.90
9	Coastal SE	6	79.53
10	Mid-South	6	83.10
11	Inland SE	6	83.09
12	Northern Plains	6	83.28
13	Heartland	6	83.94

The PCs are incorporated as independent variables into the DFA, with the initial weather type (defined in section 3.2.2 above) representing the dependent (grouping) variable.

The DFA procedure is undertaken in SPSS using the step-wise procedure for the entry of the PCs into (and the removal of the PCs from) the analysis at each step, with the term that minimizes Wilks' Lambda entered at each stage. Wilks' lambda is a ratio between 1 and 0 that quantifies within-type variability across all types for each independent variable (PC) at each step of the analysis, with a value near zero representing minimal within-type variability (Poulsen and French, 2008). Within SPSS, the associated F-

statistic of Wilks' lambda is used in an ANOVA test to determine if each PC is significantly contributing to the discriminant function at each step (Poulsen and French, 2008). Standard threshold values of F were used for significance testing at each stage ($F \geq 3.84$ for entry and $F \leq 2.71$ for removal). The coefficients in the functions were set to be automatically adjusted to assume the same probability of occurrence of each of the initial types (computing these probabilities from the frequencies of each weather type of the grouping variable; SPSS Inc., 2007). The DFA procedure in SPSS also allows for the creation of 11 new variables in the data set (one for each type) that quantify the probability of each day being classified into each type – with the day ultimately being classified as the weather type that has the greatest probability. These probabilities are saved to be used in the spatial smoothing portion of the classification described below.

While temperature and humidity still weigh the heaviest in the classification (as they are, alone, determining the original categories into which all other data will be classified via the DFA), utilizing DFA helps ensure that days that have temperatures and/or humidities that lie very near thresholds of more than one initial weather type will be partitioned into the most representative category based upon the values of the other meteorological variables (such as cloud cover or wind direction) of that day. For example, a fictional July day in Ohio might have an afternoon temperature of 31°C and a dew point of 19°C, and could therefore be considered to belong to either the Warm (W) or Dry Warm (DW) weather types. However, based upon its wind speed being 1.5 m/s

and percentage of total cloud cover being only 10%, it is correctly placed into the DW category, as low values of each of these variables is much more representative of the DW type than the W type.

The use of DFA here, and formatting the DFA in this manner, allows weather types (and their frequencies) to remain mostly dependent upon temperature and humidity characteristics (and thus, be universally understood throughout the year and throughout all locations), while also incorporating key contributing variables other than temperature and humidity that might significantly impact the partitioning of surface weather situations for each individual location at any time of year.

For the 13 regional representative locations (from Table 3 above), on average, about 20% of days initially classified into one of the nine core weather types are classified into a different group at this secondary stage. The majority of these reclassifications are to an 'adjacent' temperature or humidity category (i.e. very few jump two categories for either temperature and/or humidity, and few jump both one temperature category and one humidity category). Although much less frequent overall, days initially classified as CFP or WFP see higher reclassification percentages at this step as well, especially in regions not commonly subjected to frontal passages (i.e. the California coast and the Desert SW).

3.2.5 – Spatial Smoothing Component and Final Typing

Until this point in the classification procedure, the aforementioned steps have all been undertaken for a single location (grid point) at a time – with no consideration of the daily meteorological conditions or the general climatology of any neighboring locations. However, it is well-known that the weather/climate of a location is highly correlated to that of its immediate surrounding locations. Especially for a classification that aims to define synoptic weather types across a broad area, it is logical that some sort of a spatial sharing of information be integrated into the scheme. To incorporate this spatial relationship, the redeveloped SSC (Sheridan, 2002) used a “roadmap” to transfer actual seed days between neighboring stations. While this novel concept officially integrated a spatial element into the SSC, it also served to dramatically enhance the cohesiveness of the classification, improving the spatial match percentages between neighboring stations.

A gridded domain provides an intrinsic spatial structure that can be utilized to enhance the present GWTC. With this in mind, rules were developed to incorporate the classification of all adjacent locations (most locations have eight adjacent stations, marine/coastal locations have fewer, with the tip of the Florida Keys only having one) into the final classification of each day at a location of interest. Thus, after the preceding steps were completed for the entire spatial domain, this spatial smoothing component

of the scheme is then undertaken, reclassifying a day at a location if all three of the following criteria are met:

1. A majority (at least 51%) of the immediately adjacent locations are classified into a different weather type than the classification at the location of interest, AND
 - the constituents of this majority (the locations belonging to the $\geq 51\%$) must be classified into the same weather type amongst themselves.
2. The weather type representing the majority amongst the adjacent stations has the second highest probability at the station of interest (computed from the DFA results that saved the probability of group membership into each group).
3. The probability (percent chance) of the day being classified into this “second place” weather type at the station of interest is within (i.e. less than or equal to) 0.25 (i.e. 25 percentage points) of the winning classification.

If only two (or fewer) of these criteria are met, then the classification does not change (see example in Table 4). These criteria were developed to reclassify days that were near the threshold (of temperature or humidity, for example) of being classified into two or more types, but compared to adjacent stations, were just on the ‘other side’ of that threshold in multivariate space. They were also developed to prevent an improper *reclassification* of a day at a location where there is a distinct weather type that is present only at that location and not in the immediately surrounding locations (third

rule). This situation would most likely occur in neighboring locations within mountainous terrain.

Overall, this reclassification step resulted in “smoother” daily maps qualitatively, with fewer outlier locations and more easily identifiable regions of air masses. Quantitatively, this spatial smoothing component improved spatial cohesion – both overall and on a daily basis (discussed in Chapter 7). Generally the greatest reclassification percentages are found in the varying topography of the western US. The average reclassification percentages are listed in Table 5.

Table 4 – Theoretical example of how spatial smoothing criteria would work to change a day’s secondary weather type classification. Note: bottom table is a continuation of the top table (to the right).

Date	% probability of WT occurrence (via DFA) at location of interest											SECONDARY TYPE
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP	
3/27/1981	0%	0%	5%	0%	0%	45%	0%	0%	50%	0%	0%	DW
9/15/1996	0%	0%	0%	11%	0%	0%	89%	0%	0%	0%	0%	DC
2/21/2002	0%	9%	25%	1%	21%	22%	0%	0%	5%	0%	17%	HW

Date	Secondary types at adjacent locations								Criteria 1 met?	Criteria 2 met?	Criteria 3 met?	Final Type
	Location1	Location2	Location3	Location4	Location5	Location6	Location7	Location8				
3/27/1981	DW	D	D	W	W	W	W	W	Y	Y	Y	W
9/15/1996	C	C	C	C	C	C	C	C	Y	Y	N	DC
2/21/2002	H	HW	S	W	HW	S	W	W	N	Y	Y	HW

Table 5 – Average reclassification percentage (by season and all locations within each region) between secondary typing and spatial smoothing steps. Region numbers correspond to those in Figure 4 below.

REGION	WINTER	SPRING	SUMMER	FALL	ANNUAL
1	8.7%	8.1%	8.8%	8.3%	8.5%
2	7.8%	7.7%	9.3%	7.7%	8.1%
3	7.7%	8.8%	9.3%	8.5%	8.6%
4	7.5%	7.7%	7.7%	8.0%	7.7%
5	7.1%	8.1%	8.7%	8.1%	8.0%
6	6.2%	6.3%	6.3%	6.5%	6.3%
7	5.6%	5.4%	5.6%	5.6%	5.5%
8	6.2%	7.6%	9.7%	6.9%	7.6%
9	6.0%	6.3%	7.1%	6.5%	6.5%
10	5.3%	5.3%	6.4%	5.6%	5.7%
11	5.0%	5.3%	8.1%	5.5%	6.0%
12	6.3%	6.3%	6.6%	6.1%	6.3%
13	5.9%	5.8%	7.0%	6.0%	6.2%
DOMAIN	6.6%	6.8%	7.8%	6.9%	7.0%

3.3 – Evaluation Metrics

As with any synoptic classification, the goal is to produce a classification that is effective at partitioning the climate into meaningful and representative categories that wholly encompass the domain of variability of the climate that is being classified. How to determine if a classification is ‘effective,’ however, is difficult. While ultimately the *utility* of the GWTC will be measured based upon its ability to partition out the application of interest (e.g. spike days in ozone levels, high mortality days, precipitation

events, etc.) with repeated usage over the long term, measures for examining its *effectiveness* in the short-term are necessary to determine if the methodology partitions representative categories of surface weather situations, and therefore, whether or not future use is justified. To this end, four metrics were used during the development process to continually assess and hone the classification. Due to the sheer number of statistics that were produced for each evolution of the GWTC, however, quantitative results demonstrating the effectiveness of the classification are provided below only for the finished product described by the final methodology outlined above.

One measure for assessing the GWTC during the development process were simple **comparisons to existing classifications** – mainly the SSC. The average monthly weather type frequency, temperature, dew point and other variables were quantitatively compared with those of similar SSC weather types at grid points near selected SSC stations.

One of the inherent assumptions of synoptic climatology is that the dynamic atmosphere can be successfully partitioned into static states that typify a day at a location and across a region (Yarnal, 1993). The constantly evolving atmosphere, however, is not static, and therefore some measure of the temporal and spatial consistency of weather types is important in regards to the success of any classification. As mentioned in the background section above, spatial consistency was one of the

primary concerns of other point-based, broad-scale WTCs. One of the main benefits of Sheridan's (2002) redevelopment of the SSC and of the adjusted TSI (the spatial synoptic index) outlined by Davis and Kalkstein (1990) was improving the matches of weather types between adjacent stations. If scattering of differing weather types across a small spatial area occurs (which is not uncommon especially along frontal boundaries), the enhanced spatial resolution of the GWTC in comparison to these previous WTCs could magnify this disconnect. Therefore, an important aspect of the assessment was the examination the consistency of the weather types from place to place and day to day.

Spatial consistency was evaluated using **spatial match percentages** to examine what percentage of the days were classified as the same weather type on the same day for a 'grid point (location) of interest' and the corresponding set of adjacent grid points (up to 8). While match percentages in the 60-70% range are not uncommon in the SSC (Sheridan, 2002), these statistics are expected to differ substantially by location, weather type and season. Match percentages can also be compared with those obtained in the redevelopment of the SSC (Sheridan, 2002). Temporal consistency can be assessed in a similar manner, through looking at **persistence percentages** from one day to the next, again by weather type, location and season. However, for both spatial and temporal consistency assessments, it is important to note that a certain degree of inconsistency is necessary and expected in both dimensions, as one would not expect the same weather type to occur across the entire spatial domain on a particular day.

Similarly, mid-latitude climates are prone to quick changes in weather, and transitions to differing weather types on consecutive days will undoubtedly keep temporal persistence percentages reasonably low.

3.3.1 – Development of the Variability Skill Score (VSS)

At its fundamental core, the goal of every synoptic classification is to both minimize within-type variability while also maximizing between-type variability (Yarnal, 1993).

Kalkstein et al. (1987) introduced a method to calculate both types of variability specifically with an application for a WTC, though never expanded this into a single intuitive score that could be compared easily among various methods. Thus, an important part of the research was the development of a **variability skill score** (VSS; based off those first introduced by Kalkstein et al., 1987) that quantifies the ability of the classification to characterize distinct weather types.

The VSS is simply a ratio of the within-type variability calculation (the standard deviation of a variable within each weather type, averaged over all weather types; ideally minimized) over the between-type variability calculation (represented by the standard deviation of the means of a variable among the 11 weather types; ideally maximized) that were developed by Kalkstein et al. (1987). This unit-less score is calculated using the 48 deseasonalized z-score variables (z_{iv} above – shortened simply to v in the equation below; for the 6 original variables, each at 8-times daily resolution):

$$VSS_v = \frac{\sum_{K=1}^K (S_{kv}) / K}{\sqrt{\sum_{K=1}^K (\overline{X_{kv}} - \overline{X_v})^2 / (K - 1)}}$$

where the VSS_v is the variability skill score for deseasonalized z-score variable v , K is the number of weather types ($K=11$), S_{kv} is the standard deviation of variable v within type k , $\overline{X_{kv}}$ is the mean of variable v in type k , and $\overline{X_v}$ is the grand mean for variable v (usually very close to zero, because they are z-scores). For humidity, dew point z-scores (z_{iv}) are used in the calculation of VSS rather than within temperature category dew point z- scores (TDZ_{iv}).

Theoretically, the “ideal” classification would be one in which the ratio was equal to zero – indicating that there is no within-type variability, though in a practical sense, this is virtually impossible. Within a single classification the VSS gives an accurate portrayal of the partitioning of the deseasonalized variables. However, for comparisons of the GWTC to other classifications the VSS would have to be modified to consider the number of types, as the VSS is sensitive to this, generally improving (decreasing in value) with additional types. Throughout the initial and secondary typing procedures described in section 3.2 above, the averaged VSS for temperature and dew point were used as a metric for judging whether individual adjustments to the methodology yielded improved results. These were analyzed at selected locations within different climate zones (based

upon the SSC as defined in: <http://sheridan.geog.kent.edu/ssc/clusters/clusters.jpg>) throughout the domain.

These VSSs can be averaged for all 48 variables to get a VSS for each station, and these (2,070) station VSSs can be averaged to get a VSS for the entire classification. A VSS can also be computed on a seasonal basis, and various representations of VSSs are presented in the results below.

CHAPTER 4

REGIONALIZATION

In addition to weather typing, of the more common perspectives among synoptic climatologists undertaking a classification is that of regionalization – a delineation of spatial boundaries demarcating sections (regions) of geographic space representing cohesive units of climatological similarity (Yarnal, 1993). Regionalization is undertaken for a variety of reasons, with one of the most common simply being the delineation and description of climate regions based upon one or more variables (Bonnell and Sumner 1992; Comrie and Glenn, 1998). While the primary aim of this research is the development of the GWTC, the sheer magnitude of locations, variables, weather types, seasons, etc. classified would present an unwieldy amount of statistics. Thus, in order to present results and analyze the effectiveness of the classification more intuitively, a post-weather typing regionalization was also undertaken in the present research, utilizing the results of the classification itself. Regionalization was employed using an R-mode approach, with each row in the data set representing one of the 2,070 grid point locations (to be categorized), and each column representing the average percent frequency of each weather type in each month (11 weather types by 12 months,

yielding 132 columns) at each grid point. This type of an automated regionalization, based solely upon the frequencies of weather types, was also used to create climatological regions based upon the SSC (<http://sheridan.geog.kent.edu/ssc/clusters/clusters.jpg>; Sheridan, personal correspondence).

A commonly used two-part procedure for classification within the synoptic literature base was employed to classify each station into one of several discrete regions. First, unrotated principal components analysis with the correlation matrix was used to both reduce the data set and remove multicollinearity from the 132 variables. Principal components with eigenvalues greater than one were retained in the PCA, reducing the 132 columns to 19 principal components (PCs) that explain 82.9% of the variance in the original data set. These retained PCs were then subjected to the TwoStep Clustering Component in SPSS (SPSS Inc., 2001), which was set to determine the appropriate number of clusters (regions) automatically. The distance measure was set to use log-likelihood to measure the (dis)similarity between the regions, and Schwarz's Bayesian Criterion was used as the model to automatically determine the appropriate number of clusters. Using just the average monthly percent frequency of weather types at the 2,070 locations, 13 cohesive spatial climatological regions (Figure 4) resulted.

Within each region, selected locations are used to analyze the results of the GWTC classification scheme in the sections that follow. The aim was to select a single location within each region that was most representative of that region. Thus, for each region, these locations were determined by first calculating the sum of the squared differences between the average score within the region of each of the 19 retained PCs, and the corresponding score of each PC for each location that was classified into each region. The location within each region that had the lowest sum of squared differences was determined to be the location most representative of that region (Figure 4). In addition to specific representative locations, averages of all of the locations contained within a region are also used to express these results in the chapters that follow.

Figure 4 – The 13 US regions created from regionalization step, with the representative locations marked for each region (white dots).

CHAPTER 5

REGIONAL WEATHER TYPE CHARACTER

The following sub-sections of Chapter 5 outline the mid-season (e.g., July represents mid-summer) character of some of the more dominant weather types at the regional representative location for each region (Figure 4). The lone exception to this is in section 5.7 on the Northeast Region – which has an additional discussion on the weather type character of the first testing location used in honing the classification procedure near Cleveland, OH and Kent State University. Overall, these individual locations were thought to be more illustrative of weather type character than reporting the average of a meteorological variable across all locations within a region (especially in regions with varying topography), and are thus discussed here. However, region-wide monthly averages of each variable for each weather type are available in Appendix A. In addition to the means presented in this chapter and Appendix A, scatter plots of January and July afternoon temperature and dew point by weather type for each of the regional

representative locations are presented in Appendix D, highlighting the variability that can exist in the classification. Section 5.14 presents a brief discussion on the regional WT character. This regional approach is followed with the presentation of the weather type frequency climatology for the entire continental US (Chapter 6), and finally a presentation of the diagnostic statistics evaluating the performance of the classification (Chapter 7).

In order to avoid confusion when discussing the weather types (WTs) in the chapters that follow, when referring to the Dry (D) weather type it (the word “dry”) will be capitalized, while when talking about the three dry weather types collectively (DW, D and DC), it will not be capitalized. This convention will also be used when discussing the Humid (H) type vs. the collective humid types (HW, H and HC); the Warm (W) type vs. the collective warm types (DW, W and HW); and the Cool (C) type versus the collective cool types (DC, C and HC). Rarely, the collective moderate temperature types (D, S and H), or the collective average humidity types (C, S, and W) are also referenced. The CFP and WFP types are often referred to collectively as transition(al) weather types.

5.1 – Desert Southwest

Located about 75km west of Phoenix, AZ, the regional representative of the Desert Southwest (latitude/longitude: 33.63404, -112.92046) experiences high temperatures

and very dry conditions with all July WTs, with average temperatures ranging from 35°C to 42°C among the weather types (Figure 6). All three warm types break the 40°C mark for average temperature and no WT has a dew point greater than 16°C (HC). Pressure, wind speed, wind direction and cloud cover are all quite similar in summer. Though still comparatively warm considering other regions, winter does usher in a greater range of many weather conditions. Temperatures and dew points are still quite invariant between types; however, January wind directions and cloud cover do dictate quite different conditions depending on type. The three dry types are accompanied by north to northeasterly winds and sparse cloud cover, while humid types on average experience south to southwesterly winds and more cloudiness.

HC	HUMID	HW
COLD	SEASONAL	WARM
DC	DRY	DW
	CFP	WFP

Figure 5 – GWTC weather type legend to be used for Figures 6-19 in Chapter 4.

Figure 6 – Mean monthly conditions for the regional representative of the Desert Southwest region within each weather type for the afternoon (specifically, the fifth observation; see Table 1 for exact time of day) for temperature (TEMP, °C, top left), dew point (DWPT, °C, top middle), pressure (P, mb, top right), wind speed (Wspd, m/s, bottom left), wind direction (Wdir, 16 directions, bottom middle), and cloud cover (CC, %, bottom right) used in the classification (see Figure 5 for WT legend).

Figure 7 – Mean monthly conditions for the regional representative of the Southern High Plains region within each weather type for the afternoon observation (specifically, the fifth observation; see Table 1 for; see Figure 5 for WT legend).

Figure 8 – Mean monthly conditions for the regional representative of the Intermontane region within each weather type for the afternoon observation (specifically, the fifth observation; see Table 1 for; see Figure 5 for WT legend).

Figure 9 – Mean monthly conditions for the regional representative of the West Coast region within each weather type for the afternoon observation (specifically, the fifth observation; see Table 1 for; see Figure 5 for WT legend).

Figure 10 – Mean monthly conditions for the regional representative of the Northwest region within each weather type for the afternoon observation (specifically, the fifth observation; see Table 1 for; see Figure 5 for WT legend).

Figure 11 – Mean monthly conditions for the regional representative of the Great Lakes region within each weather type for the afternoon observation (specifically, the fifth observation; see Table 1 for; see Figure 5 for WT legend).

Figure 12 – Mean monthly conditions for the regional representative of the Northeast region within each weather type for the afternoon observation (specifically, the fifth observation; see Table 1 for; see Figure 5 for WT legend).

Figure 13 – Mean monthly conditions for the original Ohio location used for testing (at 40.62128, -82.85197) within each weather type for the afternoon observation (specifically, the fifth observation; see Table 1 for; see Figure 5 for WT legend).

Figure 14 – Mean monthly conditions for the regional representative of the Southern Texas region within each weather type for the afternoon observation (specifically, the fifth observation; see Table 1 for; see Figure 5 for WT legend).

Figure 15 – Mean monthly conditions for the regional representative of the Coastal Southeast region within each weather type for the afternoon observation (specifically, the fifth observation; see Table 1 for; see Figure 5 for WT legend).

Figure 16 – Mean monthly conditions for the regional representative of the Mid-South region within each weather type for the afternoon observation (specifically, the fifth observation; see Table 1 for; see Figure 5 for WT legend).

Figure 17 – Mean monthly conditions for the regional representative of the Inland Southeast region within each weather type for the afternoon observation (specifically, the fifth observation; see Table 1 for; see Figure 5 for WT legend).

Figure 18 – Mean monthly conditions for the regional representative of the Northern Plains region within each weather type for the afternoon observation (specifically, the fifth observation; see Table 1 for; see Figure 5 for WT legend).

Figure 19 – Mean monthly conditions for the regional representative of the Heartland region within each weather type for the afternoon observation (specifically, the fifth observation; see Table 1 for; see Figure 5 for WT legend).

5.2 – Southern High Plains

The representative location of this region is situated along the New Mexico and Texas border (34.29223, -102.73529), about 125km southwest of Amarillo, TX, and experiences quite a bit of seasonal change by comparison to the Desert SW. Winter is the most variable season, as average afternoon WT temperatures can range from 17°C with DW, to 1°C with DC (Figure 7). Along with DC, comes high pressure and relatively calm NNW winds. Generally wind speeds increase with temperature and become more southerly and westerly, as DW ushers in the windiest weather. By comparison, summer conditions are more consistent, with temperatures only ranging 7°C between the cool types (all about 30°C) and the warm types (36-37°C). Summer also averages the strongest winds and sunniest weather of any season, with average cloudiness reaching above 30% only on HC days.

5.3 – Intermontane

The impact of topographic variability on WT character is quite noticeable when examining the representative location for the Intermontane region (41.20720, -109.88332) with the regional averages exhibited in Appendix A. At about 2100m in elevation, this remote location in extreme southwestern Wyoming has mild temperatures, with average July temperatures ranging from 22°C (DC) to 30°C (DW), and January temperatures ranging from -11°C (DC) to 1°C with the warm types (Figure 8). The transitional seasons, on the other hand, experience quite a bit more variability in

temperatures, with average temperatures ranging 15°C and 14°C in April and October, respectively. Dew points, however, are much more variable, not appearing to be as well partitioned as temperatures in these seasons, and as shown below, have a poor VSS for dew point. While average wind direction has a westerly component for every type in every season, slightly more southerly winds do correspond to the warmer types nearly year-round.

5.4 – West Coast

The regional representative of the West Coast region is (38.86364, -122.39891) located about 75km northwest of Sacramento, CA in remote, mountainous terrain, but only at an elevation of about 700m. This whole region is also quite topographically diverse, though WT frequencies at the regional representative location do not differ dramatically from the regional averages. Winters are very mild, with no average temperature of any WT reaching below 8°C (Figure 9). January humid types experience low pressure, SE winds and very cloudy conditions; conversely, all dry types receive winds from the NW, are under higher pressure, and overall are much less cloudy. Julys have high temperatures and are dry with average temperatures ranging from 26°C (C) to 35°C (all warm types) and dew points never topping 11°C (with the humid types). Summer is also dominated by southerly winds, often with a slight eastern component, and nearly cloudless skies for all core WTs.

