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A Hybrid Procedure for Classifying Synoptic Weather Types for Louisiana with an Application to Precipitation Variability

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A HYBRID PROCEDURE FOR CLASSIFYING SYNOPTIC WEATHER TYPES
FOR LOUISIANA WITH AN APPLICATION TO PRECIPITATION
VARIABILITY

A Thesis

Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
in partial fulfillment of the
requirements for the degree of
Master of Geography

in

The Department of Geography and Anthropology

by
Amanda Billiot
B.S., University of South Alabama, 2011
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ABSTRACT

An automated synoptic weather classification system, based on the weather types devised by Robert Muller for