5.5 – Northwest

The regional representative of the Northwest (44.12963, -105.18375) is located in northeastern Wyoming, situated east of the Rocky Mountains at over 1300m in elevation. This location experiences much more of a continental climate than its regional counterparts in coastal Washington and Oregon. Winters are typified by widely ranging conditions, from DC with -15°C temperatures, -19°C dew points, high pressure, calm winds and relatively cloudless skies; to HW with 4°C temperatures and -2°C dew points, low pressure and stronger winds (Figure 10). Surprisingly, only CFP types are accompanied by a northerly wind component in January at this location. Summers also have widely varying temperatures, ranging from 22°C (DC) to 33°C (DW), though overall it is quite dry (average dew points range from 2°C to 10°C) and cloudless. Wind direction appears to play a major role in dictating July weather types at this location, as warm types are associated with southerly winds, dry types with westerly winds, humid types with easterly wind components, and cool types with more northerly wind components.

5.6 – Great Lakes

For part of the winter at least, some of the lakes are partially frozen over (acting more like land), impacting the seasonal character of the weather types. Located on Lake Michigan, about 80km east of Green Bay, WI, the regional representative of the Great Lakes (44.57278, -86.97681) experiences cold winters but fairly mild summers. Average January temperatures and dew points range 14°C and 16°C respectively (Figure 11), with

DC having the lowest temperatures (-12°C) and HW ushering in the highest temperatures (2°C). All winter weather types are associated with high amounts of cloud cover. Wind speeds are greatest with the CFP type, and least with DW. July conditions are very mild and much less variable, with average WT temperatures ranging from 16°C (DC) to 25°C (HW). HW days are accompanied by 21°C dew points, and wind speeds greater than all but the WFP type. The most frequently occurring type in July, HC, is also the cloudiest, ushering in chilly and humid weather (18°C temperatures and 16°C dew points) for the middle of summer.

5.7 – Northeast

The regional representative of the Northeast (43.16655, -76.55479) is located about 40km northwest of Syracuse NY, just off the shore of Lake Ontario. Winters are cold and variable with the lowest temperatures on average accompanying DC (-13°C ; Figure 12). This type also is associated with the highest pressures and lowest cloud cover of any type in January, though it is still fairly cloudy (72% on average). Westerly wind components play a large role in bringing in cool and average (humidity) weather, with southerly wind components playing a more dominant role in bringing about warm WTs and WFP. At this latitude and this proximity to the lake, summers are still relatively mild in comparison to the other location discussed in this region discussed below. HW brings about the warmest July weather (30°C), while DC again brings in the lowest

temperatures (20°C) of the month – the former ushered in via NW winds, the latter via SW – representing the top two windiest core WTs.

The original station used for testing different classification permutations is located (at 40.62128, -82.85197) about 150km southwest of Cleveland, OH. Although similar to the regional representative of the Northeast region above, this location does have a bit more variability due to its location relative to the Great Lakes (Figure 13). January temperatures range over 21°C, from -12°C with the DC type to 9°C with the HW type, and dew points are also highly variable, ranging from -16°C to 7°C respectively. At this location, DC can bring about pressures 4mb higher, winds that are 1.0 m/s faster, and cloud cover that is dramatically lower (45% vs. 72%) in comparison to the regional representative near Syracuse. Summers tend to be warmer than the NY location discussed above. Notably, the DW type ushers in the warmest weather here (as opposed to HW in the NY location), with average temperatures around 32°C and dew points of 17°C, nearly 4°C higher and 3°C drier than DW in the regional representative location.

5.8 – Southern Texas

Less than 5° of latitude away from the tropics, located about 150km south of San Antonio, TX (27.87932, -98.80473), the regional representative of Southern Texas unsurprisingly is warm year-round. January temperatures range from 11°C with the Dry

Cool type all the way up to 27°C with HW. This area, however, is still dominated by winter dryness, as dew points only reach above 15°C with HW – still representing a 12°C dew point depression (Figure 14). The cool types are often ushered in via mild northeasterly winds, while warmth and dryness come from a southerly and/or westerly direction. July is also relatively warm and dry, with no average WT temperatures falling below 32°C (DC) and no dew points above 22°C (HC). DW features the highest temperatures, reaching 40°C on average. While cloud cover appears to be quite well partitioned among different WTs (ranging from 16% with DW to 52% with HC and CFP), July winds are not, appearing to always originate from the Southeastern quadrant. July is also quite windy, with no average wind speed less than 3.4 m/s (in the infrequent DC type), and the H type bringing wind speeds of 6.0 m/s.

5.9 – Coastal Southeast (SE)

Located only about 20 kilometers south of Tampa Bay, near Bradenton, FL, the regional representative location for the Coastal SE (27.46239, -82.47976) has little variability between summer WTs (Figure 15). Likely due to the oppressive humidity (no average dew points fall below 21°C), average July temperatures only range 4°C between the type with the lowest (DC at 29°C) and the highest (HW at 33°C) temperatures. Average pressure, wind direction and cloud cover all appear poorly partitioned as well; however, wind speed does appear to decrease with increased temperatures and/or humidity. Winter does exhibit greater between-type variability of temperature and humidity,

however. January temperatures range from 13°C (DC) to 26°C (HW) and dew points range nearly 17°C across types, from 3°C (DC) to 20°C (HW). These two types also represent the extremes of pressure. Average January cloud cover tends to increase with humidity within each temperature category, and wind speed can vary from 4.6 m/s (CFP) to 0.8 m/s (H).

5.10 – Mid-South

The regional representative of the Mid-South is located about 30km southwest of Blacksburg, VA (36.96562, -80.60083) in the Appalachian Mountains at about 840m in elevation. Due to its elevation, the character of the types here is different than at locations at lower elevations within the region. This said, due to its latitude, average WT temperatures in January are still mild, ranging from -7°C with the DC type to 13°C with HW (Figure 16). DC weather is likely due to high pressure (1027mb), low cloud cover (28%), and strong northwesterly winds. Conversely, HW is associated with the lowest pressure of any type, winds from the SSW, and cloud cover that is nearly double that of the DC type. At this location, July is much less variable, with mild temperatures in all WTs and HW having the highest average temperature of any type at only 29°C. However, region-wide averages (Appendix A) indicate that average afternoon July temperatures and dew points are about 3°C higher than this – indicating that quite a bit of heat and humidity are present throughout most of the region.

5.11 – Inland Southeast (SE)

Representing the Inland SE region is a location right along the Georgia and South Carolina border (at 33.94784, -82.64610), about 175km east of Atlanta, GA. In comparison to the Coastal SE region, without locations right along the coast, a slightly decreased marine influence here allows temperatures to be a bit more extreme (Figure 17). Average winter temperatures range from 2°C with the DC type to 19°C with the HW type. Dew points are also highly ranging, from -10°C (DC) to 14°C (HW). The three cool types are brought about by winds with a northerly input, while southerly components of the wind are associated mostly with warm types. January cloud cover is also variable in the Inland SE, with dry types only being about half as cloudy as the humid types. Summer is oppressively hot and humid. All three warm types have average Julys that are over 34°C (with DW reaching 35°C), with average dew points above 20°C in all but the dry WTs (and CFP). Cooler summer weather often is the result of clouds preventing insolation from reaching the ground; evident from the 71% average cloud cover of the HC type causing temperatures 5°C lower than its HW counterpart. At this location, HC has 7% greater frequency than the HW type.

5.12 – Northern Plains

About 50km south of Bemidji, MN, the regional representative of the Northern Plains (46.95910, -94.77746) lies on flat land right in the middle of the region. Latitude and continentality of the location lead to extremes in all seasons. January weather here is

the coldest and driest of any region, with DC averaging -21°C temperatures and dew points of -25°C (Figure 18). These conditions are the result of relatively cloudless conditions (31%) due to high pressure (1031mb), and are accompanied by strong WNW winds (3.6 m/s). The only January WT to break the freezing point on average is the HW type (0°C and -2°C dew point). Julys are less extreme, and somewhat mild due to the latitude. Summer DC typically occurs with afternoon temperatures of about 20°C , while HW brings in the highest temperatures on average, at about 31°C . Unsurprisingly warmer and more humid types are advected from a southerly direction, with cloud cover closely negatively-related to dew point depression (53% with HC and 18% with DW).

5.13 – Heartland

The regional representative of the Heartland is located about 80km southeast of Lincoln, NE (at 40.08104, -96.24637) and in the middle of the region. Much like the Northern Plains (but warmer overall) the Heartland exhibits a large annual temperature range with DC in January averaging -13°C , while DW in July averages 38°C (Figure 19). The highest average January temperature is with HW (9°C), which accompanies the lowest average pressure of any January type in the region (1010mb) and one of the two cloudiest. In addition to July DW, overall the summer has quite high temperatures, with all but the cool types (and CFP) having average afternoon temperatures of at least 32°C , and all warm types at least 35°C . This region is also susceptible to both dry and humid

summer weather, with dew points ranging from 13°C (DC) to 22°C (H and HW) and dew point depressions ranging from 7°C (HC) to 24°C (DW). The warm WTs are often accompanied by relatively strong winds (above 3.2 m/s for all warm types) arriving from a southern trajectory.

5.14 – Discussion of Regional Results

The classification is effective in each region at partitioning out the correct temperature and humidity conditions associated with its respective weather type (i.e. DW, for example, is indeed dry and warm relative to the other WTs in each region). The degree to which these two variables are partitioned among weather types differs by region and season, as higher-latitude locations with more variable weather experience much more variability in the average temperature and humidity of the WTs than what is exhibited in the southern regions. However, even the southern regions do show a greater range in average conditions among weather types outside of the summer (especially in winter). As one of the major goals of the classification is to have a more equal frequency of each WT in each season for all locations, it was expected that weather type character would be better defined in the higher latitudes and the colder seasons.

While temperature and humidity were well partitioned among WTs everywhere, effective partitioning of other meteorological variables was predictably more limited. Pressure was usually fairly well partitioned, especially in winter and in the more

northerly locations. For example, DC types were often associated with the highest average pressures in the winter, while HW types were often the lowest, with the range being quite large (e.g. in the Northeast, Heartland, Northern Plains). This trend usually held throughout the other seasons as well, but was greatest in winter. Cloud cover, wind speed and wind direction were more poorly partitioned, though many associations of these variables to their respective WTs were logical (e.g. more northerly components to the wind for colder types, more southerly for warmer types) especially in the northerly locations. Also, as expected in the southern latitudes, high cloud cover often resulted in cooler conditions in summer, as the only relief from the usual heat is above-normal cloudiness blocking incoming solar radiation.

As is also noticed in the weather type frequency climatology maps below, weather type character was influenced by topography and continentality. High topography resulted in some regional representative locations having temperature and dew point averages that differed substantially from the region-wide averages (in Appendix A), as lower temperatures and dryer conditions often prevailed (Intermontane and Mid-South). As expected, continentality also played a role in defining the range of weather type averages in each region, as the coastal locations and regions experience less variability between weather type averages, while land-locked areas had a more extreme character to their DC and HW types especially. This is quite apparent when contrasting the two

Northeast region locations (discussed in 5.7 above) – one being close to the Great Lakes, and the other being 150km away.

Overall, these weather type character results provide evidence that the classification is actually doing what it is supposed to be doing – a major assumption of synoptic climatological classifications (Yarnal, 1993).

CHAPTER 6

WEATHER TYPE FREQUENCY CLIMATOLOGY

The seasonal frequency climatology of each of the 11 weather types is presented in the subsections of this chapter (Figures 20-25). All maps in Chapters 6 and 7 are made using IDW interpolation in ArcGIS 10. Tables of the region-by-region average monthly frequency of each weather type are presented in Appendix B, along with the weather type climatology maps for all months (including those not explicitly discussed below) in Appendix C.

6.1 – Humid Cool (HC)

Across the US as a whole, the HC type occurs most often in the summer months, especially in the Inland Southeast US (Figure 20), where relatively cool weather can be due to abnormally cloudy conditions (blocking incoming solar radiation) associated with above average dew points – especially where temperatures vary minimally between types. At most other times of year, this type is most often seen in the West Coast region, especially along the coast of Southern California – where it occurs 15% of the

time in January. This frequency is unsurprising considering the Mediterranean climate of the area ushers in the greatest precipitation in the winter months as the offshore subtropical high shifts south of the US, diverting Pacific cyclonic systems onto the California coast. In the West Coast region as a whole, this type averages at least a 10.1% frequency in every month, the only region in which this type's minimum monthly frequency is above 8.2%.

6.2 – Humid (H)

The Humid weather type represents above average humidity with near average temperatures. This type occurs most frequently in the summer months, with July frequencies reaching into the 18-20% range for much of the Inland Southeastern US, the Mid-South, and the Heartland (Figure 20) – areas subjected to summer moisture advected from the Gulf of Mexico and regularly experiencing high dew points in the summer. A secondary area of H-type frequency occurs in the Four Corners area (about 18% frequency). Southern Texas experiences the H-type most often just outside of the peak of summer, and stands out as a preferred location of this WT in April, along with the Upper Great Lakes. In winter, the Humid type occurs most often in the western and southwestern United States where it occurs on 14% of January days, with the exception of the Central Valley in California – which noticeably stands out at only a 10% average January H-type frequency – highlighting the sensitivity of the classification to topography at a relatively fine spatial resolution.

6.3 – Humid Warm (HW)

The HW weather type maintains a marked presence throughout the year, though with different geographic preferences in different seasons. January HW is near-equally frequent throughout the domain with the exception of areas south and west of the Great Lakes (where it occurs about 6% of the time on average), and spotty frequency in certain areas west of the Rocky Mountains (Figure 21). The locus of HW migrates south and east in the transition seasons (spring and autumn) with portions of the Inland Southeast and Southern Texas each featuring HW about 13-16% of the time in these months. The western portions of the Northeast and Mid-South regions are the geographic preference for summer HW, with most of Texas and Oklahoma experiencing noticeably fewer HW days than surrounding regions (about 6% in July) – indicating the preference for dry air rather than humid air accompanying higher temperatures at this time of year. This weather type maintains at least an 11% monthly frequency throughout the year in the Coastal SE region – indicative of the region’s near-tropical climate.

6.4 – Cool (C)

The Cool type represents relatively average seasonal humidity accompanying below average seasonal temperatures for a location. The C type is least common in summer,

with a preference for areas along the Pacific coast and Great Lakes in all seasons, and a noticeable dearth in the southern half of the country (Figure 21). The Cool type occurs most often in the transitional seasons, with the Northeastern US experiencing this type over 15% of the time on average in October. This may likely result from large ranges in humidity accompanying cooler weather in these seasons in the Northeastern US. These ranges would cause high standard deviations in the z-score calculation, forcing a day to be quite anomalous (dry or humid) to fall outside of the “average” humidity category. Cool types also frequent the Mississippi and Ohio River Valleys in April, occurring about 15% of the time on average across those areas. In January, this type occurs most frequently in the southeastern US (about 14% of the time) and the Central Valley of California (where it can occur up to 16% of the time), though only two regions experience this type less than 10% of the time in January – the Desert Southwest (9.8%) and Northwest (9.9%) regions.

6.5 – Seasonal (S)

The Seasonal WT represents the seasonal average conditions for a particular location in both temperature and humidity – and holistically in other meteorological variables as well. Due to this, it is unsurprising that the S-type maintains ample frequency in most seasons, especially in summer in areas that are not subjected to a lot of climatic variability. Most of the southern US including Southern Texas, the Southern High Plains and the Coastal SE regions maintain an average July frequency of 16-18% for the

seasonal weather type (Figure 22), with coastal Southern California experiencing the Seasonal type on up to 23% of July days. January S-type activity focuses on the Mid-South region and spotty portions of the western half of the United States, where the Seasonal type occurs about 17% and 14% of the time, respectively. April S-type preference is in the Northern Plains and Desert Southwest, while in October, the locus of S-type occurrence is in the Southern High Plains. The Great Lakes region experiences quite a few S-type days in both April and October, while coastal California experiences the Seasonal WT quite frequently year-round.

Figure 20 – Monthly percent frequency of the HC and H weather types for the middle month of each meteorological season.

Figure 21 – Monthly percent frequency of the HW and C weather types for the middle month of each meteorological season.

Figure 22 – Monthly percent frequency of the S and W weather types for the middle month of each meteorological season.

Figure 23 – Monthly percent frequency of the DC and D weather types for the middle month of each meteorological season.

Figure 24 – Monthly percent frequency of the DW weather type for the middle month of each meteorological season.

Figure 25 – Monthly percent frequency of the CFP and WFP weather types for the middle month of each meteorological season (note the change in scale from previous figures).

6.6 – Warm (W)

The Warm WT is indicative of average humidity conditions that accompany relatively warm weather. The W type is fairly frequent for the majority of the year in the Coastal SE region – with at least 15% frequency in each month from September to April, and only summer showing a slight drop off, though still occurring 13% of the time on average. Peak July frequency is found in the Midwestern US in the Indiana and Ohio regions, along with the Appalachian Mountain area – where the W-type occurs about 15% of the time on average (Figure 22). January occurrences of this type are quite common in a curved band from the Pacific NW, through the Heartland and into the Northeast, where 17% to 20% frequency is not uncommon. April and October geographical preference of the Warm type is similar but muted in comparison to January, with occurrences of the type focused on the diverse topography of the Basin and Range area of the US, along with the Appalachians.

6.7 – Dry Cool (DC)

Like all of the dry types, the Dry Cool weather type overall has a slightly lower frequency than the moderate or humid WTs and occurs more frequently outside of summer with a peak in winter (Figure 23). While on average January DC occurs about 8% of the time across the country, in the Northern Plains averages are closer to 11-12% for many locations. New England sees DC types occurring nearly 10% of the time, as do areas south and east of the Appalachians. Centers of DC occurrence shift in spring, as the

northern parts of the West Coast experience DC up to 10% of the time. July DC frequency plummets to about 5% across the US as a whole, with the southwestern US and areas immediately surrounding the Great Lakes often seeing the greatest frequency of this type, but still only about 6-7% of the time. The DC type becomes more frequent in autumn, up to about 7% frequency across the US as a whole, with most of the eastern half of the US experiencing DC about 8-9% of October days. Overall this seasonal frequency of DC mimics the preference for cooler air to accompany dry conditions as winter approaches.

6.8 – Dry (D)

The Dry WT represents days with relatively low dew point and moderate temperatures. Overall, this type is more common throughout the year than DC (especially in July), but not as common as DW. Geographic January D-type occurrence is centered on the Desert SW region of the US, occurring nearly 13-14% of the time at many locations (Figure 23), despite only an 8% average occurrence throughout the US as a whole. A dearth of January Dry WT occurrence is noticed in the Heartland region where moderate winter temperatures are often ushered in by more humid conditions, while dry winter days are often associated with warmer or cooler than average conditions (and thus more DC/DW days than Dry days). April D-type preference shifts slightly eastward into areas just east of the Rockies, especially the Southern Plains. July D-type climatology is focused on the western half of the US including the Intermontane region, where this WT can occur up

to 14 to 15% of the time in some locations. Overall, July frequency of the Dry WT is about 7.6% across the US as a whole. In autumn, the Dry type again shifts its geographical preference to the Desert SW, where it occurs up to 10% of the time. This is unsurprising considering the arid to semi-arid nature of much of the southwestern US.

6.9 – Dry Warm (DW)

The Dry Warm WT is the most common of the dry types, occurring about 9% of the time on average throughout the year. January DW is quite frequent in the northern parts of the US, with the Northern Plains experiencing DW about 14-15% of days (gradually decreasing to 11% frequency into the Heartland) and New England with about 12% frequency on average (Figure 24). The lowest January DW frequencies are in Southern Texas at about 6%. April DW again focuses on the Northern Plains region (although slightly less frequent at about 12-13%), along with the Southern Great Plains where it occurs about 11% of the time on average. July DW is fairly infrequent comparatively, occurring only 8.5% of days across the US, most commonly occurring throughout the Great Plains of the US where desert air can often be ushered in by southwesterly winds. Autumn DW is most frequent in the western half of the US, especially near the four corners region, though only occurring 11% of October days on average even in this area.

6.10 – Cold Front Passage (CFP)

While the Cold Front Passage WT is commonly associated with an actual cold front, this

is not always the case, and more accurately represents days on which there was simply a substantial change in weather conditions throughout the day, where dew points dropped and pressure trended higher. CFP is quite frequent in winter, occurring about 5.5% of the time throughout the US as a whole, with the highest number of occurrences in parts of the Central Rockies just upwind from areas of cyclogenesis (Zishka and Smith, 1980). Further, this area is often subjected to migrating Pacific cyclones entering the US from a northwesterly direction, with trailing cold fronts. Most places east of the Rockies have CFP occurrences on 5-7% of days, while the West Coast and Desert SW have much lower frequencies of the type (Figure 25). April CFP climatology is quite similar, with slightly northward shifted centers of activity gaining frequency in the Heartland region and further into the Northwest, though the Northern Plains and New England each receive fewer CFP WT than in winter. July CFP occurrences are shifted to the northern tier of the US (with 6-7% frequency quite common), while occurring only about 2-3% of the time in the southern US as the polar front shifts northward. The climatology of October CFP is very similar to that of April.

6.11 – Warm Front Passage (WFP)

As was the case for CFP, the Warm Front Passage WT also represents transitional weather; however, this type of change sees dew points trending upwards and pressures falling throughout the day. While commonly associated with a warm front, due to the slower moving nature of this front (comparatively with cold fronts), these weather types

proved more difficult to identify in the classification within the scope of a day, and are thus much less frequent overall. January CFP activity is focused on the Northern Plains, where it occurs about twice as often (6.5%) as the national average (3.2%). The southern US, especially the southwest and Florida are under WFP conditions less than 1% of January days (Figure 25). April WFP climatology is similar to April CFP, however, quite a bit less frequent – at less than 3% of days throughout the US and only about a 4-5% average in the Plains and Northwest. With the exception of a small area of the Gulf Coast, July WFP is limited mostly to the Northern US, especially the Northern Plains where frequencies average about 4%, despite a national average of less than 2%. October is quite similar, however, with an area of 3-4% frequency reaching further south into the Heartland and Southern Plains, and also into the Northeast.

6.12 – Discussion on Weather Type Frequency Climatologies

In summary, since the GWTC aims to classify weather types that are both seasonally and spatially relative, the weather type frequency maps presented above are not very intuitive. While this was expected, this could be considered a limitation of the classification, as the frequency of a WT is not meant to be associated to the true character of the climate for that location. Instead, these frequencies are more indicative of the relationship between temperature and humidity at a particular location – the degree to which dew point distributions are skewed within different temperature categories. The frequency maps presented above outline the spatial patterns of this

relationship. While pressure, cloud cover and wind also play a role, these maps highlight areas where, for example, relatively lower/higher than average temperatures often accompany above/below average humidity. This is because, herein, weather types are defined simply by relative differences from average. This contrasts from the traditional synoptic climatological perspective on weather types as synoptic-scale air masses that form in source regions, modifying as they move and impacting the weather of the locations they traverse. This differing perspective on weather types results in some interpretations of the WT frequency maps being straightforward, while others manifest from more complex origins.

An example of the complexity involved in some interpretations of these frequency maps is exhibited in the January DW type frequency in the Northern Plains. Although this area has a high frequency of DW in winter, this does not mean that this area is “warm and dry” relative to the domain-wide (US) average (or to the year-round average). Rather, this can best be interpreted in terms of the fact that among relatively warmer than average winter days in this location, the accompanying dew points are more often low (dry) than they are high (humid), mostly because it is still cold in absolute terms, but high relative dew points must still be below the temperature. Thus, because DW is the coldest of the warm types, it is more frequent than HW. This is somewhat counterintuitive when considering that the warmest conditions are often a result of high

humidity (as exhibited in the weather type *character* of the region, and as would be expected), even though DW is slightly more frequent than HW.

A more straightforward interpretation of these maps is exhibited in many seasons where the geographic preference of some types is more related to the humidity category than it is the temperature category. For example, in the eastern two-thirds of the US where Gulf of Mexico moisture heavily impacts the summer weather, the humid types (mostly HC and H) often have a summer dominant seasonality. The rise in HC frequency in most regions is fairly straightforward – as cloud cover often brings about slightly lower than average temperatures due to decreased insolation reaching the surface. The Humid type likely occurs for similar reasons, but with slightly less cloudiness (or clouds at different levels) to impact temperatures, keeping temperatures relatively average. HW is also summer-dominant in northern portions of this section of the country because they are still impacted by varying air masses in the summer. A strong southerly flow (with less of a westerly component to the wind) will bring classical maritime tropical (mT) air masses with relatively humid and warm conditions to the area. However, in the southern portions of the eastern US that are constantly under mT influence, in a WTC that is spatiotemporally relative, HW is much less frequent by comparison to HC and H. Here, the oppressive humidity has a limiting influence on high temperatures (relative to average), preventing HW from occurring very often.

In the winter, dry air is much more common everywhere, and thus in most locations (especially east of the Rockies) the dry types (especially DC and DW) have a winter-dominant seasonality – DW due to the reasons discussed above, and DC because the coldest air is brought about by northerly winds, cloudless skies and dry air, and thus, a higher frequency of DC. In the transitional seasons, when humidity and temperature vary more due to the characteristics of incoming air masses and wind direction, more equal dry and humid WT frequencies are observed north of the average position of the polar front.

While given a lot of attention in this Chapter, the differences in percent frequencies of the weather types from one region to another are often quite minimal, with the average range of monthly frequencies of all core WTs within a region at only about 9.8%. This is by design, again, as a goal of the classification is more-equal frequency. By comparison with the SSC (Sheridan, 2002), some WTs in some locations (e.g. the Moist Tropical weather type in Miami, FL in summer) can have frequencies upwards of 80%, resulting in some WTs (Moist Polar, Dry Tropical, and Dry Polar) never occurring for large portions of the year. Thus, from a qualitative perspective considering the results from this chapter and Chapter 5, both the GWTC's goals of more-equal group sizes throughout the year (than what is exhibited by the SSC) and the goal of spatiotemporally representative weather type character, are achieved. The fact that there is any spatial clustering exhibited in these maps at all (i.e. that they are not spatially random),

indicates that the classification methodology does successfully account for the natural spatial relationship that exists between temperature and dew point, albeit in a somewhat complex manner. This point, however, underscores the designed future usage of the classification mostly on a day-by-day basis (i.e. using the WT calendar at a single location) or on a continental basis (looking at the distribution of weather types across the US on a single day – outlined below), but not necessarily for delineating a seasonal weather type frequency climatology.

As mentioned above, the dry types are less frequent in comparison to the humid and average types. This is likely a result of the use of the mean (rather than a median, or a percentile-ranking strategy) in the calculation of deseasonalized z-scores, as some locations do have distributions of TDZ_{iv} that deviate from normal. Within a given temperature category, there is an upper limit to the dew points (as dew points cannot be higher than temperatures), however, there is no lower limit, allowing dry extremes to pull the mean slightly downwards and resulting in more days being classified as humid or average by comparison in the initial typing procedure. This effect can then be magnified when DFA is utilized in the secondary typing procedure. While this may be viewed as a limitation of the classification, as mentioned in section 3.2.2, the mean was ultimately selected in the final methodology due to better VSS_{TD} values than a percentile ranking strategy. A percentile ranking strategy also proved to be substantially more computationally expensive. Using the mean results in more seasonal and spatial

variability in the frequency of all types, contrary to the goal of more-equal frequency; this aim, however, must be balanced with defining weather types that have dew point and temperature characteristics that are seasonally and geographically representative. Ultimately, whether the mean, median, or percentile ranking strategy was used, the goals of the classification likely could have been successfully met, and thus, the better VSS_{TD} was the deciding factor in choosing the final methodology.

CHAPTER 7

CLASSIFICATION DIAGNOSTIC STATISTICS

The following chapter presents the diagnostic statistics used to help judge the partitioning ability of the GWTC, including variability skill scores (section 7.1), spatial match percentages (section 7.2) and temporal persistence percentages (section 7.3). In this chapter, when discussing results in different meteorological seasons, the values are obtained by averaging across the whole season, rather than being represented by the middle month of the season (as in chapter 6).

7.1 – Variability Skill Score (VSS)

The VSS was developed to quantify the ability of the classification to effectively partition meteorological variables into groups that minimize within-WT variability and maximize between-WT variability (scatter plots in Appendix D show this graphically for afternoon temperature and dew point for selected months for each of the regional representatives discussed in Chapter 5). This value can only be positive, and theoretically this value is ideally close to zero – however, this is unrealistic in practice. While interpretation of the

magnitude of the VSS as satisfactory or not is qualitative, it can nonetheless be used as a *relative* metric to investigate a number of entities. Beyond gauging the improvement of each evolution of the GWTC, the VSS was also used herein to evaluate:

- 1) where in the domain the classification performs better or worse
- 2) the time of year when the classification performs better or worse
- 3) the variables the classification is better or worse at partitioning

The VSS of the 8 times daily averaged deseasonalized z-score temperature and dew point observations (VSS_{TD}) was used to help gauge the skill of each new version of the classification methodology during development and will thus be focused on here.

Overall, skill scores were better (lower) in the eastern two-thirds of the US (Figure 26), especially in the northern tier and topographically flat regions east of the Rockies. The highest VSS_{TD} scores were found in the Rocky Mountains themselves and extending into the high plains, especially in the Southern Plains. The average VSS_{TD} for all delineated regions west of the Heartland was at least 0.65, greater than the US average of 0.63. This is likely due to the poorer partitioning of dew points (VSS_D) rather than temperatures (VSS_T) in these areas, as each of these regions' average VSS_D was at least 0.69 (compared to the domain-wide average of 0.67), while VSS_T was generally much better. This noted, overall VSS_{TD} only ranged 0.24 units (0.52 to 0.76) among all 2070

grid points, and stayed well below the 1.00 mark, indicating that these variables had more variability between WTs than within WTs – an indication of a successful partitioning of these two variables. Among the delineated regions, the best VSS_{TD} was found in the Northeast region (0.57).

Seasonal VSS_{TD} is somewhat variable, though much like the annual results, the western third of the country usually has the poorest scores each season. The classification generally performs best in the winter season (December-February), where VSS_{TD} for the entire US is 0.52 (compared to the annual average of 0.63). The northern reaches of the domain garner the lowest VSS_{TD} on average, with the Northern Plains (0.43), Great Lakes (0.43), Northeast (0.48) and Northwest (0.49) having scores below the winter mean – the only season in which the Northwest achieves this. As evidenced in Appendix D, each of these regions has a very strong positive relationship between temperature and dew point (with dew point depressions often less than 5°C throughout January days), allowing *both* temperature and dew point to vary dramatically between each WT. The Coastal SE region also experiences better than average VSS_{TD} (0.47) in the winter. Winter likely has the lowest VSS_{TD} due to more variable weather compared to other seasons throughout much of the domain. As the polar front migrates southward, even the Gulf Coast can experience frost and freeze events on occasion, while the northern Plains experience their most drastic transitions in weather and wide ranging temperatures and dew points. These phenomena likely cause between-type variability to rise, creating

more distinct weather types, especially along the DC to HW “axis” (in Figure 31),
resulting in lower VSS_{TD} .

Figure 26 – Variability Skill Scores (VSS) for deseasonalized temperature and dew point z-scores for meteorological seasons.

Figure 27 – Variability Skill Scores (VSS) for all deseasonalized z-scores for meteorological seasons (note the different scale from the previous figure).

Figure 28 – Annual Variability Skill Scores (VSS) for individual deseasonalized z-scores (note different scale for each map).

At the opposite end of the calendar, meteorological summer (June-August) exhibits poor skill scores for Southern Texas (0.75), the Coastal SE (0.73), and the Southern High Plains (0.70). Though considerably poorer than the domain-wide average for summer (0.66), these scores are still relatively good due to the fact that when between-type variability is poor, within-type variability is quite good under the invariable conditions in the Coastal SE. Near the front range of the Rockies, the poorer within-type variability due to dry extremes is compensated by better between-type variability (as is exhibited in the July scatter plots for these regions in Appendix D). The California coast exhibits some of the best summer VSS_{TD} , likely due to the influence of the reliable marine layer. Days on which this layer does not completely burn off creates enough variability in temperature between types to lower the overall VSS_{TD} – this effect only being seen right along the coast. The Northeast (0.59) is the only region with VSS_{TD} lower than 0.60, with the Mid-South (0.62), Heartland (0.63), Northern Plains (0.64), and West Coast (0.64) regions also exhibiting VSS_{TD} better than the seasonal average.

The spring (March-May) and autumn (September-November) seasons are quite similar to each other, with the better skill scores in the eastern half of the US, and the worse scores in the west. Further, both seasons have similar domain-wide VSS_{TD} of 0.60 and 0.61, respectively. Perhaps the most noticeable difference between spring and autumn VSS_{TD} maps is the difference in the gradient of the scores moving from east to west across the Plains states. In spring this gradient is drastic, with scores ranging consistently

some 0.10 units across just eight grid points from well above average to well below average. In autumn, there is quite a bit more spatial variability in adjacent locations throughout the US.

The spring map also highlights a distinct difference between the VSS_{TD} in the Great Lakes (0.65) and surrounding land in the Northeast (0.56) and the Northern Plains (0.59). This could be due to the influence of the cold lakes slowly warming up from sub-freezing winter temperatures into the spring (compared to the temperature of the land which would be more variable). In the autumn, there is much more equality, with the Great Lakes region having a better VSS_{TD} on average than the adjacent regions. At this time of the year, land and water thermal conditions are not likely all that different, and thus, there is little difference in the VSS_{TD} between the two regions.

Southern Florida experiences quite different VSS_{TD} between these two seasons, with a VSS_{TD} much worse than the domain average in autumn (about 0.69) and right around average for spring (about 0.60). This is likely due to the heat capacity of the surrounding water as well, with both water and land temperatures quite high well into the fall creating relatively invariable weather and poor VSS_{TD} , while cool waters and warm land in the spring are creating more variability and better VSS_{TD} .

Table 6 – Region-wide average variability skill score for all eight daily observations of temperature (T), dew point (D), pressure (P), zonal winds (U), meridional winds (V), cloud cover, and combinations of these variables. Regions are on horizontal axis of each table. Annual (top) and winter (bottom) averages presented. Color scale by column.

ALL-YEAR	T	D	P	U	V	C	TD	TDPC	ALL
1	0.61	0.69	2.34	2.69	2.14	2.20	0.65	1.46	1.78
2	0.62	0.76	1.46	2.76	1.74	2.96	0.69	1.45	1.72
3	0.58	0.76	2.12	2.73	2.41	2.72	0.67	1.54	1.89
4	0.60	0.73	2.67	1.99	2.18	2.59	0.67	1.65	1.79
5	0.58	0.73	1.73	2.74	2.40	3.05	0.66	1.52	1.87
6	0.61	0.60	1.70	3.50	1.70	3.98	0.61	1.72	2.02
7	0.57	0.57	1.86	2.73	1.62	2.85	0.57	1.46	1.70
8	0.66	0.70	1.31	2.49	1.35	2.79	0.68	1.37	1.55
9	0.63	0.63	2.26	2.70	1.55	3.30	0.63	1.70	1.84
10	0.59	0.59	1.89	2.85	1.59	2.23	0.59	1.33	1.62
11	0.62	0.64	1.84	2.81	1.50	2.05	0.63	1.29	1.58
12	0.57	0.63	1.39	2.80	1.74	3.91	0.60	1.63	1.84
13	0.59	0.64	1.29	2.89	1.56	3.36	0.61	1.47	1.72
TOTAL	0.60	0.67	1.83	2.74	1.85	2.81	0.63	1.48	1.75

WINTER	T	D	P	U	V	C	TD	TDPC	ALL
1	0.58	0.62	1.41	1.86	1.64	2.03	0.60	1.16	1.36
2	0.56	0.64	1.29	2.77	1.83	2.91	0.60	1.35	1.67
3	0.52	0.64	1.51	2.29	1.98	2.04	0.58	1.18	1.50
4	0.57	0.60	1.81	1.50	1.53	1.60	0.59	1.14	1.27
5	0.47	0.51	1.46	2.25	1.83	2.56	0.49	1.25	1.51
6	0.44	0.42	1.58	3.54	1.80	4.90	0.43	1.84	2.11
7	0.47	0.49	1.66	2.37	1.76	3.10	0.48	1.43	1.64
8	0.55	0.55	1.10	2.19	1.17	2.25	0.55	1.11	1.30
9	0.48	0.45	1.84	2.04	1.10	2.49	0.47	1.32	1.40
10	0.51	0.51	1.55	2.38	1.50	2.31	0.51	1.22	1.46
11	0.51	0.47	1.45	2.45	1.23	2.07	0.49	1.13	1.36
12	0.43	0.44	1.18	2.89	1.81	4.60	0.43	1.66	1.89
13	0.49	0.53	1.11	3.24	1.70	4.31	0.51	1.61	1.90
TOTAL	0.51	0.54	1.45	2.43	1.66	2.73	0.52	1.31	1.55

Table 6 (continued) – for spring (top) summer (middle) and autumn (bottom) seasonal averages presented. Color scale by column.

SPRING	T	D	P	U	V	C	TD	TDPC	ALL
1	0.57	0.66	2.02	2.25	1.80	2.40	0.62	1.41	1.62
2	0.62	0.70	1.48	2.06	1.54	2.70	0.66	1.37	1.52
3	0.55	0.73	2.01	2.47	2.16	2.70	0.64	1.50	1.77
4	0.58	0.67	2.59	1.70	2.00	2.25	0.62	1.52	1.63
5	0.58	0.68	1.71	2.31	2.27	2.43	0.63	1.35	1.66
6	0.66	0.64	1.59	3.05	1.72	2.95	0.65	1.46	1.77
7	0.56	0.56	1.84	2.38	1.46	2.30	0.56	1.31	1.52
8	0.63	0.61	1.18	1.89	1.24	2.88	0.62	1.33	1.41
9	0.60	0.55	2.20	2.13	1.24	2.77	0.57	1.53	1.58
10	0.56	0.53	1.99	2.49	1.39	2.03	0.55	1.28	1.50
11	0.58	0.53	1.91	2.35	1.24	2.05	0.56	1.27	1.44
12	0.57	0.62	1.33	2.76	1.53	2.94	0.59	1.36	1.62
13	0.58	0.58	1.31	2.31	1.38	2.45	0.58	1.23	1.44
TOTAL	0.58	0.62	1.79	2.32	1.65	2.46	0.60	1.37	1.57

SUMMER	T	D	P	U	V	C	TD	TDPC	ALL
1	0.64	0.70	3.70	2.71	2.58	2.17	0.67	1.80	2.08
2	0.65	0.74	1.45	2.42	1.63	2.88	0.70	1.43	1.63
3	0.62	0.72	2.73	2.49	2.87	3.16	0.67	1.81	2.10
4	0.58	0.69	3.13	2.40	2.61	3.38	0.64	1.95	2.13
5	0.62	0.74	2.03	2.01	2.68	3.22	0.68	1.65	1.88
6	0.71	0.65	1.64	2.91	1.52	3.39	0.68	1.60	1.80
7	0.60	0.59	1.89	2.59	1.46	2.52	0.59	1.40	1.61
8	0.76	0.74	1.72	3.09	1.58	2.45	0.75	1.42	1.72
9	0.74	0.72	3.06	2.47	2.48	3.56	0.73	2.02	2.17
10	0.63	0.61	2.27	2.39	1.50	2.16	0.62	1.42	1.59
11	0.68	0.66	2.44	2.49	1.59	1.98	0.67	1.44	1.64
12	0.64	0.65	1.56	2.37	1.63	2.82	0.64	1.42	1.61
13	0.62	0.64	1.37	2.84	1.45	3.31	0.63	1.48	1.70
TOTAL	0.64	0.68	2.22	2.50	1.99	2.78	0.66	1.58	1.80

AUTUMN	T	D	P	U	V	C	TD	TDPC	ALL
1	0.59	0.65	1.86	2.18	1.72	2.15	0.62	1.31	1.52
2	0.61	0.66	1.43	2.64	1.58	2.66	0.64	1.34	1.60
3	0.56	0.71	1.86	2.47	1.99	2.35	0.64	1.37	1.66
4	0.60	0.70	2.44	1.80	1.89	2.39	0.65	1.53	1.64
5	0.57	0.69	1.53	2.44	1.95	2.69	0.63	1.37	1.65
6	0.56	0.53	1.74	2.74	1.55	2.73	0.54	1.39	1.64
7	0.57	0.56	1.77	2.46	1.60	2.64	0.57	1.39	1.60
8	0.64	0.60	1.30	2.40	1.17	2.27	0.62	1.20	1.40
9	0.61	0.59	1.90	2.26	1.43	2.58	0.60	1.42	1.56
10	0.58	0.57	1.70	2.55	1.61	1.88	0.58	1.18	1.48
11	0.60	0.57	1.68	2.43	1.40	1.60	0.59	1.12	1.38
12	0.58	0.61	1.38	2.36	1.70	3.22	0.59	1.45	1.64
13	0.59	0.61	1.31	2.52	1.51	2.84	0.60	1.34	1.56
TOTAL	0.59	0.63	1.67	2.43	1.66	2.42	0.61	1.33	1.57

Since previous literature has shown that temperature and dew point are the most critical factors delineating surface weather types (Yarnal, 1993; Kalkstein and Corrigan, 1986), the VSS_{TD} was treated as the key metric for skill of the classification rather than the VSS for all deseasonalized variables (VSS_{All}). Thus, it is unsurprising that the GWTC performs worse for these other variables by comparison, with the domain-wide annual VSS_{All} being 1.75. Much like with temperature and dew point, VSS_{All} is better in winter (1.55) and worse in summer (1.80), though spring and autumn are comparable to winter (1.57 in both seasons). Geographically, the VSS_{All} is similar to the VSS_{TD} with better scores in the east and worse scores in the west. The big exceptions to this similarity are Texas and the Great Lakes/Northern Plains regions. Texas exhibits some of the best VSS_{All} values of anywhere in the country despite poor VSS_{TD} – pressure and meridional winds play a more important role here than anywhere else in the country in partitioning weather types. The Great Lakes and Northern Plains on the other hand have some of the better VSS_{TD} , while the VSS_{All} values are moderate to poor. This is a result of some of the highest variability skill scores for cloud cover and zonal winds of any region.

Among the other variables, on a year-round basis, pressure is often the best partitioned into representative WTs with a VSS of 1.83, followed closely by the v-wind (north/south) component at 1.85 – though v-wind VSS is better in all seasons except winter. The u-

wind component (annual VSS = 2.74) and cloud cover (annual VSS = 2.81) are consistently the poorest partitioned of the six variables used in the classification. However, in areas such as the Southeastern US, where cloud cover usually is responsible for lower-than-average summer temperatures, the annual VSS for cloud cover is comparatively good. Despite these high VSS values for variables other than temperature and dew point, the classification still displays good skill in partitioning these variables relative to a random classification. For example, ten randomly generated classifications (into 11 types) for each of the regional representative locations resulted in a VSS_{All} value of 35.10 (standard deviation=3.07) on average – substantially worse than the 1.75 VSS_{All} value for the GWTC averaged over the whole US.

7.2 – Spatial Cohesion

The spatial consistency of the classification is measured through spatial match percentages – the percent of the time a grid point of interest has the same weather type on the same day as its immediately adjacent grid points (up to 8 maximum). While previous synoptic literature has not established a threshold for rating these match percentages as satisfactory, the SSC (Sheridan, 2002) did calculate spatial matches with the nearest neighboring surface station and routinely found them to be in the 70-80% range.

The domain-wide average annual spatial match percentage for the GWTC is 74.4% (Table 7). This percentage is up 4.6% from the spatial match percentage calculated for the classification prior to implementing the spatial smoothing process described in section 3.2.5 above. On a seasonal basis, the best domain-wide average spatial match percentages are found in autumn (76.3%), followed by spring (75.5%), winter (73.6%) and then summer (72.4%). Year-round and in most seasons, the highest spatial consistency (much like the best VSS_{TD} values) is found in the topographically homogeneous regions of the US, while mountainous and coastal regions (and the Great Lakes) are found to have the poorest spatial matches. These findings are unsurprising considering that drastic elevation changes from one location to its adjacent locations and dramatic land cover changes (from water to land) are known to influence weather on the small-scale. The major exception to this is the Florida Keys which have high spatial match percentages, likely due to only 1-3 adjacent grid points from which to calculate this metric, and all of which having very tropical marine climates.

Table 7 – Average seasonal (and annual) spatial match percentage by region (horizontal axis).

	WINTER	SPRING	SUMMER	AUTUMN	ANNUAL
1	75.4%	81.3%	78.4%	79.9%	78.8%
2	77.1%	78.8%	75.7%	79.8%	77.9%
3	64.0%	72.6%	76.7%	76.1%	72.4%
4	61.6%	62.3%	58.0%	62.3%	61.0%
5	66.3%	72.0%	73.5%	74.1%	71.5%
6	68.6%	65.0%	60.0%	68.7%	65.5%
7	75.7%	75.3%	71.4%	75.4%	74.4%
8	81.0%	77.4%	70.8%	78.2%	76.8%
9	76.4%	69.5%	57.9%	70.4%	68.5%
10	77.8%	77.6%	71.2%	76.9%	75.8%
11	81.0%	79.0%	71.7%	78.9%	77.6%
12	74.7%	77.2%	74.8%	78.1%	76.2%
13	77.7%	79.7%	75.8%	79.7%	78.2%
US	73.6%	75.5%	72.4%	76.3%	74.4%

Winter spatial matches follow these general trends, with the greatest percentages found in Southern Texas and the Inland SE region (each with 81.0% average). Surprising in the winter, however, is the Coastal SE region which experiences dramatically higher matches in this season (76.4%) than in any other. As in each season, the Rockies, the Appalachians and the Great Lakes are all well defined on the winter map as areas of poorer spatial matching. Spring spatial matches are greatest in the Desert SW region, averaging 81.3% across the region as a whole (the highest of any region in any season), including some locations above 87%. Autumn is similar, though most of the High Plains (especially in the south) have matches much closer to those of the Desert SW (in the 78-

80% range) in this season. Summer does buck the trend slightly, with many locations in the Intermontane region matching over 80% of the time, and 76.7% of the time across the region as whole – the second highest of any region in summer.

Figure 29 – Annual and seasonal spatial match percentages.

Among the delineated regions, the best annual spatial match percentages are found in the Desert SW (78.8%). This is in large part due to this region's high spring (81.3%), autumn (79.9%) and summer (78.4%) matching rates – the greatest of any region in their respective seasons. The worst spatial match percentages are found in the West Coast region (61.4%), unsurprising in a region with lots of coastline *and* variable topography. This region, however, is among the most consistent in terms of the seasonal variability in match percentages, ranging only 4.4% from its highest in spring (62.3%) to its lowest in summer (58.0%). The Plains (Southern High Plains, Northern Plains, and Heartland) and the Northeast also have seasonal consistency in their spatial match percentages, each having less than a 5% range among seasonal spatial match percentages. The greatest seasonal variability belongs to the Coastal SE, ranging 18.4% between its high in winter (76.4%) to its low in summer (57.9%). The Intermontane region (12.8% seasonal range) and Southern Texas (10.2% seasonal range) also experience dramatic changes in spatial consistency depending on the time of the year, though the Intermontane region has its greatest spatial matching in summer (when high pressure and stable conditions can dominate the region for days) – the only region to exhibit this trend.

7.3 – Temporal Persistence

In addition to spatial cohesion, temporal cohesion in the classification is also evaluated, using temporal persistence percentages – the percent of the time an individual WT is followed by the same WT on the succeeding day at a single location. The regional- to continental-scale persistence of WTs is not often evaluated in the synoptic literature, and thus there is no threshold to satisfactorily judge the effectiveness of the classification in this regard. Considering the transient nature of mid-latitude synoptic systems, however, these percentages were expected to be reasonably low.

Overall, the average, year-round, domain-wide temporal persistence of all WTs is 36%, and 38% for just the core WTs (Table 8). Regionally, weather types persist much more so in the southern and western US, especially in the Desert SW region (47%) – which is 6% higher than the West Coast (41%) – the region with the second highest persistence percentages (Table 8; Figure 30). The other regions with WT persistence greater than the national average are also in the western or southern portions of the US, including Southern Texas (39%), the Intermontane region (39%), the Southern High Plains (38%) and the Inland SE (36%). The lowest persistence percentages are mostly in the northern reaches of the US, including the Northeast (29%) and Great Lakes (30%) regions.

Table 8 – Average temporal persistence percentages by region (horizontal axis) and weather type (vertical axis) for annual (top) and winter (bottom). Note: for regions without WFP in certain seasons, persistence is set to 0%.

	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP	TOTAL
Desert SW	50%	49%	55%	44%	39%	53%	48%	44%	53%	3%	3%	47%
Southern High Plains	43%	40%	47%	37%	35%	39%	41%	33%	46%	1%	2%	38%
Intermontaine	43%	40%	51%	39%	33%	43%	43%	35%	51%	3%	3%	39%
West Coast	42%	38%	56%	42%	36%	44%	47%	34%	50%	4%	3%	41%
Northwest	38%	32%	46%	38%	32%	39%	49%	28%	45%	2%	3%	35%
Great Lakes	30%	27%	50%	33%	25%	35%	41%	21%	32%	1%	1%	30%
Northeast	29%	24%	48%	31%	26%	34%	40%	18%	33%	1%	1%	29%
Southern TX	46%	42%	53%	38%	34%	41%	42%	34%	43%	1%	2%	39%
Coastal SE	34%	35%	54%	33%	29%	38%	43%	25%	34%	1%	2%	35%
Mid-South	32%	33%	52%	33%	26%	34%	43%	21%	37%	1%	1%	32%
Inland SE	38%	38%	53%	35%	28%	36%	46%	25%	40%	0%	1%	36%
Northern Plains	33%	28%	48%	35%	28%	37%	46%	23%	39%	1%	2%	32%
Heartland	36%	35%	48%	35%	31%	40%	45%	25%	45%	1%	2%	35%
US	38%	36%	50%	36%	31%	39%	44%	28%	43%	2%	2%	36%

	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP	TOTAL
Desert SW	42%	52%	54%	43%	39%	53%	49%	43%	54%	2%	0%	46%
Southern High Plains	35%	36%	46%	37%	33%	38%	47%	32%	41%	1%	0%	35%
Intermontaine	29%	34%	51%	39%	33%	41%	51%	35%	50%	4%	1%	37%
West Coast	37%	38%	55%	39%	33%	43%	53%	38%	54%	2%	0%	42%
Northwest	30%	26%	46%	42%	34%	40%	61%	29%	44%	2%	2%	36%
Great Lakes	20%	17%	50%	33%	21%	40%	49%	20%	28%	1%	0%	29%
Northeast	21%	17%	45%	29%	30%	38%	43%	16%	30%	1%	1%	28%
Southern TX	30%	26%	50%	33%	24%	30%	39%	28%	33%	0%	0%	30%
Coastal SE	19%	20%	51%	28%	20%	36%	42%	19%	23%	1%	0%	29%
Mid-South	26%	21%	46%	31%	27%	26%	41%	19%	27%	1%	1%	27%
Inland SE	27%	21%	49%	33%	22%	25%	45%	20%	23%	0%	0%	28%
Northern Plains	20%	15%	49%	33%	27%	41%	52%	20%	30%	1%	2%	30%
Heartland	27%	26%	45%	33%	32%	42%	49%	23%	41%	1%	1%	33%
US	28%	27%	48%	35%	30%	37%	48%	27%	38%	2%	0%	33%

Table 8 (continued) – Average temporal persistence percentages by region (horizontal axis) and weather type (vertical axis) for spring (top), summer (middle) and autumn (bottom). Note: for regions without WFP in certain seasons, persistence is set to 0%.

	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP	TOTAL
Desert SW	49%	44%	54%	43%	37%	53%	41%	36%	51%	3%	1%	44%
Southern High Plains	38%	35%	45%	34%	29%	35%	38%	27%	42%	1%	2%	33%
Intermontaine	41%	36%	50%	39%	30%	43%	39%	28%	48%	2%	3%	36%
West Coast	38%	35%	55%	41%	34%	42%	44%	28%	42%	4%	0%	38%
Northwest	36%	30%	45%	39%	31%	39%	46%	28%	44%	2%	3%	34%
Great Lakes	25%	27%	53%	35%	29%	35%	39%	25%	41%	1%	1%	31%
Northeast	29%	23%	49%	33%	27%	33%	41%	21%	35%	0%	1%	30%
Southern TX	42%	40%	53%	35%	32%	41%	42%	29%	40%	0%	0%	38%
Coastal SE	32%	32%	55%	33%	31%	39%	44%	25%	37%	1%	1%	36%
Mid-South	26%	24%	51%	32%	22%	35%	43%	20%	34%	0%	0%	30%
Inland SE	27%	26%	53%	32%	25%	39%	46%	24%	37%	0%	1%	33%
Northern Plains	34%	31%	50%	38%	31%	38%	46%	27%	47%	1%	2%	35%
Heartland	35%	27%	49%	36%	28%	37%	44%	24%	36%	1%	2%	32%
US	35%	31%	50%	36%	29%	39%	42%	26%	41%	1%	0%	34%

	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP	TOTAL
Desert SW	56%	49%	54%	46%	39%	50%	53%	49%	54%	5%	5%	49%
Southern High Plains	51%	45%	46%	42%	41%	44%	39%	41%	53%	2%	3%	43%
Intermontaine	53%	45%	52%	40%	35%	42%	41%	41%	51%	3%	3%	43%
West Coast	48%	40%	59%	47%	40%	44%	47%	33%	47%	7%	4%	44%
Northwest	43%	36%	47%	34%	30%	38%	34%	28%	45%	2%	4%	35%
Great Lakes	37%	30%	50%	32%	20%	28%	36%	22%	32%	1%	2%	30%
Northeast	34%	28%	51%	30%	23%	33%	38%	18%	37%	1%	1%	30%
Southern TX	60%	53%	51%	45%	42%	48%	50%	45%	53%	5%	7%	49%
Coastal SE	45%	42%	54%	40%	32%	36%	46%	30%	43%	3%	4%	40%
Mid-South	41%	43%	56%	35%	29%	39%	44%	24%	51%	1%	1%	39%
Inland SE	52%	52%	52%	37%	35%	41%	52%	29%	57%	1%	3%	45%
Northern Plains	38%	30%	47%	32%	26%	33%	37%	23%	45%	1%	2%	31%
Heartland	40%	45%	48%	37%	34%	42%	41%	30%	62%	1%	2%	39%
US	46%	42%	51%	38%	33%	40%	42%	32%	50%	2%	3%	40%

	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP	TOTAL
Desert SW	51%	49%	56%	44%	40%	54%	48%	46%	54%	4%	2%	48%
Southern High Plains	45%	39%	51%	37%	34%	39%	40%	33%	48%	1%	1%	38%
Intermontaine	44%	42%	51%	38%	33%	46%	41%	36%	55%	3%	3%	40%
West Coast	43%	39%	53%	42%	36%	45%	42%	34%	54%	4%	3%	42%
Northwest	41%	34%	45%	37%	31%	40%	52%	26%	45%	2%	1%	35%
Great Lakes	29%	28%	48%	30%	25%	34%	39%	14%	25%	0%	0%	28%
Northeast	30%	23%	45%	32%	24%	31%	37%	16%	29%	1%	1%	28%
Southern TX	43%	42%	57%	39%	33%	43%	42%	33%	43%	1%	1%	40%
Coastal SE	33%	35%	55%	34%	30%	39%	42%	24%	31%	1%	2%	36%
Mid-South	33%	32%	53%	36%	26%	34%	42%	21%	39%	0%	2%	33%
Inland SE	36%	37%	57%	38%	28%	36%	45%	27%	44%	0%	2%	38%
Northern Plains	37%	30%	47%	36%	28%	34%	47%	20%	37%	1%	1%	32%
Heartland	39%	33%	48%	36%	30%	37%	43%	24%	41%	1%	2%	33%
US	39%	36%	51%	37%	31%	39%	43%	28%	43%	1%	2%	36%

Seasonally, the highest persistence percentages across the domain are in the summer (40%), dominated by regions in the western and southern portions of the US, including the Desert SW and Southern Texas, each with persistence percentages of 49% (Table 8). The Great Lakes and the Northeast regions are the lowest with 30% persistence in both. Winter experiences the lowest amount of persistence (33% overall), with even parts of the southern tier of the US below average, including Southern Texas (30%) and the Inland SE (28%). Again, the greatest persistence is found in the Desert Southwest (46%), while the lowest is in the eastern US centered around the Mid-South region at 27%. Despite their transitional nature, spring and autumn still have persistence percentages higher than winter, at 34% and 36% domain-wide, respectively. While geographic patterns of persistence in autumn are very similar to the annual patterns, spring persistence geography is slightly different, most notable is the low persistence in the Southern High Plains (33%), a region with higher than average persistence in all other seasons.

In addition to seasonal analyses, persistence can also be evaluated by individual weather type (Figures 30-34, Table 8). Among the different WTs, by far the most persistent is the HW type, persisting 50% of the time overall, including 51% of the time in both summer and autumn. Regionally, the HW type is most persistent in the West

Coast (56%), the Desert SW (55%) and the southeastern quadrant of the US (52-54% in those regions). The DC and DW types are the next most persistent at 44% and 43% respectively on a year-round basis. The DC type is most persistent in winter (48%), while the DW type is most persistent in summer (50%) – each rivaling HW in persistence in those seasons (within 0.3% of the HW persistence). In fact, these two types (DW and DC) feature the highest regional average persistence percentages of any type in any season, including a 62% persistence of the DW type in summer in the Heartland, and 61% persistence of the DC type in winter in the Northwest region. Among the nine core WTs, the Dry type exhibits the least amount of persistence overall (28%) and in each season. Further, the D type has the lowest regional average persistence in any season with only 14% persistence in the Great Lakes in autumn. While the transitional WTs (CFP and WFP) do show a geographic preference for the West Coast region in terms of their persistence, neither type persists more than 5% of the time on average, and 7% of the time in any one season in any one region – considerably lower than all other weather types.

Taken together, the seasonal and geographic patterns of persistence described above reflect the known climatology of the US. In areas known for consistent weather in a particular season, (e.g. summers in the southeast, desert southwest and California), we see high degrees of persistence. Similarly, in areas where there is more variability (e.g. the Plains, Midwest, and New England), there is less persistence in the weather types.

While large-scale, slow-moving anticyclones are likely the culprit for winter DC and summer DW persistence highs, the remarkable (and consistent) persistence of HW relative to all other WTs is surprising, considering that HW is consistently accompanied by the fastest wind speeds of any of the core WTs.

Figure 30 – Annual persistence percentages for every weather type (note the difference in scale between Core WTs and transitional weather types).

Figure 31 – Winter persistence percentages for every weather type (note the difference in scale between Core WTs and transitional weather types).

Figure 32 – Spring persistence percentages for every weather type (note the difference in scale between Core WTs and transitional weather types).

Figure 33 – Summer persistence percentages for every weather type (note the difference in scale between Core WTs and transitional weather types).

Figure 34 – Autumn persistence percentages for every weather type (note the difference in scale between Core WTs and transitional weather types).

CHAPTER 8

CONTEXTUALIZING THE CLASSIFICATION

While the TSI and SSI are also similar to the GWTC in terms of being a weather typing classification, the redeveloped SSC (Sheridan, 2002) is the most analogous synoptic climatological classification to the GWTC due to the spatiotemporal relativity of the weather types and the universality of the weather type names that exists in the architecture of both classifications. Thus, despite the differing methodologies, meteorological data used (NARR vs. station observations), and even the number of core weather types between the SSC and GWTC, the SSC provides the best context through which the GWTC can be perceived in the literature base. This chapter begins this contextualization with a comparison of the frequency and character of comparable SSC and GWTC weather types. This comparison is followed by an evaluation of the two classifications' weather type frequency climatologies, and finally an assessment of the categorization of weather types across individual daily maps for both methodologies.

8.1 – Comparisons with SSC Weather Type Frequency and Character

Due to the differing number of types in the SSC (7+) and the GWTC (11), the most useful comparisons of the frequency and character of the weather types within each classification is with the four extreme types – HC (GWTC) to MP (SSC), HW to MT(+), DC to DP and DW to DT (these pairs hereafter are referred to as comparable weather types). Figures 36-47 display the frequency and average afternoon temperature and dew point for the GWTC and SSC weather types in January and July for selected locations. All comparisons are made between an actual SSC airport station within each climatological region (derived from the regionalization procedure outlined in Chapter 4) and the nearest GWTC grid point to that station. All SSC data discussed below are based upon station observations and were obtained from <http://sheridan.geog.kent.edu/ssc.html>.

In almost all regions there is a large difference between the SSC and GWTC in the *frequency* of comparable WTs. The most noticeable trend related to this frequency difference is that, with a few exceptions, when analyzing comparable WTs between the classifications, the WT in the classification that has a lesser frequency often is more “extreme” (e.g. the DP type in the SSC being cooler and/or drier than the DC type of the GWTC; or HW being much warmer and/or more humid than the MT/MT+ type, etc.). This is unsurprising, as if one were to move a WT-delineating threshold further and further into a tail of the temperature or dew point distribution, the more extreme the

nature of those days would likely be, and the less frequent. Due to the widely ranging WT frequencies in the SSC, most often it has the lower frequency of the two, and thus, the more extreme nature. The paucity of one SSC WT, however, will necessarily drive up the frequency of at least one other SSC WT (often the opposite extreme, e.g. if DC is rare, then MT and/or DT will often be quite frequent), leading to the corresponding GWTC type being the less frequent WT between this pair of comparable weather types, and it then having a more distinct/extreme nature compared to its SSC counterpart.

For example, Figure 36 displays the WT character and frequency of both the GWTC and SSC for the Phoenix, Arizona area. The frequency of the WTs vary quite dramatically in both winter (January) and summer (July), as among the 9 core WTS, the GWTC ranges only 8% and 10% in winter and summer, respectively, while the SSC types range 41% and 43%. In this particular area, the character of GWTC extreme WTs is less extreme than those of the SSC; with HC being warmer and drier (in terms of dew point depression) than MP, DC being warmer than DP, and HW being cooler and drier than MT+ (but not MT). The character of each of these types is more extreme in the SSC because of the extremely low frequency, 1%, 5% and 2%, compared to at least 8% frequency of each corresponding GWTC type. This low frequency in the SSC allows the classification to partition fairly rare meteorological days into distinct weather types. However, the DW type is warmer and drier than the DT type, but with 8% frequency in the GWTC versus 33% frequency in the SSC. In July, the warm WTs dominate the

location in the SSC classification, while the GWTC types are again much more equal. The average afternoon temperatures, however, of the extreme types is more extreme in the GWTC, with DW having temperatures 2°C higher and dew points 4°C lower, and HW having temperatures at least 3°C higher than either MT or MT+. Neither of the polar types (DP and MP) occurs at all in July in the SSC, while DC and HC occur 8% and 14% of the time, respectively in the GWTC. Although they do occur, due to the warm and dry nature of Phoenix in summer, these two GWTC types still have very high afternoon temperatures and large dew point depressions. The SSC does define one type (MM) that is characterized by temperatures under 30°C – though with only 2% frequency. The GWTC, due to fairly equal frequency of its weather types, has no weather type that matches the character of the MM SSC type. Again, this relationship between frequency and character of the comparable SSC and GWTC types is noticed in all regions (Figures 36-47).

MP	MM	MT+
N/A		MT
DP	DM	DT
VAR	TR	

Figure 35 – SSC weather type legend for use in the figures that follow in this subsection. Weather types are arranged to correspond with similar WTs of the GWTC from Figure 5. N/A indicates that there are no comparable weather types in the SSC to the Seasonal or Cool types in the GWTC. MT is also not directly comparable to Warm. Note that in all instances, MT+ is a subset of MT, and thus will have equal or less frequency than MT.

Figure 36 – Mean monthly weather type conditions for January and July for the GWTC (top two rows) and the SSC (bottom two rows) for the Phoenix, Arizona Airport (PHX) SSC station and the nearest GWTC grid point. Average afternoon (specifically, the fifth observation; see Table 1 for exact time of day) temperature (TEMP, °C, left) and dew points (DWPT, °C, middle), and average monthly frequency (FREQ, %, right). See Figure 5 for GWTC weather type legend and Figure 35 for SSC weather type legend. Blank cells indicate that no averages were computed due to no/low frequency. N/A indicates that comparable SSC WTs do not exist.

Figure 37 – Mean monthly weather type conditions for January and July for the GWTC (top two rows) and the SSC (bottom two rows) for the Amarillo, Texas Airport (AMA) SSC station and the nearest GWTC grid point. Average afternoon (specifically, the fifth observation; see Table 1 for exact time of day) temperature (TEMP, °C, left) and dew points (DWPT, °C, middle), and average monthly frequency (FREQ, %, right). See Figure 5 for GWTC weather type legend and Figure 35 for SSC weather type legend. Blank cells indicate that no averages were computed due to no/low frequency. N/A indicates that comparable SSC WT's do not exist.

Figure 38 – Mean monthly weather type conditions for January and July for the GWTC (top two rows) and the SSC (bottom two rows) for the Elko, Nevada Airport (EKO) SSC station and the nearest GWTC grid point. Average afternoon (specifically, the fifth observation; see Table 1 for exact time of day) temperature (TEMP, °C, left) and dew points (DWPT, °C, middle), and average monthly frequency (FREQ, %, right). See Figure 5 for GWTC weather type legend and Figure 35 for SSC weather type legend. Blank cells indicate that no averages were computed due to no/low frequency. N/A indicates that comparable SSC WTs do not exist.

Figure 39 – Mean monthly weather type conditions for January and July for the GWTC (top two rows) and the SSC (bottom two rows) for the Medford, Oregon Airport (MFR) SSC station and the nearest GWTC grid point. Average afternoon (specifically, the fifth observation; see Table 1 for exact time of day) temperature (TEMP, °C, left) and dew points (DWPT, °C, middle), and average monthly frequency (FREQ, %, right). See Figure 5 for GWTC weather type legend and Figure 35 for SSC weather type legend. Blank cells indicate that no averages were computed due to no/low frequency. N/A indicates that comparable SSC WTs do not exist.

Figure 40 – Mean monthly weather type conditions for January and July for the GWTC (top two rows) and the SSC (bottom two rows) for the Great Falls, Montana Airport (GTF) SSC station and the nearest GWTC grid point. Average afternoon (specifically, the fifth observation; see Table 1 for exact time of day) temperature (TEMP, °C, left) and dew points (DWPT, °C, middle), and average monthly frequency (FREQ, %, right). See Figure 5 for GWTC weather type legend and Figure 35 for SSC weather type legend. Blank cells indicate that no averages were computed due to no/low frequency. N/A indicates that comparable SSC WT's do not exist.

Figure 41 – Mean monthly weather type conditions for January and July for the GWTC (top two rows) and the SSC (bottom two rows) for the Lansing, Michigan Airport (LAN) SSC station and the nearest GWTC grid point. Average afternoon (specifically, the fifth observation; see Table 1 for exact time of day) temperature (TEMP, °C, left) and dew points (DWPT, °C, middle), and average monthly frequency (FREQ, %, right). See Figure 5 for GWTC weather type legend and Figure 35 for SSC weather type legend. Blank cells indicate that no averages were computed due to no/low frequency. N/A indicates that comparable SSC WTs do not exist.

Figure 42 – Mean monthly weather type conditions for January and July for the GWTC (top two rows) and the SSC (bottom two rows) for the San Antonio, Texas Airport (SAT) SSC station and the nearest GWTC grid point. Average afternoon (specifically, the fifth observation; see Table 1 for exact time of day) temperature (TEMP, °C, left) and dew points (DWPT, °C, middle), and average monthly frequency (FREQ, %, right). See Figure 5 for GWTC weather type legend and Figure 35 for SSC weather type legend. Blank cells indicate that no averages were computed due to no/low frequency. N/A indicates that comparable SSC WTs do not exist.

Figure 43 – Mean monthly weather type conditions for January and July for the GWTC (top two rows) and the SSC (bottom two rows) for the Orlando, Florida Airport (MCO) SSC station and the nearest GWTC grid point. Average afternoon (specifically, the fifth observation; see Table 1 for exact time of day) temperature (TEMP, °C, left) and dew points (DWPT, °C, middle), and average monthly frequency (FREQ, %, right). See Figure 5 for GWTC weather type legend and Figure 35 for SSC weather type legend. Blank cells indicate that no averages were computed due to no/low frequency. N/A indicates that comparable SSC WTs do not exist.

Figure 44 – Mean monthly weather type conditions for January and July for the GWTC (top two rows) and the SSC (bottom two rows) for the Nashville, Tennessee Airport (BNA) SSC station and the nearest GWTC grid point. Average afternoon (specifically, the fifth observation; see Table 1 for exact time of day) temperature (TEMP, °C, left) and dew points (DWPT, °C, middle), and average monthly frequency (FREQ, %, right). See Figure 5 for GWTC weather type legend and Figure 35 for SSC weather type legend. Blank cells indicate that no averages were computed due to no/low frequency. N/A indicates that comparable SSC WTs do not exist.

Figure 45 – Mean monthly weather type conditions for January and July for the GWTC (top two rows) and the SSC (bottom two rows) for the Jackson, Mississippi Airport (JAN) SSC station and the nearest GWTC grid point. Average afternoon (specifically, the fifth observation; see Table 1 for exact time of day) temperature (TEMP, °C, left) and dew points (DWPT, °C, middle), and average monthly frequency (FREQ, %, right). See Figure 5 for GWTC weather type legend and Figure 35 for SSC weather type legend. Blank cells indicate that no averages were computed due to no/low frequency. N/A indicates that comparable SSC WTs do not exist.

Figure 46 – Mean monthly weather type conditions for January and July for the GWTC (top two rows) and the SSC (bottom two rows) for the Fargo, North Dakota Airport (FAR) SSC station and the nearest GWTC grid point. Average afternoon (specifically, the fifth observation; see Table 1 for exact time of day) temperature (TEMP, °C, left) and dew points (DWPT, °C, middle), and average monthly frequency (FREQ, %, right). See Figure 5 for GWTC weather type legend and Figure 35 for SSC weather type legend. Blank cells indicate that no averages were computed due to no/low frequency. N/A indicates that comparable SSC WTs do not exist.

Figure 47 – Mean monthly weather type conditions for January and July for the GWTC (top two rows) and the SSC (bottom two rows) for the Lincoln, Nebraska Airport (LNK) SSC station and the nearest GWTC grid point. Average afternoon (specifically, the fifth observation; see Table 1 for exact time of day) temperature (TEMP, °C, left) and dew points (DWPT, °C, middle), and average monthly frequency (FREQ, %, right). See Figure 5 for GWTC weather type legend and Figure 35 for SSC weather type legend. Blank cells indicate that no averages were computed due to no/low frequency. N/A indicates that comparable SSC WTs do not exist.

The frequency variability of SSC types has two drawbacks: some weather types do not exist at all in certain months (e.g. MP and DP in July in Phoenix, Arizona), and some types have very high frequencies (e.g. DT in July in Phoenix, Arizona). Both of these could potentially limit the utility of the classification when used with an application, especially with outcomes that respond to seasonally-*relative* and/or geographically-*relative* conditions, rather than *absolute* conditions. This does not appear to be too much of a limiting factor, however, as the SSC has still been quite successful in conjunction with myriad outcomes (Hondula et al., 2013). These limitations of the SSC are benefits of the GWTC, as an adequate frequency of each type at every location at all times of the year, will yield sufficient sample sizes when applied to examine a surface event of interest. Further, the classification does not have WT frequencies that reach into the 40-50% range, and thus contains less within-type variability than the SSC (because the variability of the exact same days is spread out across multiple WTs in the GWTC) – though this could change with future updates to the classification (due to climate change). These benefits of the GWTC, however, come at the expense of less between type variability, and often fewer types that represent extreme conditions for a certain area/season.

When the frequency of an extreme WT is nearly equal in both classifications, the character of the corresponding types are usually much more similar. For example in Lincoln, Nebraska (LNK; Heartland region), when comparing July DC vs. DP, both types

occur 5-6% of the time and have temperatures and dew points that are within 1-2°C of each other (Figure 47). This similarity also extends to the DW and HW July GWTC types compared to the DT and MT+ types in the same location. This trend underscores the conclusion that most of the difference between these two classifications is likely due to the different frequency of comparable types, rather than a difference in the data used for the classification itself.

Another one of the key differences between the SSC and the GWTC that is exhibited in many of the locations examined in this section is the extreme spatiotemporal relativity of the GWTC compared to the SSC. An example of the impacts of this can be seen in the location near San Antonio, Texas (SAT; Figure 42) in July. Ignoring all other variables involved, a theoretical day with a 33°C afternoon temperature and 21°C afternoon dew point would be classified as either HC or Humid in the GWTC, but MT in the SSC. In a location with an average afternoon temperature/dew point of 35/18°C in July, this day is slightly cooler and more humid than average. However, this weather is also likely under the influence of a maritime tropical (mT) type of classical air mass brought in from a source region in the Gulf of Mexico and slightly modified along the way. Thus, this day could be properly classified as MT in the SSC even though it is cooler than average (due to its relationship to air masses from source regions) *and* properly classified as HC in the GWTC even though it is due to an mT air mass (due to its cool and humid conditions

relative to the average) because of the differing classification methodologies arising from different goals of each classification.

For comparative purposes, an adjusted VSS (VSS_{ADJ}) was calculated in an attempt to quantify the partitioning ability of each classification scheme in terms of within- and between-type variability. The adjustment to the VSS was made to account for the differing number of weather types between the two classifications, as the VSS naturally improves with a greater number of types. While this is a benefit of the GWTC (a better VSS_{TD} nearly everywhere; Table 9), a balance must be struck between the number of types and how easy the classification is to use. That is, a classification with dozens of weather types might have a great VSS, but if the types are not easy to use and understand, then the utility of the classification again could be limited.

To derive the VSS_{ADJ} for a location, first the VSS equation for deseasonalized temperature and dew point z-scores (VSS_{TD} ; described in sections 3.3.1 and 7.1 above) is calculated for both the GWTC and the SSC for the entire time series. The resulting VSS_{TD} is then divided by the averaged VSS_{TD} calculated for 10 *random* classifications (VSS_{RNDM}) of these same variables into either 11 (for the GWTC) or 7 (for the SSC types) to offset the impact of the *number* of groups on the VSS_{TD} values. All missing SSC days were removed from the calculations and all MT+ and MT++ days were reclassified into MT days. The resulting quotient was then multiplied by 100 to reduce the number of

significant digits. The VSS_{ADJ} was calculated for each of the SSC station locations shown in Figures 36-47 and its closest GWTC grid point. Similar to the regular VSS_{TD} , the lower the VSS_{ADJ} value is, the better the partitioning ability of the classification. When interpreting the following results it is important to note that the data that are used for these calculations are the same data that the GWTC uses to run the classification scheme (gridded NARR model data), while the SSC is based off of observed airport station data from a slightly different location. Thus, the VSS_{ADJ} is an *estimation* of the SSC's true partitioning ability of actual observed station data.

As is noted in Table 9, the VSS_{ADJ} is better (lower) for the GWTC than for the SSC at each location examined, with the exception of San Antonio, Texas (SAT; Southern Texas region). At this location, the SSC VSS_{TD} (0.79) is better than every other location examined, while the GWTC performs its worst ($VSS_{TD}=0.70$), thus contributing to this outcome. The reason why the SSC performs better than the GWTC here (as opposed to anywhere else) is not clear from Figure 42. However, relative to the VSS_{TD} scores in other regions, it is not that the GWTC performs all that poorly (for example, compared to locations near Amarillo, Texas or Medford, Oregon), just that the SSC performs very well. Perhaps this location/region, more so than others, truly has only a few different types of weather in most seasons, where dew points are either humid or dry, but not moderate, and are consistently occurring within only certain temperature categories (as evidenced by the high VSS_{RNDM} values for both 11 and 7 categories).

While the GWTC has a better VSS_{ADJ} than the SSC at all other locations, relative to the SSC it performs best near the Nashville, Tennessee SSC station (BNA; Mid-South region). The reason behind this result also is not completely clear from the character of the types presented in Figure 44. The only comparable types with similar frequencies are January HW and MT – which are nearly identical in character – while the relationships noted above between comparable WT frequency and character are present otherwise. Noteworthy is the substantially low VSS_{RNDM} for 7 types (35.89 – nearly equal to that of 11 types) which drives the VSS_{ADJ} up for the SSC. This situation could also be attributable to the difference in the data used.

Table 9 – Regular and adjusted variability skill scores for temperature and dew point for the GWTC and the SSC for selected SSC stations and the nearest GWTC grid point. DIFF calculated from a simple subtraction of the VSS_{ADJ} score for the SSC from that of the GWTC [i.e. negative values indicate a better (lower) VSS_{ADJ} for GWTC, positive values indicate a better VSS_{ADJ} for the SSC].

		GWTC			SSC			DIFF
REGION	CITY/REP	VSS_{TD}	$RNDM$	VSS_{ADJ}	VSS_{TD}	$RNDM$	VSS_{ADJ}	VSS_{ADJ}
1	PHX	0.60	33.49	1.79	0.86	44.55	1.94	-0.14
2	AMA	0.68	32.58	2.09	1.07	44.41	2.42	-0.33
3	EKO	0.66	34.06	1.94	1.07	40.39	2.64	-0.70
4	MFR	0.67	33.62	2.00	1.21	42.53	2.85	-0.85
5	GTF	0.66	32.90	2.01	1.05	41.16	2.54	-0.53
7	LAN	0.57	31.86	1.79	0.95	41.56	2.29	-0.50
8	SAT	0.70	36.40	1.91	0.79	45.25	1.74	0.17
9	MCO	0.65	33.99	1.93	0.86	41.58	2.06	-0.13
10	BNA	0.57	33.44	1.71	1.01	35.89	2.81	-1.10
11	JAN	0.60	38.04	1.58	0.96	45.94	2.09	-0.51
12	FAR	0.61	30.54	1.99	1.10	43.79	2.52	-0.53
13	LNK	0.62	31.37	1.96	1.17	44.05	2.65	-0.69

In summary, both classifications are successful at partitioning out weather types that typify a certain segment of the climatology of the location and that correspond to the name of the weather type (i.e. DC and DP are indeed dry and cold relative to the other types). Further, both perform very well in terms of the VSS_{TD} relative to that of a random classification. The two differing methodologies, however, do result in quite different frequencies of comparable weather types, with the SSC WT frequencies routinely ranging more than 40%, while the GWTC WT frequencies are more equal. When/where the differences in the frequency of comparable weather types is large (small), the difference in character is also large (small). When a WT in either classification has a particularly low frequency, it often results in a more extreme/distinctive weather type, resulting in very good (large) between-type variability of the mean afternoon conditions of the days classified into each type. Due to the classification architecture of the SSC, this low frequency happens much more often, but comes at the expense of a high frequency of occurrence of some other types (>40%). This results in poorer within-type variability of these frequent types relative to the within-type variability of the GWTC types, but is usually offset by the better between-type variability mentioned above. This all results in widely varying VSS_{TD} values for the SSC compared to those for the GWTC. That is, the GWTC appears to perform nearly equally well everywhere, while the SSC performs markedly better in areas that are dominated by one or two types of weather

at certain times of the year (e.g. Phoenix, San Antonio, Orlando), but more poorly in areas with more variable weather (e.g. Lincoln, Medford, Fargo). This is likely due to the manual selection of seed days allowing the SSC WT frequency to form around the true climatology. The automation of the GWTC results in consistently good VSS_{TD} everywhere, but slightly worse scores in relatively climatologically-invariable locations/seasons due to forcing of the climate into 9 core WTs.

In addition to the different frequency of the weather types, the different number of weather types (11 vs. 7) and the different data used also likely contribute to some of the differences in WT character between the two classifications. All of these differences between the classifications, however, result in different benefits of the two classifications, and perhaps different future uses as well.

8.2 – Comparison with SSC Weather Type Frequency Climatology

By comparison to the weather type frequency climatology maps displayed for the GWTC in Chapter 6 above, the monthly SSC climatology maps (not shown, available at: <http://sheridan.geog.kent.edu/ssc.html>) for the US are much more intuitive.

Qualitatively, the SSC climatology maps are highly related to source regions of classic air masses for the North American continent. For example, DT peaks in the hot and dry deserts of the southwestern US (especially in July), MT peaks in the Gulf Coast states (especially in July), MP peaks in the Pacific Northwest (especially in January) and DP

peaks in the interior north (especially in winter). On the other hand, the GWTC maps mostly describe the spatial relationship between temperature and dew point, and thus these patterns exhibited by the SSC climatology maps are not present for the corresponding GWTC types, especially not to the same magnitude (e.g. >50% frequency of January DP in the interior north; >50% frequency of July MT in Florida). Among these extreme weather types, the only spatial *patterns* that are somewhat similar are the April and October HW (compared to MT), though the *magnitudes* are still quite different. These results are expected, as the differing methodologies of the two classifications yields drastically different core WT frequencies, and thus, vastly different spatial patterns.

Comparatively, the weather type climatology maps for WFP and CFP are much more similar to those exhibited by the TR SSC type in both the magnitude and the pattern of geographic distribution. This is likely due to the methodology used to define transitional days in the initial weather typing methodology being similar to that used in the SSC (both using thresholds of pressure and dew point ranges).

8.3 – Daily Maps

In addition to the weather type climatology maps, weather type maps can also be produced on a day-by-day basis. These daily maps display not only the type of weather that a particular area of the country is experiencing, but also the spatial cohesiveness of

the classification. While it was not an initial aim of the classification to identify synoptic scale air masses (in as much as identifying point-based surface weather types), nonetheless, when the spatial distribution of a single day's WTs for all locations are mapped, larger-scale, seasonally-relative air masses often emerge. In order to present this feature of the classification, four days were selected that were associated with significant weather events, along with one ambiguous summer day, representing fairly uneventful weather across the US. These days are discussed below in context of their relationships to the daily SSC weather maps (available from the "Daily SSC Maps" link at: <http://sheridan.geog.kent.edu/ssc.html>) and the actual daily weather maps of the US (hereafter HPC weather maps; each obtained from the National Weather Prediction archive for 7am Eastern Standard Time of the day of interest: <http://www.hpc.ncep.noaa.gov/dailywxmap/>).

Figure 48 displays the GWTC, SSC and HPC daily weather maps for February 5, 2008 – a day with a substantial tornado outbreak in parts of Alabama, Tennessee and Kentucky. This area of the country was subjected to relatively warm and humid weather for that time of the year, as represented in both the SSC maps (by the MT type) and in the GWTC daily maps (a large swath of HW across the eastern third of the US). In addition, a cold front positioned just to the south and west of the outbreak area is quite prominent on both the GWTC and SSC maps (TR in the SSC map), corresponding with the cold front indicated by the HPC weather map. Further, as would be expected behind the front, an

area of Dry Cool weather dominates westward (and DP with the SSC). The cold front in the Upper Great Lakes and the warm front pushing its way into the Pacific Northwest are also well indicated on the GWTC and HPC maps. Areas marked on the HPC maps with precipitation also correspond well to areas on the GWTC map with humid weather types. The major difference between the HPC and GWTC maps is the extent of the front – indicated to extend all the way into the Great Lakes on the HPC map, but only into Oklahoma with the GWTC. This noted, the low associated with the more northerly cold front does disappear from the next day's HPC map (not shown), while the low centered in Texas moves northeastward after the 7am observations depicted on the HPC map. The GWTC and SSC maps are more similar in this regard – not designating this area as a transitional zone. A major difference between the GWTC and SSC maps on this particular day, however, is the extent of DP on the SSC map through the Northern Plains (where there is more variability in WTs on the GWTC map), and the transition to DM in California (where the GWTC shows DC dominating). This particular day also experienced quite high spatial match percentages with the GWTC, nearly 82% across the US as a whole – well above the winter average (74%).

Figure 49 depicts the weather maps for January 15, 2004 – a day corresponding to an extreme cold outbreak in the northeastern US. The HPC map shows both the 32°F (0°C) and 0°F (-18°C) line running south of New England, indicating very low temperatures in these locations; correspondingly, the GWTC map exhibits a large region of DC in this

portion of the country, as does the SSC map with DP. However, while the SSC map indicates DP extending south of the Great Lakes, these areas transition to Cool and Dry types on the GWTC map. All maps are also quite similar in representing the frontal situation in the Mid-Atlantic states, with the SSC depicting a small area of TR, and the GWTC indicating a CFP type for these same locations. The north/south oriented stationary front in the northern Plains indicated by the HPC map can be seen as a sharp boundary between DW and more humid (and average) and cooler (moderate types) in these locations, as a stationary front would not be expected to show up as a transitional type in the GWTC due to its stationarity. Interestingly, the GWTC has this boundary extending well to the south of the front depicted on the HPC map; however, when examining the maximum and minimum temperature maps for the following day (not shown) – as the displayed HPC map is from 7am EST on January 15 – the thermal boundary does appear to extend well into the southeast. On the contrary, the SSC map depicts this entire area as a broad region of DM. Along the southern border of the US from Texas to Arizona, the SSC and GWTC maps are in good agreement, indicating fairly warm weather throughout, but with drying conditions further west, including a pocket of DW (and DT in the SSC). While not easily seen on the HPC surface map, in studying maps of maximum temperature and 24-hour precipitation from the HPC (not shown), these weather types appear accurate. While the Intermontane area of the US is much more jumbled, the general trend of warmer/drier types in the south with more humid/cooler types in the north are displayed on both the SSC and GWTC maps. This

spatial variability in the west, however, drops the domain wide match percentage to 70%.

A major heat wave across the Plains (especially the Northern Plains – where temperatures in some South Dakota locations reached 47°C) occurred on July 16, 2006, and the corresponding maps of this day are displayed in Figure 50. While difficult to ascertain from just the HPC surface map alone, the SSC and GWTC maps show the broad area of high temperatures quite well. Further, the sharp transition from DW to HW (and DT to MT+) in the Northern Plains is also noticeable in both maps, and corresponds to areas of precipitation on the HPC 24-hour precipitation map for the day (not shown). The additional humidity category of the GWTC in comparison to the SSC is also quite noticeable here as well, with an area of the Warm WT around Missouri breaking up two larger areas of DW, while the SSC shows this region to be DT throughout. While the GWTC has DW extending much further to the east than the SSC maps, it is important to note that many SSC stations in the Mid-South region do categorize the day as dry (either DT or DM), despite the larger air mass being defined (later) as MT. Another area of agreement between the SSC and GWTC is the transitional area along the US/Mexico border in Texas and New Mexico, where WFP and CFP both show up, and the presence of MT/HW just to its west. While the SSC map indicates relatively dry (DM or DT) weather in the Pacific Northwest, the GWTC presents a much more spatially variable situation. Of note here is the pocket of HW that is present from north-central California

through Idaho, which is dominated by dry conditions in the SSC map. Despite the variability in the Pacific Northwest, overall spatial match percentage of the GWTC for the day is nearly 77%.

Figure 48 – Daily weather type maps for the GWTC (top) and SSC (bottom left), along with the NCEP/HPC surface map (bottom right) for 5 February 2008.

Figure 49 – Daily weather type maps for the GWTC (top) and SSC (bottom left), along with the NCEP/HPC surface map (bottom right) for 15 January 2004.

Figure 50 – Daily weather type maps for the GWTC (top) and SSC (bottom left), along with the NCEP/HPC surface map (bottom right) for 16 July 2006.

Figure 51 – Daily weather type maps for the GWTC (top) and SSC (bottom left), along with the NCEP/HPC surface map (bottom right) for 22 January 2005.

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Figure 52 – Daily weather type maps for the GWTC (top) and SSC (bottom left), along with the NCEP/HPC surface map (bottom right) for 12 September 2006.

The Great Plains experienced extreme weather again on January 22, 2005, as a major snowstorm pushed its way across the northern areas of the region (Figure 51). The major highlight of both the SSC and GWTC maps are the large swaths of the country blanketed by transitional weather, including a portion of CFP from the Appalachians to the High Plains and areas of WFP in the western Dakotas/Montana and along the east coast. Examining the HPC maps from January 22 and 23 (not shown) the *rapidity* of the cyclone in the Ohio Valley and the anticyclone trailing out of the Canadian Shield are the likely culprits for these immense transitional areas. The region of DP in the northern Plains of the SSC map differs from the weather depicted in the GWTC map (mostly Cool, Dry, or HC), and does not extend back into Colorado. While this difference between classifications could exist for a number of reasons (e.g. station data vs. reanalyzed data, the slightly differing ways transitional types are defined, or the timing of the frontal passage; Hondula and Davis, 2011), the GWTC does appear to better mimic the front depicted on the HPC map. The SSC and GWTC also diverge in their classifications of the western US, with the GWTC classifying all but a small section of the Intermontane region as one of the warm types, while the SSC only indicates a handful of stations are tropical (MT(+) or DT). This is likely due to the GWTC identifying weather types that are much more seasonally-relative than the SSC. The cutoff thermal low in the Idaho/Nevada border region indicated by the maximum temperature HPC map (not shown) is well depicted on the GWTC maps (as more moderate temperature categories, H, S and HC),

but not as evident in the SSC map (showing up as a much broader region of MP), likely due to SSC station paucity in the area. Spatial match percentage for the day is over 80%.

Among many qualitatively “ambiguous” weather days across the US, September 12, 2006 was selected due to few (five) severe weather reports archived at the Storm Prediction Center (http://www.spc.noaa.gov/climo/reports/060912_rpts.html) and no major tropical systems or their remnants moving through the domain. The major synoptic feature of the HPC surface map is the typical mid-latitude cyclone moving through the Midwestern states. While the GWTC map is somewhat successful at picking up parts of the trailing CFP (spotty locations in Missouri, Illinois, Arkansas, Oklahoma and Texas), the leading WFP is not well-defined, though neither is present on the SSC map (Figure 52). This is likely due to the fact that, as with most summer cyclones, the associated fronts are not all that transitional; indeed the temperature maps for the day show only a slight gradient oriented along the axis of the cold front. Behind the cyclone, from the Heartland northeastward into the Upper Great Lakes, both the SSC and GWTC are consistent in their assessment of humid and cool weather (MP and HC), though the GWTC further delineates separate areas dominated by H and C types in certain parts of the region. The two classifications are also quite similar in their depiction of DC (DP) and Cool types along the east coast (as signified by lows dipping into the mid 30s (°F) on the HPC temperature maps), and a relatively warm and dry western third of the US. The two classifications diverge quite drastically ahead of the cold front, however, where the

GWTC is classifying DW and Warm types (with some Humid types), but the SSC is indicating Moist Moderate. This disconnect is even further evident in Florida, where much of the area is classified as HC in the GWTC, but MT in the SSC. This is due to the spatiotemporal relativity of the GWTC compared to that of the SSC; where for example in July, and likely September, in Orlando (MCO; Figure 43), the HC GWTC type and the MT SSC type have similar characters, and no HP exists for the SSC. The different data used in the two classifications coupled with the unusual amount of spatial variability in the weather of the area may have also contributed to this, as afternoon temperatures range from 25°C in Jacksonville to 33°C in Tampa on this day (according to the SSC website). This ambiguous day also results in a relatively low spatial match percentage for the domain, at just 71%.

Taken together, this small sample of five days provides evidence that the classification, despite its automation, is in fact doing what it is expected to be doing, as the spatial distribution of weather types throughout the domain corresponds well with synoptic-scale air masses associated with the actual surface weather map for the day, and the SSC maps. Other general aspects of the classification derived from these daily maps include:

- Despite only a small portion of the classification incorporating any spatial component, on a daily basis, weather types cluster in certain areas – mimicking broader-scale air masses
- CFP and WFP (to a lesser extent) correspond well to frontal boundaries on the actual HPC surface maps and the TR areas of the SSC maps
 - Despite not being explicitly categorized, stationary fronts showed up as sharp boundaries between differing weather types
- The extreme weather types (DC, DW, HC, HW) coincide well with extreme weather events, especially those involving temperature
 - Even on non-extreme event days, many of these extreme types are often bordered by regions of their “middle type” counterparts (e.g. a core of DC being surrounded by Cool or Dry types, or a core of HW being surrounded by Humid or Warm types)
- Stronger (non-summer) mid-latitude cyclones are well defined by the GWTC
- The humid types (especially HC and H), appear to correspond well to areas of precipitation

Among differences between the SSC and GWTC maps, most of them are likely due to the additional humidity category of the GWTC (resulting in 9 core types, rather than 6) and/or the ‘more-equal’ frequency of the GWTC weather types (e.g. DP in Colorado on 12 September 2006). Where this is not the case, these two classifications may also differ

due to the difference in the data used (surface station observations for the SSC vs. NARR model for the GWTC) or the spatial resolution of the classification.

As can be inferred based upon the seasonal spatial match percentages (Chapter 7) along with this small sample of daily maps, wintertime daily maps will often contain better spatial cohesion (and distinct air masses) than relatively uneventful summer days. This said, a summer day with only a 71% spatial match (e.g. 12 September 2006) still exhibits distinct air mass types. Due to this spatial cohesion, contrary to the weather type climatology maps presented in Chapter 6 above, these daily maps are quite intuitive and can quickly inform the user of both the thermal and moisture characteristics (and, in a holistic sense, other associated meteorological variables) of locations across the entire domain (Sheridan, 2000), along with the general location of synoptic systems.

CHAPTER 9

SUMMARY AND CONCLUSIONS

This research details the development of a gridded weather typing classification (GWTC) system. While this system is employed herein only for the continental United States, the methodology used is transportable to any mid-latitude location. In addition to enhancing the spatial resolution of previous weather type classification systems and providing a more automated methodology than the SSC (Sheridan, 2002), this classification was constructed with the primary goals of creating a set of universal surface weather types that were spatiotemporally relative and that occurred at all times of the year at every location. To meet these goals, each individual location's daily weather type is classified in two primary steps. The initial weather typing procedure uses seasonally-relative z-score thresholds to delineate three temperature categories, and three dew point (humidity) categories within each temperature category. Transitional weather is also identified through dew point and pressure ranges of these z-scores, and then sub-typed into cold front and warm front passage types according to the diurnal trend of z-scores of these two variables. A secondary typing procedure then utilizes principal components analysis and discriminant function analysis that together

incorporate cloud cover, wind speed and wind direction into the classification in addition to dew point, temperature and pressure data used in the initial step. Once the data set for each individual location is weather typed separately, a tertiary step integrates a spatial smoothing component to help the classification system mimic the natural spatial consistency of mid-latitude weather. The resulting classification consists of nine core weather types characterized mainly by their temperature and humidity components, along with two transitional weather types characterizing the change of weather in a certain direction.

Descriptive statistics reveal that each weather type does possess a character that is consistent with its name, the time of year it occurs, and the location at which it occurs (e.g. a Dry Warm type in July near Lincoln, Nebraska is indeed dry and warm relative to the other weather types classified for July in that location). Further, while some seasonal preference is shown in the frequency of weather types, all core types do occur in all months at all locations. In comparison to the SSC, however, GWTC weather type frequency is much less variable. The difference in frequency of comparable weather types between the classifications results in differing character of comparable types, whereby the weather type in the classification that is less frequent is often more extreme than its counterpart in the other classification. When comparable types in the GWTC and SSC have similar frequencies, their characters are also similar. Individual daily

maps also reveal many similarities between the SSC and GWTC, including each classification's high-degree of agreement with historical surface weather maps.

Variability skill scores for temperature and dew point show that the GWTC performs best in winter and east of the Plains states – indicating more skill in areas/seasons that have more climatological diversity. All of these scores, however, range quite minimally both geographically and seasonally, are substantially better than a random classification, and indicate that within-type variability is less than between-type variability (i.e. $VSS_{TD} < 1.00$) at all regions at all times of year. In comparison to the SSC (Sheridan, 2002), the GWTC performs better, even when adjusted for the differing number of weather types between the two classifications. Variability skill scores for variables other than temperature and dew point are poorer, but still much better than random. The classification also exhibits high spatial match percentages, especially in the transitional seasons, indicating spatial consistency in daily weather type classifications. The lowest spatial matches are found at coastal locations and areas of varying topography. The temporal persistence of weather types is greatest in areas known for consistent weather at certain times of the year, and seasonally in summer.

Despite the success of the classification on many levels, the employed methodology does exhibit certain limitations. By comparison to the SSC, the GWTC does not contain nearly as much between-type variability. At some locations in some seasons, the

difference between two or more types might only be 1°C in temperature and/or dew point (e.g. Florida in summer). This is a result of the GWTC's goal of more-equal frequency of all weather types using spatiotemporally-relative z-scores; ultimately forcing all climates – including those that are quite invariable (in absolute terms) – into nine core weather types. The tradeoff of this limitation is that the GWTC exhibits better (lower) within-type variability than the SSC, and maintains an adequate frequency of all types at all locations – a potentially valuable attribute in some applications.

The relative infrequency of dry weather types in seasons outside of winter may also be viewed as a limitation of the classification. This is caused by using the mean in association with non-normally distributed dew points within temperature categories. While this results in more humid and average types relative to dry types (contrary to the goal of parity among WT frequencies), the methodology allows dry types to be better partitioned (i.e. more extreme in temperature and/or humidity) and results in better overall VSS_{TD} scores for the classification. This said, the mean range of WT frequencies among all WTs at a location is still less than 10 percentage points, indicating that differences in WT frequencies are fairly small.

Unlike with the SSC, the GWTC weather type frequency climatology maps are quite uninformative and not easily interpretable. While this could be considered a limitation of the GWTC, this is perhaps the best indicator of how the SSC and GWTC are different

in their aims. The former manually classifies seed day parameters that are highly relatable to classic synoptic-scale air masses that originate and migrate/modify from source regions (but not always; e.g. Hondula et al., 2010). The GWTC, on the other hand is automated and unaware of source regions, defining the character of these weather types (and thereby, their frequency) almost entirely based upon a day's weather relative to the average and variability of the weather on that exact day of the year, and at that exact geographic location.

Each of the above limitations is ultimately brought about by the overall goals of the GWTC discussed in Chapter 2 above. Thus, each of these limitations was by design – it resulted in a benefit of the classification that was thought to offset/outweigh the perceived limitation it brought about. While the statistics revealed the GWTC to be successful in its partitioning ability of the variables historically important in surface weather typing (temperature and dew point), it is important to note that no useful classification is going to be perfect (i.e. VSS = 0.00), and each will have limitations that must be balanced with benefits – both of which are subjectively chosen.

Along with the goals that were met by using the specific methodology employed, the utilization of the NARR data set herein to run the GWTC provides a number of other benefits that not only incorporate the features of the SSC, but also overcome some of its perceived limitations. Some of these benefits include the following:

- **Gridded Structure of Data Set Used:** Synoptic climatological research has become increasingly more interested in future climate change impacts (Sheridan and Lee, 2010). Most such research is carried out using global climate models (GCMs) that output data in a gridded nature. Naturally, a gridded weather-type classification makes compatibility with such studies much easier; avoiding the complex downscaling that is often necessary when evaluating future weather types at station-based classifications. The structure of a gridded data set also helps expand the spatial scales at which any investigation can take place, shifting applications of weather type classifications merely from point-based to regional-, synoptic-, or even continental-scale.
- **Transportable Automated Methodology:** With continuing advancements in computer processing power over the past decade, automated and more ‘objective’ methods are typically preferred in synoptic-based research over manual methods that inherently involve more subjectivity and reduce repeatability. The use of a more-objective z-score based methodology based completely on historical climate records eliminates the time consuming task of estimating *a priori* definitions of weather types at every location (as is done with the SSC). Further, the automated nature of the method makes it easily replicated by other researchers. The classification *methodology* can therefore be easily

transferred to other mid-latitude climates across the globe, and/or other levels of the atmosphere that may be of interest in some applications. Further, it can also be transferred to other reanalysis data sets that may be developed over time with better resolution, or for use directly with GCM data once humidity and cloud cover become more accurately projected.

- **Enhanced Spatial Resolution Allows for New Applications:** Prior to gridded reanalyses, all synoptic classifications relied on observed meteorological data at random locations – with the most reliable often being restricted to stations at airports near urban areas. Thus, studying weather-type relationships to events in an area not near a weather station with a lengthy and (relatively) complete record, is difficult. With the mainstream use of different gridded reanalysis data sets, synoptic climatological applications necessitating the finer-scale spatial resolution offered by reanalysis data sets (or those in relatively rural areas without airports) could benefit from using the GWTC. This is especially true in mountainous regions, where there are few airport weather stations, but a large amount of spatial climate variability.
- **100% Temporal Coverage:** A drawback of many station-based classifications that utilize observational data only is that of missing days and station re-location. When a weather station switches locations, an instrument fails, or an operator

forgets to log the data, discontinuities arise in the record. Reanalyses – being based off observations that have subsequently been subjected to spatial and temporal interpolation – have a complete record, offering an added benefit of using such data in this classification system.

- **Transitional Sub-Types**: One of the more novel additions to the classification is the identification of the sub-type of transition that is occurring. With previous research showing that changes in weather and/or the passage of frontal boundaries could be impactful on human mortality (e.g. Plavcova and Kysely, 2010; Allen and Sheridan, 2013), this feature of the GWTC could be beneficial for a variety of applications.

Much like the current SSC, the GWTC is meant not only to be a *methodology* for classifying weather types (which can be used in other applications and/or with other data sets), but more so even for its end product – the resultant weather types themselves. Thus, future developments for the GWTC include the eventual creation of a GWTC website that is updated annually (after new NARR data are available; similar to that of the SSC) where calendars of GWTC weather types at all locations can be accessed easily and used free of charge for any applied climatological research. The ease of use of the GWTC will be beneficial in climate-related interdisciplinary work where the investigators are less concerned with how to successfully partition weather types, and

more interested in how weather types impact their ‘event of interest.’ Other future developments may include:

- an adjustment for climate change in future studies so that the warm types don’t become dominant, but rather stay relative to a specific/moving climate normal;
- data sets, tables and maps of *probabilities* of each weather type on each day (as DFA in the secondary typing procedure calculates probabilities of each day belonging to each weather type, and then classifies the day into the type with the highest probability), which may prove useful for researchers desiring continuous data rather than categorical. It may also aid in creating a multivariate map pattern classification based upon daily fields of these probabilities; and
- the production of daily maps that are available on-line, as these may be easier for some researchers to understand than surface weather maps (Sheridan, 2000), and could yield valuable spatial relationships for case study applications.

The research herein discusses both the quantitative and qualitative *success* of the classification in partitioning different weather situations, however, the *utility* of the classification over the long-term is also important. That is, how well is it able to partition the surface event/environment of interest in applied research (Yarnal, 1993), and what

types of applications is it well-suited for? While a long-term evaluation of the GWTC's utility is impossible to analyze now, some applications of the classification have already been explored. Preliminary results near Cleveland, Ohio show that the air quality in the warm season is significantly poorer than average on HW, W and DW days, and significantly better than average on DC, C, HC and CFP days, with these results remaining consistent from April through November. Further, initial results examining cardiovascular-related mortality in the meteorological winter (December to February) reveal a significant increase in cardiovascular-related deaths 1 to 5 (or more) days after the occurrence of the DC weather type in various cities, and a decrease in cardiovascular-related deaths on days following the occurrence of the HW weather type. This relationship is consistent even in locations in very different climate zones (e.g. near both Chicago and Atlanta), and is also quite pronounced into the transitional seasons as well.

In addition to these applications currently under way, the GWTC may be particularly useful in research involving spatiotemporally-relative relationships to multiple weather elements (e.g. human health/comfort/mortality, energy usage). Other possible future uses of the GWTC may include the examination of the magnitude and extent of the urban heat island effect on neighboring urban and rural grid points (examining differences in the character or frequency of the same types at two neighboring locations), or investigating the relationship of air quality to weather types in a similar

capacity. As mentioned above, the GWTC may naturally be useful in conjunction with gridded GCM data to project the impacts of future climate change on a wide range of surface events (e.g. tornadoes, heavy precipitation events), environments (e.g. urban heat island, air quality) or human health outcomes, all on varying spatial scales.

CHAPTER 10

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APPENDIX A

Each of the following tables displays the monthly region-wide averages by GWTC weather type for different meteorological variables used in the research. Please see Figure 4 or Table 3 for the geographical region corresponding to the region numbers on the vertical axis.

Table A.1 – Region-wide average January temperatures (°C; top) and dew points (°C; bottom) for the second daily observation for each weather type (horizontal axis) and each region (vertical axis; please see Figure 4 for region numbers).

JANUARY TEMPERATURE (OBS #2; MORNING)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	2	4	7	-1	3	6	-2	2	6	3	4
2	-3	0	5	-6	-1	3	-9	-2	2	2	-6
3	-9	-5	0	-11	-6	-2	-15	-7	-2	-4	-8
4	3	6	9	1	4	7	-1	3	6	5	4
5	-9	-3	2	-12	-5	0	-17	-6	-1	-2	-9
6	-9	-5	2	-11	-6	-1	-16	-7	-3	-3	-9
7	-12	-6	2	-15	-8	-2	-19	-9	-5	-4	-12
8	7	10	15	3	7	12	1	7	11	13	3
9	10	14	19	7	12	17	4	10	15	16	9
10	-4	1	9	-7	-1	4	-11	-3	1	3	-4
11	1	6	13	-2	3	9	-5	1	6	9	0
12	-19	-13	-4	-22	-14	-8	-28	-16	-10	-10	-20
13	-11	-5	1	-14	-7	-2	-18	-7	-3	-3	-12

JANUARY DEW POINT (OBS #2; MORNING)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	-2	1	2	-7	-5	-4	-13	-11	-10	-3	-9
2	-6	-3	0	-10	-7	-5	-15	-11	-10	-4	-12
3	-11	-7	-3	-14	-10	-7	-20	-15	-13	-7	-14
4	2	4	7	-2	1	2	-7	-4	-3	3	0
5	-11	-5	-1	-15	-7	-4	-21	-11	-8	-5	-12
6	-11	-6	0	-13	-8	-3	-18	-10	-5	-5	-12
7	-14	-7	1	-17	-10	-3	-22	-12	-7	-6	-14
8	4	8	14	0	3	9	-5	0	4	10	-3
9	8	13	18	4	10	16	0	7	13	14	6
10	-6	0	8	-10	-4	2	-15	-7	-2	2	-8
11	0	4	13	-4	1	8	-10	-2	4	8	-3
12	-21	-14	-5	-24	-15	-9	-30	-18	-12	-11	-22
13	-12	-6	0	-16	-9	-4	-21	-11	-8	-5	-14

Table A.2 – Region-wide average January temperatures (°C; top) and dew points (°C; bottom) for the fifth daily observation for each weather type (horizontal axis) and each region (vertical axis; please see Figure 4 for region numbers).

JANUARY TEMPERATURE (OBS #5; AFTERNOON)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	6	10	14	7	11	15	6	12	16	7	10
2	2	8	14	1	8	14	-2	9	15	6	6
3	-4	-1	4	-5	-1	3	-8	0	4	-3	-1
4	6	8	12	6	9	13	5	10	14	6	9
5	-5	0	5	-7	0	4	-12	-1	4	-3	-2
6	-7	-2	2	-9	-4	0	-14	-6	-2	-6	-4
7	-7	-2	5	-10	-3	1	-15	-5	0	-6	-3
8	11	17	24	11	17	23	8	18	23	17	16
9	15	19	24	14	18	22	10	18	21	16	18
10	0	5	15	-1	5	10	-6	4	10	3	4
11	7	13	21	7	13	18	3	13	17	11	12
12	-13	-6	0	-16	-8	-2	-21	-11	-4	-11	-9
13	-5	1	9	-8	0	6	-13	-1	5	-3	-1

JANUARY DEW POINT (OBS #5; AFTERNOON)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	-1	1	3	-6	-4	-3	-12	-9	-8	-7	-5
2	-3	0	2	-7	-4	-2	-13	-9	-7	-7	-5
3	-6	-4	-1	-9	-6	-4	-13	-9	-8	-9	-6
4	3	5	8	0	3	4	-5	-1	0	1	3
5	-7	-2	1	-10	-4	-2	-16	-7	-5	-7	-5
6	-10	-4	1	-13	-7	-2	-17	-9	-5	-9	-7
7	-10	-4	3	-13	-6	-1	-19	-10	-5	-10	-6
8	6	10	15	1	5	11	-6	-1	4	3	5
9	9	14	19	5	12	17	0	8	14	9	13
10	-3	2	11	-7	-1	6	-14	-5	1	-3	0
11	2	9	16	-2	5	12	-8	1	7	3	6
12	-16	-8	-2	-19	-10	-4	-25	-14	-7	-14	-11
13	-7	-2	3	-12	-5	-1	-18	-9	-6	-8	-5

Table A.3 – Region-wide average daily pressure (mb; top) and wind speed (m/s; bottom) for January for each region (vertical axis).

JANUARY PRESSURE (AVG. DAILY)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	1017	1016	1017	1022	1019	1019	1025	1021	1019	1017	1014
2	1022	1018	1014	1026	1020	1015	1030	1021	1015	1018	1018
3	1023	1019	1016	1027	1022	1018	1030	1024	1021	1018	1017
4	1016	1017	1018	1021	1020	1019	1023	1023	1021	1016	1012
5	1021	1017	1012	1025	1020	1014	1029	1022	1017	1018	1016
6	1020	1015	1009	1024	1018	1013	1025	1022	1016	1014	1018
7	1020	1015	1011	1024	1018	1013	1026	1022	1017	1015	1019
8	1023	1020	1015	1026	1021	1016	1030	1022	1016	1018	1020
9	1022	1019	1018	1023	1021	1019	1026	1021	1020	1017	1019
10	1021	1018	1015	1025	1020	1016	1029	1023	1019	1017	1020
11	1021	1019	1016	1025	1021	1018	1029	1023	1019	1018	1020
12	1024	1017	1008	1028	1021	1013	1031	1023	1016	1019	1019
13	1024	1017	1011	1029	1021	1015	1033	1025	1019	1019	1019

JANUARY WIND SPEED (AVG DAILY)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	1.6	1.8	1.4	1.4	0.4	0.2	1.9	0.8	0.2	3.3	2.4
2	0.4	0.6	2.3	0.8	1.6	2.2	0.8	1.8	2.5	2.9	3.2
3	1.5	2.1	3.1	1.4	1.7	2.3	0.9	1.1	1.6	4.0	3.2
4	2.2	3.0	3.3	1.0	0.5	1.3	1.8	1.0	1.2	3.3	4.3
5	1.4	2.0	3.4	0.6	2.2	2.9	0.3	1.5	2.2	3.5	3.2
6	2.8	1.5	2.5	3.8	2.5	1.9	4.2	2.9	1.8	5.6	3.9
7	2.2	1.4	3.0	3.2	2.1	1.7	4.2	2.6	2.2	5.5	3.5
8	2.2	1.5	3.5	2.0	0.7	2.2	2.4	0.4	0.9	3.5	3.4
9	3.3	1.4	3.0	3.1	1.5	1.8	4.5	1.6	0.7	4.5	2.5
10	1.8	0.3	3.8	2.3	1.5	1.6	3.4	1.7	2.0	4.8	3.4
11	1.6	0.7	3.5	1.7	0.5	1.7	2.6	0.8	0.9	3.7	3.2
12	1.2	0.9	2.0	1.9	1.0	1.6	2.9	1.3	1.4	5.0	3.0
13	0.5	0.4	1.7	1.3	1.1	1.4	2.5	1.3	1.8	4.6	3.4

Table A.4 – Region-wide average daily wind direction (16 directions; top) and cloud cover (in %; bottom) for January for each region (vertical axis).

JANUARY WIND DIRECTION (AVG DAILY)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	SW	SSW	SSW	NNW	NW	SSW	N	N	ENE	WNW	S
2	NNE	SW	SW	WNW	W	WSW	NNW	W	WSW	NNW	SSW
3	WSW	SW	SW	W	WSW	SW	WNW	WSW	SW	WNW	SSW
4	SW	SSW	S	NW	SSW	SSE	NNE	ENE	E	WSW	SSE
5	WSW	WSW	SW	WSW	WSW	SW	NNE	WSW	SW	WNW	SSW
6	WNW	W	SSW	NW	WNW	SW	WNW	WNW	W	NW	S
7	WNW	W	SSW	WNW	W	SW	WNW	WNW	WSW	WNW	S
8	NE	ESE	SSE	NNE	SE	SSE	NNE	NW	SSW	NNW	SSE
9	N	NE	S	NNW	NNE	SE	NNW	NNW	SE	NW	SE
10	NW	WNW	SSW	NW	W	SSW	NW	W	SW	WNW	S
11	N	ENE	S	NNW	NW	S	NNW	NW	SW	NW	SSE
12	WNW	SW	WSW	WNW	WNW	WSW	WNW	WNW	W	NW	SSW
13	WNW	W	SSW	NW	WNW	WSW	NW	WNW	WSW	NW	S

JANUARY CLOUD COVER (AVG DAILY)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	53	55	48	19	30	32	13	21	29	23	64
2	52	46	44	32	23	29	31	17	24	35	36
3	48	61	66	29	39	51	25	26	36	51	69
4	73	76	75	44	50	53	23	32	34	59	78
5	58	66	68	46	53	57	39	40	43	66	69
6	76	75	77	72	77	74	66	78	77	80	83
7	60	69	74	51	60	71	45	57	60	62	79
8	71	58	46	45	35	37	37	20	25	33	49
9	55	63	55	30	46	55	24	29	44	44	60
10	63	73	67	42	49	66	38	41	46	56	74
11	60	70	61	28	43	60	28	28	41	43	67
12	51	49	57	48	52	52	36	55	53	54	59
13	50	54	53	45	40	41	37	39	34	49	47

Table A.5 – Region-wide average April temperatures (°C; top) and dew points (°C; bottom) for the second daily observation for each weather type (horizontal axis) and each region (vertical axis; please see Figure 4 for region numbers).

APRIL TEMPERATURE (OBS #2; MORNING)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	7	10	14	5	9	13	4	8	13	9	10
2	7	9	13	4	8	12	3	7	11	11	4
3	0	3	6	-2	2	6	-4	1	5	3	0
4	6	8	11	4	6	10	2	5	9	7	7
5	2	5	8	0	3	7	-3	2	6	5	0
6	1	3	11	0	2	7	-3	2	6	5	1
7	3	6	12	1	4	8	-2	3	7	8	3
8	15	17	19	12	15	18	9	14	17	18	11
9	17	19	22	15	18	20	12	17	19	20	16
10	8	11	16	5	8	13	2	7	11	13	6
11	11	14	18	8	11	16	5	10	14	16	9
12	0	4	8	-2	2	5	-5	1	4	6	-1
13	6	8	13	2	5	10	0	4	8	10	2

APRIL DEW POINT (OBS #2; MORNING)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	1	1	1	-4	-4	-4	-9	-9	-9	-3	-7
2	4	5	7	-1	1	2	-6	-4	-2	3	-3
3	-4	-2	-1	-7	-5	-4	-11	-9	-8	-4	-10
4	4	6	7	2	3	4	-1	-1	0	4	1
5	0	2	3	-4	-2	0	-7	-5	-3	1	-5
6	0	1	7	-3	-1	2	-7	-3	-2	3	-3
7	1	4	9	-2	1	5	-7	-2	1	6	-1
8	13	16	18	8	12	16	3	7	11	16	6
9	15	18	20	12	16	19	8	14	17	18	13
10	6	9	14	2	5	11	-2	3	7	11	3
11	9	13	17	5	10	15	2	7	12	15	7
12	-2	2	5	-5	-2	1	-10	-5	-3	2	-6
13	4	6	11	-1	2	6	-5	-1	2	8	-1

Table A.6 – Region-wide average April temperatures (°C; top) and dew points (°C; bottom) for the fifth daily observation for each weather type (horizontal axis) and each region (vertical axis; please see Figure 4 for region numbers).

APRIL TEMPERATURE (OBS #5; AFTERNOON)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	15	20	25	15	21	26	15	21	26	16	20
2	14	21	26	14	21	26	13	21	27	18	21
3	6	11	16	5	11	16	4	11	17	6	10
4	10	14	20	10	14	19	10	15	20	11	15
5	7	11	18	6	11	17	4	11	18	8	12
6	2	4	14	1	4	9	-1	5	9	3	5
7	7	11	21	6	11	17	4	12	17	9	12
8	23	28	32	22	28	32	21	28	32	27	27
9	22	24	27	22	25	26	20	25	27	23	25
10	12	17	24	13	18	22	10	18	22	15	17
11	19	23	28	19	24	27	16	24	27	21	23
12	5	11	21	4	11	18	1	11	17	9	13
13	11	16	25	10	17	23	8	17	23	15	19

APRIL DEW POINT (OBS #5; AFTERNOON)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	0	1	1	-4	-4	-4	-10	-9	-8	-7	-5
2	5	6	7	-1	1	2	-7	-5	-4	-2	2
3	-3	-1	0	-6	-4	-3	-10	-8	-6	-7	-5
4	5	8	10	3	5	7	0	2	4	3	5
5	0	3	5	-3	-1	2	-7	-4	-1	-2	0
6	0	2	9	-2	0	4	-6	-3	-1	0	1
7	3	7	13	-1	3	9	-5	0	4	2	5
8	15	17	18	9	13	14	2	6	7	8	11
9	16	19	21	12	17	19	8	14	16	14	18
10	8	12	16	4	9	14	0	6	10	8	11
11	12	17	20	8	14	18	4	10	14	12	15
12	0	4	8	-4	-1	3	-9	-5	-2	-2	1
13	6	9	14	1	5	10	-4	0	4	4	7

Table A.7 – Region-wide average daily pressure (mb; top) and wind speed (m/s; bottom) for April for each region (vertical axis).

APRIL PRESSURE (AVG. DAILY)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	1012	1012	1013	1013	1012	1013	1015	1014	1013	1011	1009
2	1015	1012	1011	1017	1013	1009	1020	1013	1008	1010	1012
3	1013	1012	1013	1017	1014	1013	1019	1016	1013	1011	1013
4	1015	1016	1015	1017	1017	1016	1019	1018	1017	1016	1015
5	1015	1012	1010	1018	1015	1011	1022	1017	1013	1013	1015
6	1013	1011	1010	1018	1016	1013	1022	1020	1017	1012	1012
7	1012	1011	1012	1017	1015	1012	1020	1019	1016	1012	1013
8	1016	1013	1010	1018	1014	1011	1020	1015	1009	1012	1012
9	1017	1016	1015	1017	1018	1016	1018	1018	1017	1014	1015
10	1014	1013	1014	1017	1016	1014	1020	1018	1016	1013	1013
11	1015	1015	1014	1018	1017	1015	1020	1018	1016	1013	1013
12	1014	1011	1006	1020	1017	1011	1023	1019	1015	1012	1012
13	1013	1011	1007	1018	1015	1011	1023	1017	1012	1011	1011

APRIL WIND SPEED (AVG DAILY)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	3.3	2.9	2.3	2.6	2.4	1.9	2.0	1.3	1.7	4.3	4.3
2	2.0	2.5	3.4	1.2	1.3	3.0	1.8	2.0	3.2	2.8	4.3
3	1.9	2.1	2.0	2.4	2.3	2.3	2.5	1.7	2.5	4.9	2.9
4	2.4	2.0	1.3	2.5	2.0	1.3	3.1	2.1	0.9	3.9	1.4
5	0.8	1.0	1.0	1.6	1.6	1.4	1.8	1.3	1.2	3.9	2.2
6	1.4	0.8	3.3	2.0	0.8	1.4	3.4	1.0	0.7	3.7	3.3
7	1.4	1.0	3.5	2.8	0.8	2.1	3.9	0.8	1.3	4.2	4.1
8	2.8	4.4	4.6	1.6	3.6	4.0	1.8	1.3	1.5	2.5	4.9
9	1.5	2.2	3.0	1.5	1.7	2.3	3.2	0.6	0.8	3.5	3.3
10	1.0	1.8	3.9	2.0	0.9	2.8	3.1	1.0	2.1	3.7	4.0
11	0.9	2.4	3.6	1.3	1.6	3.0	2.5	0.4	1.6	3.1	4.1
12	2.0	1.2	2.6	2.2	0.9	1.3	3.4	0.9	0.8	4.7	4.2
13	2.3	1.7	4.0	2.1	0.1	2.8	3.0	0.9	1.8	3.6	4.5

Table A.8 – Region-wide average daily wind direction (16 directions; top) and cloud cover (in %; bottom) for April for each region (vertical axis).

APRIL WIND DIRECTION (AVG DAILY)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	SW	SW	SW	WSW	SW	SW	NW	WSW	SW	W	SSW
2	ENE	SE	S	N	SSW	SSW	NNW	WSW	SW	NW	S
3	W	WSW	SW	WNW	WSW	SW	NW	WSW	SW	W	SSW
4	WSW	WSW	W	W	WNW	WNW	NW	NNW	NNW	W	SSW
5	WNW	SW	SW	WNW	W	SW	WNW	W	SW	WNW	S
6	NNE	ESE	S	N	N	S	NW	N	S	NW	SE
7	N	SE	SSW	NW	NW	S	NW	NW	SW	WNW	SSE
8	ESE	SE	SSE	E	SE	SSE	NNE	SE	S	N	SSE
9	ENE	SE	S	N	ESE	SSE	NNW	NE	SSE	WNW	SSE
10	N	SSE	SSW	NW	SW	SSW	NW	WSW	SW	WNW	SSE
11	NE	SSE	S	NW	S	S	NNW	WSW	SSW	WNW	SSE
12	NNE	ENE	SSE	N	NNE	S	NNW	NNW	SSW	NNW	S
13	NE	ESE	SSE	NNW	NE	S	NNW	WNW	SSW	NW	SSE

APRIL CLOUD COVER (AVG DAILY)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	47	30	26	25	21	20	15	16	21	19	48
2	60	36	32	35	21	25	26	16	21	30	32
3	64	54	41	48	41	36	37	29	31	57	52
4	67	57	40	51	42	36	35	28	27	54	59
5	77	69	51	61	53	44	53	39	34	68	52
6	76	71	47	59	52	49	60	39	32	66	70
7	82	78	51	58	53	57	49	34	35	60	72
8	51	37	35	32	21	27	19	14	18	25	28
9	49	46	46	25	32	43	20	23	31	35	47
10	73	69	52	42	40	46	40	25	25	49	63
11	60	57	51	26	30	44	24	18	23	36	52
12	74	69	45	62	50	42	53	35	31	59	49
13	78	62	40	51	37	32	44	25	25	48	36

Table A.9 – Region-wide average July temperatures (°C; top) and dew points (°C; bottom) for the second daily observation for each weather type (horizontal axis) and each region (vertical axis; please see Figure 4 for region numbers).

JULY TEMPERATURE (OBS #2; MORNING)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	21	23	25	19	22	24	18	21	24	22	23
2	20	22	23	19	21	23	18	20	23	22	18
3	14	16	19	12	15	18	10	14	17	15	14
4	13	15	19	11	14	17	11	14	17	15	15
5	13	16	19	11	14	18	9	14	17	16	13
6	16	18	22	15	18	20	14	17	20	19	17
7	17	20	23	15	19	21	14	18	20	21	17
8	24	25	26	23	24	25	22	23	25	26	23
9	26	27	28	26	27	27	25	26	27	27	26
10	21	23	25	19	22	24	17	21	23	23	20
11	24	25	26	23	24	26	20	23	25	25	22
12	15	18	21	13	17	20	12	15	19	20	14
13	19	22	23	17	20	23	15	19	22	23	17

JULY DEW POINT (OBS #2; MORNING)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	12	11	10	7	7	6	1	1	0	7	4
2	17	16	15	14	14	13	11	11	10	14	12
3	6	6	5	2	2	1	-3	-3	-3	2	-2
4	10	10	11	7	8	8	5	5	5	9	7
5	9	10	10	6	7	7	3	4	4	9	5
6	15	16	19	12	14	16	10	12	14	17	13
7	15	18	21	13	16	19	10	14	16	19	14
8	22	23	22	21	22	21	19	20	20	22	20
9	24	25	26	23	24	25	22	23	23	24	23
10	19	21	22	17	20	21	14	18	19	21	17
11	23	23	24	21	22	23	18	21	21	23	19
12	13	16	19	11	13	16	8	10	12	17	11
13	17	20	21	14	17	19	12	14	15	20	14

Table A.10 – Region-wide average July temperatures (°C; top) and dew points (°C; bottom) for the fifth daily observation for each weather type (horizontal axis) and each region (vertical axis; please see Figure 4 for region numbers).

JULY TEMPERATURE (OBS #5; AFTERNOON)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	30	33	35	31	33	36	31	34	37	31	33
2	29	33	36	29	33	36	29	34	37	31	32
3	23	27	29	23	27	30	22	27	30	23	27
4	23	26	30	23	26	29	22	26	30	23	27
5	22	26	30	21	26	30	20	26	30	23	27
6	17	20	25	16	19	23	15	19	22	19	20
7	22	25	30	22	26	28	20	25	29	24	26
8	31	34	37	31	35	37	31	35	38	33	33
9	29	30	32	29	30	32	28	31	32	30	31
10	26	29	32	26	29	31	25	29	32	27	29
11	30	32	35	30	32	35	29	33	36	31	32
12	23	27	32	23	27	31	21	27	32	26	28
13	27	32	35	27	32	36	25	32	37	30	32

JULY DEW POINT (OBS #5; AFTERNOON)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	11	10	9	6	6	5	-1	0	0	5	5
2	15	15	13	13	12	10	9	9	7	12	13
3	6	6	5	2	2	2	-2	-2	-2	1	2
4	11	12	13	8	9	10	6	6	7	8	9
5	10	11	12	7	8	8	4	4	5	6	8
6	15	17	20	13	15	17	10	12	14	15	16
7	17	20	23	14	18	20	12	15	17	16	19
8	21	21	19	20	19	18	17	17	15	19	19
9	24	24	25	22	23	23	21	22	22	23	23
10	20	22	23	18	21	21	15	18	19	19	21
11	22	23	23	21	22	21	18	20	19	21	21
12	15	17	20	11	14	16	8	9	10	13	16
13	19	21	21	16	18	18	12	13	13	17	19

Table A.11 – Region-wide average daily pressure (mb; top) and wind speed (m/s; bottom) for July for each region (vertical axis).

JULY PRESSURE (AVG. DAILY)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	1013	1012	1012	1013	1012	1011	1012	1012	1011	1012	1012
2	1015	1013	1012	1016	1014	1012	1017	1013	1011	1014	1014
3	1015	1014	1014	1015	1014	1013	1015	1014	1014	1013	1014
4	1015	1014	1013	1015	1014	1014	1015	1015	1014	1014	1014
5	1015	1014	1012	1016	1014	1012	1016	1015	1012	1012	1013
6	1013	1013	1012	1017	1015	1013	1018	1018	1015	1013	1013
7	1015	1014	1013	1017	1016	1014	1018	1017	1015	1013	1014
8	1015	1014	1013	1017	1015	1014	1017	1016	1014	1015	1014
9	1018	1017	1016	1018	1018	1017	1018	1018	1017	1016	1016
10	1016	1016	1015	1018	1016	1015	1018	1017	1016	1014	1016
11	1017	1016	1015	1017	1017	1016	1017	1017	1015	1015	1015
12	1014	1012	1010	1017	1014	1011	1018	1016	1012	1011	1012
13	1015	1012	1011	1017	1014	1012	1018	1016	1012	1013	1013

JULY WIND SPEED (AVG DAILY)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	2.7	2.5	2.2	3.0	2.6	2.1	3.0	2.6	1.9	2.6	2.9
2	2.5	3.2	3.1	2.6	3.0	3.0	1.2	2.4	2.7	1.8	3.5
3	1.5	1.3	1.1	1.9	1.7	1.3	2.1	2.0	1.3	3.2	1.8
4	2.0	1.8	1.6	2.2	2.1	1.8	2.2	2.1	1.9	2.6	0.9
5	0.9	0.5	0.3	1.7	1.2	0.9	2.6	1.5	1.3	3.4	1.3
6	0.6	1.6	3.3	0.8	1.1	2.5	1.8	0.8	2.1	3.1	3.4
7	0.6	1.9	3.1	1.2	1.6	2.3	2.1	1.2	1.8	3.2	3.3
8	3.7	4.5	4.4	3.6	4.2	4.3	2.7	3.7	3.6	2.3	3.9
9	1.8	1.8	1.8	1.6	1.7	1.6	2.1	1.5	1.3	0.8	2.3
10	1.0	2.3	2.5	0.2	1.7	2.1	1.1	0.6	1.4	1.9	2.3
11	2.0	2.2	1.9	1.4	2.0	1.8	1.1	1.0	1.4	0.3	1.7
12	0.3	1.5	2.5	1.4	0.8	1.7	2.2	1.4	1.4	3.3	3.8
13	1.7	2.6	3.2	0.5	2.1	2.9	1.0	0.7	2.6	1.8	4.0

Table A.12 – Region-wide average daily wind direction (16 directions; top) and cloud cover (in %; bottom) for July for each region (vertical axis).

JULY WIND DIRECTION (AVG DAILY)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	SSW	SSW	SSW	SSW	SSW	SW	SW	SW	SW	SW	S
2	SE	SSE	SSE	SSE	SSE	S	SE	S	S	ENE	SSE
3	WSW	SW	SW	W	WSW	WSW	WSW	WSW	WSW	W	S
4	WNW	WNW	WNW	WNW	NW	NW	NW	NW	NW	W	NW
5	W	WSW	SSW	WNW	W	WSW	W	WNW	W	W	SE
6	SW	SSW	SW	NW	SW	SW	NNW	WSW	SW	NW	S
7	SW	SSW	SW	WNW	WSW	SW	NW	W	WSW	NW	SSW
8	SE	SSE	SSE	SE	SSE	SSE	SE	SSE	SSE	ESE	SE
9	S	SSW	SW	SE	S	SSW	ESE	SSE	SSW	SSE	SSE
10	S	SSW	SW	ESE	SW	SW	NNE	SW	SW	NW	S
11	S	SSW	SW	S	SSW	SW	ENE	SSW	SW	NW	SSE
12	E	SSE	S	NW	WSW	SSW	NW	WNW	SW	NW	SSE
13	SE	SSE	S	ESE	S	S	N	SSE	S	NNW	SSE

JULY CLOUD COVER (AVG DAILY)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	30	20	17	13	12	13	8	9	12	15	44
2	37	22	17	23	15	13	18	10	10	25	19
3	30	22	22	12	13	18	9	8	14	18	27
4	20	14	14	13	11	12	12	10	13	27	22
5	38	24	18	26	16	15	24	13	15	29	24
6	44	35	29	35	27	28	32	23	21	32	50
7	58	53	41	37	36	43	35	25	28	35	51
8	48	30	29	42	25	22	39	20	18	44	39
9	55	48	48	54	51	51	55	50	48	57	53
10	61	59	44	38	43	43	31	26	26	40	49
11	67	61	53	53	52	48	38	34	33	48	51
12	49	37	27	36	24	23	35	21	18	25	31
13	41	32	23	26	20	21	25	16	16	26	25

Table A.13 – Region-wide average October temperatures (°C; top) and dew points (°C; bottom) for the second daily observation for each weather type (horizontal axis) and each region (vertical axis; please see Figure 4 for region numbers).

OCTOBER TEMPERATURE (OBS #2; MORNING)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	11	14	16	9	13	16	6	12	16	12	13
2	9	11	15	6	10	13	4	9	13	13	6
3	3	6	8	0	4	8	-2	3	8	5	3
4	9	11	14	7	10	14	6	9	13	10	11
5	4	7	9	1	5	9	-2	4	8	7	2
6	7	10	14	6	9	11	5	8	11	11	7
7	5	8	14	3	6	10	1	4	8	11	4
8	17	20	22	14	17	21	11	17	20	21	14
9	19	22	25	17	20	23	14	19	22	23	19
10	9	13	17	6	10	14	3	8	12	14	8
11	13	16	21	8	13	18	5	11	15	18	11
12	2	5	10	0	3	7	-2	3	6	8	0
13	6	9	14	3	7	11	1	6	10	12	3

OCTOBER DEW POINT (OBS #2; MORNING)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	5	6	6	0	1	0	-9	-6	-5	1	-5
2	7	8	10	1	3	5	-4	-2	0	6	-1
3	-1	0	0	-6	-4	-4	-10	-10	-9	-2	-9
4	7	8	7	4	4	4	-1	-1	-1	6	1
5	1	3	4	-3	-1	0	-8	-5	-4	2	-4
6	5	8	12	2	6	9	0	4	6	8	3
7	3	7	12	0	3	8	-2	1	5	9	1
8	15	18	21	9	14	18	4	10	15	18	8
9	17	20	23	14	18	21	11	16	19	21	16
10	7	11	16	3	7	12	0	4	7	13	4
11	11	15	20	5	10	16	2	7	12	16	8
12	1	3	8	-3	0	3	-6	-3	0	4	-3
13	4	7	12	0	3	7	-4	0	3	9	-1

Table A.14 – Region-wide average October temperatures (°C; top) and dew points (°C; bottom) for the fifth daily observation for each weather type (horizontal axis) and each region (vertical axis; please see Figure 4 for region numbers).

OCTOBER TEMPERATURE (OBS #5; AFTERNOON)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	18	22	26	18	23	27	17	24	27	18	22
2	16	22	26	16	22	27	14	23	28	19	22
3	9	13	17	7	14	19	6	14	19	8	13
4	14	19	23	15	20	24	15	20	24	15	19
5	8	13	18	8	13	19	5	14	20	10	13
6	8	10	16	7	10	13	6	10	13	9	10
7	9	13	21	9	14	18	7	14	18	12	14
8	23	27	31	24	28	31	21	29	32	26	27
9	24	26	28	24	26	28	22	26	28	24	26
10	14	18	24	15	20	23	13	20	24	17	18
11	19	24	28	21	25	28	19	26	29	22	24
12	7	12	20	6	12	18	4	12	19	10	13
13	12	18	24	12	19	24	10	19	25	16	19

OCTOBER DEW POINT (OBS #5; AFTERNOON)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	5	6	5	-1	0	0	-9	-6	-4	-4	-2
2	7	9	10	1	4	5	-5	-2	0	1	3
3	-1	1	0	-5	-3	-3	-10	-8	-7	-6	-4
4	8	8	8	4	5	4	-2	-1	-1	3	3
5	2	4	5	-3	0	2	-7	-4	-2	-2	-1
6	5	9	13	2	6	9	0	4	6	5	6
7	4	9	15	1	5	11	-2	3	7	4	8
8	16	18	20	9	14	17	3	9	12	12	13
9	18	21	23	15	19	21	10	16	19	17	20
10	9	14	18	4	10	15	0	6	10	8	11
11	13	17	20	8	13	18	3	9	12	11	15
12	2	5	10	-3	1	5	-7	-3	1	0	2
13	6	10	14	1	5	10	-4	0	4	4	6

Table A.15 – Region-wide average daily pressure (mb; top) and wind speed (m/s; bottom) for October for each region (vertical axis).

OCTOBER PRESSURE (AVG. DAILY)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	1013	1014	1015	1015	1015	1015	1018	1015	1015	1012	1010
2	1017	1015	1013	1021	1017	1013	1023	1016	1012	1015	1015
3	1015	1015	1016	1020	1018	1016	1022	1019	1017	1014	1013
4	1015	1016	1016	1017	1017	1016	1018	1018	1017	1015	1014
5	1015	1014	1013	1021	1017	1014	1025	1019	1015	1015	1014
6	1014	1014	1013	1020	1017	1015	1022	1020	1016	1013	1014
7	1016	1015	1014	1021	1018	1016	1023	1020	1017	1014	1015
8	1018	1016	1013	1021	1018	1014	1023	1018	1014	1016	1013
9	1018	1017	1016	1019	1018	1016	1020	1017	1017	1014	1014
10	1017	1017	1016	1021	1020	1018	1023	1020	1018	1015	1015
11	1018	1016	1016	1020	1019	1017	1023	1019	1018	1015	1015
12	1016	1013	1010	1021	1017	1012	1025	1017	1012	1013	1013
13	1017	1015	1012	1022	1018	1013	1026	1018	1014	1014	1014

OCTOBER WIND SPEED (AVG DAILY)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	2.6	2.3	1.7	1.3	1.2	1.2	1.6	0.4	0.7	3.0	3.4
2	1.0	2.1	3.2	0.2	1.5	2.5	0.9	1.3	2.2	2.2	3.6
3	1.9	2.1	2.2	1.9	1.6	1.9	1.5	1.4	1.6	4.3	3.3
4	2.0	1.5	0.8	2.0	1.3	0.6	2.4	1.6	0.9	3.2	2.0
5	1.6	1.9	2.1	1.6	1.9	1.8	1.0	1.5	1.7	4.1	2.7
6	2.2	1.3	3.5	2.9	1.7	2.7	3.8	2.1	2.4	5.4	4.5
7	1.5	0.6	3.5	2.3	1.5	2.3	2.7	1.7	2.6	4.4	4.3
8	1.8	3.1	4.4	1.3	2.3	3.5	1.9	1.1	1.8	2.6	3.7
9	3.5	2.6	2.0	3.2	2.7	2.1	4.0	1.9	1.2	3.4	2.8
10	1.1	0.9	2.9	1.4	0.7	1.7	2.1	1.1	1.5	3.3	3.4
11	1.9	1.6	2.6	1.2	0.8	1.6	2.2	0.4	0.5	2.7	3.7
12	1.4	0.4	2.7	2.1	1.1	2.0	2.7	2.0	2.2	5.1	3.8
13	1.2	1.3	4.0	1.2	0.9	2.4	2.0	1.3	1.7	3.5	4.0

Table A.16 – Region-wide average daily wind direction (16 directions; top) and cloud cover (in %; bottom) for October for each region (vertical axis).

OCTOBER WIND DIRECTION (AVG DAILY)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	SSW	SSW	SSW	WSW	SSW	SSW	N	SW	SSW	WNW	SSW
2	E	SSE	S	ENE	SSW	SSW	NW	SW	SW	NNW	S
3	W	SW	SW	WNW	WSW	SW	NW	WSW	SW	WNW	SSW
4	SW	WSW	WSW	NW	NW	NW	N	N	NNE	WNW	S
5	W	SW	SW	W	WSW	SW	NNW	W	WSW	WNW	SSW
6	NW	SSE	S	NW	SW	SSW	NW	W	WSW	WNW	S
7	WNW	S	SSW	WNW	WSW	SSW	WNW	WSW	SW	WNW	S
8	ENE	SE	SSE	ENE	SE	SSE	NNE	SE	SSE	N	SSE
9	NE	ENE	SE	NNE	ENE	ESE	N	NE	ENE	NNW	SE
10	N	SE	S	NW	SSW	S	NW	WSW	SSW	WNW	SSE
11	NE	ESE	SSE	NNE	E	SE	N	NNE	SSE	NW	SE
12	NNW	SE	S	NW	WSW	SSW	WNW	W	WSW	NW	S
13	N	SE	S	NW	SSW	S	NW	W	SW	NW	S

OCTOBER CLOUD COVER (AVG DAILY)											
	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
1	43	29	27	15	15	20	9	13	18	13	46
2	53	33	30	25	15	20	23	12	16	28	27
3	53	46	37	30	23	26	22	18	21	45	51
4	56	46	38	30	28	25	20	20	18	41	56
5	68	57	46	46	41	35	40	31	28	57	56
6	80	68	54	70	50	48	70	47	37	69	71
7	72	73	56	53	47	53	47	36	35	53	68
8	59	46	39	22	22	32	20	11	21	36	34
9	57	55	57	27	41	56	20	27	42	43	59
10	65	69	56	30	32	43	25	20	26	42	67
11	62	63	61	17	29	47	13	14	25	37	62
12	71	63	47	57	43	36	53	39	30	58	52
13	65	52	43	36	27	29	33	23	23	43	38

APPENDIX B

The following tables display the region-wide average monthly frequency for each individual weather type. Each table represents one of the 13 regions delineated in Figure 4 (denoted in the caption). See Figure 4 or Table 3 for the regional names corresponding to the regional number the upper-left most cell of each table.

Table B.1 – Average monthly weather type frequency for the Desert Southwest (top) and Southern High Plains (bottom) regions.

1	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
JAN	7.5%	14.1%	9.8%	9.8%	14.0%	12.2%	8.4%	11.5%	9.1%	3.3%	0.3%
FEB	9.4%	13.7%	9.5%	10.0%	12.7%	14.2%	8.2%	10.2%	8.2%	3.5%	0.3%
MAR	11.3%	12.0%	9.6%	10.2%	12.4%	13.6%	8.0%	9.5%	9.0%	4.0%	0.3%
APR	8.7%	9.8%	8.3%	10.5%	14.8%	15.3%	7.3%	11.1%	9.5%	4.1%	0.6%
MAY	8.4%	11.3%	10.2%	10.0%	14.3%	14.4%	7.1%	11.6%	9.1%	3.2%	0.5%
JUN	7.3%	9.8%	8.8%	8.8%	13.5%	15.3%	7.9%	14.6%	11.3%	1.9%	0.8%
JUL	12.3%	15.8%	12.2%	9.0%	13.5%	11.8%	5.8%	10.5%	8.1%	0.6%	0.5%
AUG	11.4%	16.6%	14.5%	9.2%	13.6%	13.1%	5.7%	7.9%	6.6%	1.0%	0.6%
SEP	8.8%	15.1%	13.8%	8.4%	14.2%	13.6%	5.3%	10.3%	8.0%	2.0%	0.5%
OCT	10.2%	13.4%	9.8%	8.7%	12.6%	14.2%	7.2%	10.4%	9.8%	3.2%	0.3%
NOV	8.0%	12.4%	8.8%	9.5%	12.6%	14.2%	9.6%	11.4%	8.8%	4.3%	0.4%
DEC	7.3%	13.3%	9.5%	10.2%	13.2%	13.2%	8.7%	11.8%	8.9%	3.6%	0.3%

2	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
JAN	7.8%	10.4%	10.5%	10.2%	14.0%	13.2%	7.1%	9.4%	9.8%	5.3%	2.4%
FEB	8.0%	11.4%	10.4%	10.0%	13.9%	13.3%	6.9%	9.2%	9.9%	4.7%	2.3%
MAR	8.5%	10.5%	10.9%	9.8%	13.4%	12.9%	7.2%	9.3%	10.0%	5.3%	2.2%
APR	7.0%	9.1%	11.1%	10.4%	11.5%	13.4%	7.3%	10.8%	11.1%	5.5%	2.7%
MAY	9.4%	12.8%	12.3%	8.9%	12.2%	12.0%	6.3%	9.4%	9.9%	4.3%	2.6%
JUN	11.2%	16.2%	12.2%	7.5%	13.3%	11.9%	4.7%	8.4%	9.2%	3.3%	2.1%
JUL	11.1%	15.6%	10.1%	7.7%	16.7%	13.2%	3.3%	8.4%	9.9%	2.7%	1.3%
AUG	11.4%	16.5%	13.1%	7.2%	16.0%	14.3%	2.9%	6.8%	8.1%	2.4%	1.4%
SEP	9.9%	14.9%	14.3%	7.6%	13.3%	12.6%	5.4%	7.4%	8.1%	4.6%	1.9%
OCT	7.9%	12.5%	13.0%	8.4%	13.3%	12.2%	6.0%	8.6%	9.9%	6.1%	2.0%
NOV	8.4%	9.5%	11.2%	11.0%	12.7%	12.9%	7.4%	9.0%	9.6%	6.2%	2.2%
DEC	7.5%	10.7%	9.8%	10.0%	14.6%	13.6%	7.0%	10.0%	9.7%	4.7%	2.3%

Table B.2 – Average monthly weather type frequency for the Intermontane (top) and West Coast (bottom) regions.

3	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
JAN	7.7%	11.2%	10.9%	10.5%	13.8%	13.2%	7.3%	7.6%	9.2%	6.0%	2.5%
FEB	8.0%	11.3%	11.3%	11.8%	13.5%	13.5%	7.2%	7.5%	8.1%	5.7%	2.4%
MAR	8.9%	10.5%	10.0%	10.8%	12.2%	14.0%	7.0%	7.8%	8.8%	7.1%	2.9%
APR	8.2%	8.9%	8.9%	11.3%	12.5%	14.1%	7.8%	8.7%	10.6%	6.5%	2.7%
MAY	10.1%	10.5%	10.7%	10.8%	12.4%	13.6%	6.9%	9.0%	9.0%	4.7%	2.4%
JUN	9.8%	11.2%	9.9%	8.8%	12.5%	13.9%	6.4%	10.9%	10.4%	4.0%	2.2%
JUL	10.6%	14.4%	11.9%	8.5%	13.2%	12.4%	5.0%	10.8%	9.0%	2.6%	1.6%
AUG	10.8%	15.1%	12.6%	8.2%	13.3%	12.5%	4.8%	9.9%	8.3%	2.8%	1.7%
SEP	9.7%	11.8%	11.6%	8.6%	12.1%	14.5%	6.1%	9.7%	9.8%	4.1%	1.8%
OCT	9.8%	13.0%	9.8%	9.4%	11.4%	14.0%	6.2%	8.5%	10.6%	5.5%	1.7%
NOV	8.9%	11.1%	10.8%	11.3%	12.0%	12.8%	7.5%	7.6%	8.5%	6.9%	2.4%
DEC	7.3%	10.3%	11.4%	11.0%	14.0%	12.8%	7.3%	8.8%	8.8%	6.1%	2.3%

4	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
JAN	11.0%	13.5%	10.9%	11.5%	12.6%	11.3%	7.2%	8.9%	9.7%	2.7%	0.6%
FEB	11.4%	13.3%	10.5%	11.1%	13.6%	11.8%	7.4%	8.8%	8.8%	2.7%	0.6%
MAR	11.2%	12.0%	10.2%	12.1%	13.8%	11.9%	8.0%	8.4%	7.7%	3.5%	1.2%
APR	10.5%	10.1%	8.2%	12.2%	15.0%	13.2%	9.2%	8.3%	8.0%	4.1%	1.3%
MAY	10.4%	10.2%	9.8%	12.8%	16.3%	12.9%	7.8%	8.6%	6.7%	3.2%	1.2%
JUN	10.1%	10.7%	9.4%	12.2%	16.3%	13.1%	7.6%	8.1%	8.2%	3.1%	1.2%
JUL	11.2%	12.2%	11.7%	12.4%	16.3%	12.4%	6.2%	7.4%	6.5%	2.3%	1.3%
AUG	12.4%	11.1%	10.3%	13.3%	16.3%	12.4%	5.9%	7.9%	7.2%	2.1%	1.2%
SEP	11.5%	12.0%	10.4%	12.6%	16.4%	13.5%	5.2%	7.7%	8.2%	1.8%	0.8%
OCT	13.2%	13.1%	8.3%	12.5%	15.2%	12.4%	6.0%	7.8%	8.5%	2.2%	0.8%
NOV	12.0%	13.6%	10.1%	11.9%	13.6%	10.9%	7.1%	7.9%	8.3%	3.5%	1.1%
DEC	10.2%	13.5%	10.5%	11.6%	13.5%	10.7%	7.4%	9.2%	9.8%	3.0%	0.7%

Table B.3 – Average monthly weather type frequency for the Northwest (top) and Great Lakes (bottom) regions.

5	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
JAN	8.1%	8.4%	10.8%	9.9%	13.8%	16.3%	8.0%	7.1%	9.3%	5.0%	3.3%
FEB	8.0%	9.9%	10.0%	10.2%	14.9%	15.2%	8.0%	7.5%	9.7%	4.1%	2.6%
MAR	9.1%	10.5%	9.7%	11.3%	13.2%	12.5%	6.3%	8.5%	10.1%	5.8%	3.1%
APR	8.4%	8.4%	7.4%	12.2%	13.6%	12.8%	7.3%	10.2%	10.1%	6.1%	3.3%
MAY	9.9%	9.4%	8.1%	12.0%	14.7%	12.9%	6.6%	9.3%	8.0%	5.6%	3.5%
JUN	10.7%	11.0%	10.2%	10.9%	13.7%	12.1%	6.2%	8.4%	7.2%	6.2%	3.3%
JUL	11.8%	12.2%	10.5%	10.2%	13.7%	12.0%	4.7%	8.0%	9.5%	5.2%	2.3%
AUG	12.0%	13.0%	10.5%	9.5%	12.6%	13.1%	4.8%	8.3%	9.2%	5.1%	1.9%
SEP	11.5%	10.2%	9.2%	11.1%	12.7%	13.7%	5.8%	7.9%	10.0%	5.5%	2.4%
OCT	10.3%	12.4%	9.0%	11.1%	12.8%	12.7%	6.2%	7.7%	9.1%	6.2%	2.5%
NOV	8.8%	11.6%	10.0%	10.8%	15.4%	13.5%	6.4%	7.8%	8.1%	4.8%	2.9%
DEC	7.2%	8.3%	9.7%	11.2%	16.4%	14.2%	6.6%	8.5%	9.7%	4.9%	3.4%

6	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
JAN	7.7%	5.4%	9.2%	12.9%	10.0%	15.1%	8.4%	8.2%	12.3%	6.1%	4.7%
FEB	6.9%	3.9%	8.1%	12.9%	8.8%	17.2%	9.8%	8.4%	13.6%	5.8%	4.5%
MAR	5.8%	8.9%	6.8%	12.0%	16.1%	15.3%	8.3%	9.4%	8.6%	5.0%	3.8%
APR	9.5%	12.2%	7.2%	16.0%	14.6%	7.9%	7.0%	7.5%	10.9%	4.4%	2.9%
MAY	10.6%	7.3%	9.1%	16.1%	10.7%	10.6%	6.4%	10.1%	11.5%	4.7%	2.9%
JUN	11.7%	10.8%	9.6%	14.0%	10.6%	11.1%	6.7%	8.1%	9.0%	4.9%	3.4%
JUL	15.4%	11.1%	10.7%	12.6%	9.9%	10.4%	5.8%	7.9%	8.3%	5.0%	2.8%
AUG	17.7%	14.7%	11.2%	10.3%	10.6%	10.0%	5.6%	5.1%	7.2%	5.4%	2.2%
SEP	12.2%	13.4%	11.0%	11.1%	13.9%	12.0%	7.0%	4.7%	6.0%	6.1%	2.5%
OCT	9.0%	11.1%	8.3%	13.2%	15.6%	13.3%	8.1%	6.7%	6.8%	5.1%	2.9%
NOV	8.8%	8.7%	10.1%	12.7%	13.7%	16.2%	7.7%	5.9%	7.3%	5.4%	3.6%
DEC	8.1%	6.3%	8.5%	12.9%	11.7%	18.9%	8.1%	6.5%	9.3%	5.7%	4.1%

Table B.4 – Average monthly weather type frequency for the Northeast (top) and Southern Texas (bottom) regions.

7	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
JAN	7.9%	5.5%	8.3%	10.9%	12.4%	15.1%	9.5%	7.4%	11.3%	6.1%	5.6%
FEB	7.6%	5.1%	7.3%	12.2%	13.7%	16.0%	8.9%	6.9%	12.1%	5.6%	4.7%
MAR	7.5%	8.3%	8.1%	12.3%	16.1%	12.4%	8.3%	7.8%	10.6%	5.1%	3.5%
APR	9.6%	9.4%	9.5%	12.9%	12.9%	10.1%	8.1%	9.1%	10.4%	4.9%	3.0%
MAY	10.1%	8.7%	10.0%	12.3%	11.6%	13.0%	8.4%	7.9%	9.6%	5.2%	3.2%
JUN	10.9%	10.4%	11.7%	11.6%	11.6%	13.9%	7.1%	6.7%	7.6%	5.6%	3.0%
JUL	13.2%	12.1%	12.5%	10.2%	11.5%	12.8%	6.5%	5.8%	6.9%	5.4%	3.0%
AUG	12.4%	13.1%	12.6%	10.3%	12.2%	11.9%	5.8%	5.4%	7.8%	5.4%	3.2%
SEP	11.2%	10.5%	12.0%	12.7%	12.9%	12.1%	6.5%	5.1%	7.8%	6.2%	3.1%
OCT	10.1%	8.1%	10.0%	15.2%	12.9%	12.5%	7.9%	5.8%	8.9%	5.2%	3.4%
NOV	10.4%	9.8%	10.4%	13.2%	13.6%	11.9%	7.6%	5.9%	7.7%	5.7%	3.8%
DEC	8.6%	7.1%	7.5%	11.2%	15.1%	16.1%	8.1%	6.0%	9.1%	6.3%	4.9%

8	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
JAN	8.3%	10.5%	12.7%	11.4%	10.5%	14.6%	7.4%	8.5%	7.3%	6.6%	2.3%
FEB	9.0%	11.3%	12.5%	11.1%	10.6%	14.2%	7.4%	7.4%	8.1%	6.7%	1.7%
MAR	7.8%	12.1%	14.6%	10.1%	10.5%	15.0%	7.3%	7.1%	7.7%	6.4%	1.3%
APR	7.3%	13.4%	13.0%	9.0%	11.3%	15.5%	7.5%	7.8%	7.8%	5.9%	1.5%
MAY	11.2%	17.0%	13.5%	8.0%	13.1%	14.2%	5.7%	5.8%	6.6%	3.8%	1.1%
JUN	13.2%	20.6%	11.0%	7.2%	12.9%	13.8%	3.4%	7.9%	7.3%	1.8%	0.8%
JUL	13.1%	16.9%	7.3%	9.3%	16.0%	13.4%	1.8%	9.7%	9.4%	1.6%	1.5%
AUG	14.0%	17.7%	9.2%	5.9%	17.9%	15.2%	2.7%	7.2%	7.9%	1.3%	1.0%
SEP	11.1%	21.5%	12.8%	6.8%	12.2%	14.1%	5.3%	6.8%	6.2%	2.6%	0.6%
OCT	7.5%	13.4%	16.8%	10.6%	10.5%	15.2%	6.3%	7.1%	6.7%	5.0%	0.9%
NOV	9.5%	10.5%	15.5%	11.8%	9.4%	14.7%	7.8%	6.1%	6.2%	6.9%	1.6%
DEC	8.0%	9.7%	13.7%	11.7%	10.9%	14.1%	7.9%	8.0%	7.1%	6.9%	2.0%

Table B.5 – Average monthly weather type frequency for the Coastal Southeast (top) and Mid-South (bottom) regions.

9	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
JAN	7.7%	8.0%	12.8%	11.7%	9.0%	16.1%	9.0%	7.5%	10.8%	5.6%	1.9%
FEB	8.1%	9.2%	13.2%	10.6%	9.0%	15.8%	8.7%	7.8%	11.1%	4.6%	1.8%
MAR	7.7%	9.6%	13.9%	9.8%	10.4%	16.5%	8.0%	8.4%	10.3%	4.2%	1.0%
APR	7.5%	10.2%	12.3%	10.7%	11.7%	16.6%	8.6%	8.0%	9.9%	3.6%	0.9%
MAY	9.6%	13.4%	12.7%	10.1%	14.8%	14.0%	5.7%	7.8%	9.5%	1.9%	0.5%
JUN	11.4%	19.0%	12.5%	9.1%	14.0%	13.0%	3.7%	7.4%	8.2%	1.2%	0.7%
JUL	12.4%	16.5%	11.3%	9.2%	15.5%	12.5%	3.1%	8.3%	8.4%	1.4%	1.4%
AUG	12.9%	16.6%	11.9%	8.2%	16.4%	12.9%	3.1%	7.8%	8.1%	1.2%	1.0%
SEP	12.1%	17.7%	13.3%	8.0%	15.0%	15.1%	3.5%	5.6%	7.2%	1.5%	0.8%
OCT	8.3%	12.4%	14.6%	10.4%	12.6%	18.1%	6.8%	6.3%	7.6%	2.4%	0.6%
NOV	8.1%	9.3%	14.2%	10.6%	11.3%	16.6%	8.0%	7.0%	9.5%	4.3%	1.0%
DEC	8.4%	8.2%	13.8%	12.3%	9.4%	16.1%	8.5%	6.7%	9.8%	5.2%	1.8%

10	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
JAN	7.9%	8.5%	9.3%	11.8%	14.3%	11.5%	8.6%	8.9%	10.1%	5.9%	3.3%
FEB	8.7%	7.3%	10.0%	11.8%	13.0%	11.2%	9.3%	8.8%	11.3%	5.6%	3.0%
MAR	8.0%	9.0%	11.2%	14.0%	11.3%	11.7%	8.3%	8.4%	9.7%	5.6%	2.8%
APR	8.8%	8.2%	11.2%	13.6%	9.4%	13.7%	8.7%	8.3%	9.5%	5.8%	2.7%
MAY	8.9%	10.1%	12.2%	12.0%	10.5%	16.6%	8.0%	7.0%	7.6%	5.0%	2.1%
JUN	10.6%	13.6%	13.8%	10.0%	11.1%	14.8%	6.5%	6.6%	7.1%	4.0%	1.8%
JUL	12.8%	18.0%	12.7%	8.2%	11.8%	12.6%	5.6%	5.8%	7.1%	3.4%	1.8%
AUG	12.3%	19.5%	12.4%	9.1%	12.8%	11.1%	5.2%	5.2%	8.1%	2.9%	1.4%
SEP	11.0%	14.4%	13.2%	11.6%	12.7%	11.6%	5.9%	5.9%	7.7%	4.4%	1.6%
OCT	8.8%	9.3%	13.0%	13.8%	11.3%	13.4%	8.0%	7.0%	9.0%	4.7%	1.7%
NOV	9.5%	8.7%	12.5%	14.9%	10.1%	12.4%	7.7%	6.5%	9.0%	6.2%	2.5%
DEC	8.5%	8.8%	10.1%	13.8%	13.5%	10.6%	8.8%	8.3%	8.5%	6.1%	3.0%

Table B.6 – Average monthly weather type frequency for the Inland Southeast (top) and Northern Plains (bottom) regions.

11	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
JAN	8.6%	8.3%	11.8%	13.7%	11.3%	11.6%	9.3%	8.4%	9.0%	5.5%	2.4%
FEB	9.5%	8.6%	12.6%	13.1%	10.5%	11.5%	9.0%	8.4%	9.2%	5.4%	2.3%
MAR	8.7%	8.6%	13.4%	13.0%	10.2%	14.5%	8.2%	7.6%	8.9%	5.2%	1.7%
APR	7.5%	8.2%	13.5%	13.3%	9.2%	15.3%	8.7%	7.8%	8.7%	5.8%	2.2%
MAY	8.7%	13.1%	13.6%	9.3%	12.6%	15.4%	7.8%	6.7%	7.7%	3.7%	1.5%
JUN	13.5%	20.4%	12.2%	6.4%	12.7%	11.7%	5.9%	6.1%	7.8%	2.1%	1.1%
JUL	16.7%	20.7%	9.6%	6.7%	14.6%	11.0%	3.5%	5.7%	8.3%	1.8%	1.5%
AUG	15.3%	22.8%	10.3%	6.8%	14.1%	11.1%	4.0%	5.6%	7.9%	1.2%	0.8%
SEP	11.7%	18.4%	14.5%	10.2%	11.6%	11.4%	5.7%	5.8%	7.3%	2.4%	0.9%
OCT	8.3%	9.7%	16.0%	13.1%	10.9%	13.4%	8.0%	7.1%	8.9%	3.7%	0.9%
NOV	9.6%	8.4%	14.3%	14.4%	9.5%	12.9%	8.0%	6.6%	8.5%	6.1%	1.9%
DEC	8.9%	8.5%	12.5%	16.1%	11.2%	10.9%	8.7%	7.3%	8.1%	5.4%	2.7%

12	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
JAN	8.1%	4.1%	9.4%	11.0%	8.7%	13.0%	10.8%	8.4%	13.7%	6.4%	6.5%
FEB	7.5%	3.8%	8.6%	12.7%	11.8%	16.9%	9.6%	7.6%	11.4%	4.9%	5.2%
MAR	8.5%	8.9%	8.7%	11.3%	15.6%	15.3%	8.0%	6.3%	9.8%	4.1%	3.5%
APR	9.3%	9.5%	7.7%	11.9%	13.9%	11.9%	7.5%	9.2%	12.7%	3.9%	2.4%
MAY	10.4%	8.4%	9.6%	11.7%	12.5%	12.1%	7.7%	9.0%	10.2%	4.8%	3.4%
JUN	11.8%	10.2%	11.4%	11.5%	13.1%	11.7%	6.8%	7.2%	7.1%	5.6%	3.5%
JUL	12.9%	12.2%	12.0%	10.4%	11.6%	9.5%	5.1%	6.5%	9.5%	6.4%	4.0%
AUG	12.4%	13.0%	11.2%	9.8%	11.8%	10.7%	5.5%	6.5%	8.4%	6.8%	3.9%
SEP	11.3%	9.0%	11.3%	13.7%	12.2%	11.7%	5.8%	5.8%	8.0%	6.7%	4.5%
OCT	10.9%	10.3%	10.1%	11.0%	12.8%	11.7%	7.7%	7.2%	8.7%	5.5%	4.1%
NOV	10.0%	11.5%	8.9%	10.8%	14.6%	15.6%	6.7%	5.8%	8.6%	4.6%	3.0%
DEC	8.5%	5.4%	9.1%	11.5%	10.3%	16.9%	9.1%	6.6%	10.8%	5.9%	5.9%

Table B.7 – Average monthly weather type frequency for the Heartland region.

13	HC	H	HW	C	S	W	DC	D	DW	CFP	WFP
JAN	8.3%	7.1%	8.5%	10.2%	13.1%	16.0%	8.8%	6.5%	11.0%	6.0%	4.5%
FEB	8.2%	7.3%	8.4%	10.9%	13.4%	16.5%	8.9%	7.1%	10.9%	5.0%	3.3%
MAR	9.7%	9.3%	9.5%	11.8%	14.0%	12.4%	7.6%	8.2%	9.2%	5.5%	2.8%
APR	9.1%	8.4%	10.0%	12.6%	12.2%	12.4%	8.2%	8.6%	8.9%	6.0%	3.7%
MAY	10.3%	8.3%	11.6%	11.0%	11.9%	14.6%	7.7%	7.0%	7.8%	6.1%	3.8%
JUN	10.5%	12.6%	13.3%	9.8%	12.4%	12.0%	6.3%	6.4%	6.8%	6.3%	3.5%
JUL	11.9%	18.1%	10.2%	9.4%	13.1%	8.8%	5.3%	5.6%	9.9%	5.2%	2.4%
AUG	12.4%	18.6%	10.3%	9.3%	11.0%	10.7%	4.8%	5.6%	9.5%	5.0%	2.8%
SEP	10.7%	11.8%	12.1%	11.7%	12.2%	11.7%	5.7%	6.3%	8.3%	6.6%	2.9%
OCT	9.7%	9.9%	11.8%	11.3%	12.5%	12.3%	7.2%	6.8%	8.5%	6.8%	3.2%
NOV	10.6%	10.3%	10.3%	11.8%	13.4%	12.9%	6.9%	7.0%	7.7%	6.4%	2.7%
DEC	8.4%	8.2%	8.6%	9.6%	14.6%	16.3%	8.1%	7.3%	9.0%	5.9%	4.0%

APPENDIX C

The figures below display the geographical distribution of each weather type's frequency by month. Note the different scales (indicated by the different coloring) of the transitional types and the core types. The maps presented for January, April, July and October are the same as those presented in Chapter 6 above, however, they are ordered by month.

Figure C.1 – Average monthly weather type frequency for January. Note the different scales for the core weather types and the transitional weather types.

Figure C.2 – Average monthly weather type frequency for February. Note the different scales for the core weather types and the transitional weather types.

Figure C.3 – Average monthly weather type frequency for March. Note the different scales for the core weather types and the transitional weather types.

Figure C.4 – Average monthly weather type frequency for April. Note the different scales for the core weather types and the transitional weather types.

Figure C.5 – Average monthly weather type frequency for May. Note the different scales for the core weather types and the transitional weather types.

Figure C.6 – Average monthly weather type frequency for June. Note the different scales for the core weather types and the transitional weather types.

Figure C.7 – Average monthly weather type frequency for July. Note the different scales for the core weather types and the transitional weather types.

Figure C.8 – Average monthly weather type frequency for August. Note the different scales for the core weather types and the transitional weather types.

Figure C.9 – Average monthly weather type frequency for September. Note the different scales for the core weather types and the transitional weather types.

Figure C.10 – Average monthly weather type frequency for October. Note the different scales for the core weather types and the transitional weather types.

Figure C.11 – Average monthly weather type frequency for November. Note the different scales for the core weather types and the transitional weather types.

Figure C.12 – Average monthly weather type frequency for December. Note the different scales for the core weather types and the transitional weather types.

APPENDIX D

The following figures exhibit the afternoon temperature and dew point scatter plots of all days within a selected month (either January or July) for the regional representative of each of the 13 regions (the locations of which are identified in Chapter 5). While it is important to note that multiple variables are used in the classification process (in addition temperature and dew point) at multiple observation times (8 times daily and daily averages), these plots display the general variance in temperature and dew point that is contained within each weather type at a particular location. Please note the different scales along the x- and y-axis for each plot.

Figure D.1 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all January days for the regional representative location of the Desert Southwest (Region 1). Each observation is colored according to its final GWTC weather type.

Figure D.2 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all July days for the regional representative location of the Desert Southwest region (Region 1). Each observation is colored according to its final GWTC weather type.

Figure D.3 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all January days for the regional representative location of the Southern High Plains region (Region 2). Each observation is colored according to its final GWTC weather type.

Figure D.4 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all July days for the regional representative location of the Southern High Plains region (Region 2). Each observation is colored according to its final GWTC weather type.

Figure D.5 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all January days for the regional representative location of the Intermontane region (Region 3). Each observation is colored according to its final GWTC weather type.

Figure D.6 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all July days for the regional representative location of the Intermontane region (Region 3). Each observation is colored according to its final GWTC weather type.

Figure D.7 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all January days for the regional representative location of the West Coast region (Region 4). Each observation is colored according to its final GWTC weather type.

Figure D.8 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all July days for the regional representative location of the West Coast region (Region 4). Each observation is colored according to its final GWTC weather type.

Figure D.9 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all January days for the regional representative location of the Northwest region (Region 5). Each observation is colored according to its final GWTC weather type.

Figure D.10 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all July days for the regional representative location of the Northwest region (Region 5). Each observation is colored according to its final GWTC weather type.

Figure D.11 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all January days for the regional representative location of the Great Lakes region (Region 6). Each observation is colored according to its final GWTC weather type.

Figure D.12 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all July days for the regional representative location of the Great Lakes region (Region 6). Each observation is colored according to its final GWTC weather type.

Figure D.13 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all January days for the regional representative location of the Northeast region (Region 7). Each observation is colored according to its final GWTC weather type.

Figure D.14 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all July days for the regional representative location of the Northeast region (Region 7). Each observation is colored according to its final GWTC weather type.

Figure D.15 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all January days for the regional representative location of the Southern Texas region (Region 8). Each observation is colored according to its final GWTC weather type.

Figure D.16 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all July days for the regional representative location of the Southern Texas region (Region 8). Each observation is colored according to its final GWTC weather type.

Figure D.17 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all January days for the regional representative location of the Coastal Southeast region (Region 9). Each observation is colored according to its final GWTC weather type.

Figure D.18 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all July days for the regional representative location of the Coastal Southeast region (Region 9). Each observation is colored according to its final GWTC weather type.

Figure D.19 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all January days for the regional representative location of the Mid-South region (Region 10). Each observation is colored according to its final GWTC weather type.

Figure D.20 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all July days for the regional representative location of the Mid-South region (Region 10). Each observation is colored according to its final GWTC weather type.

Figure D.21 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all January days for the regional representative location of the Inland Southeast region (Region 11). Each observation is colored according to its final GWTC weather type.

Figure D.22 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all July days for the regional representative location of the Inland Southeast region (Region 11). Each observation is colored according to its final GWTC weather type.

Figure D.23 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all January days for the regional representative location of the Northern Plains region (Region 12). Each observation is colored according to its final GWTC weather type.

Figure D.24 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all July days for the regional representative location of the Northern Plains region (Region 12). Each observation is colored according to its final GWTC weather type.

Figure D.25 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all January days for the regional representative location of the Heartland region (Region 13). Each observation is colored according to its final GWTC weather type.

Figure D.26 – Scatter plot of afternoon temperature and dew point (observation 5 from Table 1) for all July days for the regional representative location of the Heartland region (Region 13). Each observation is colored according to its final GWTC weather type.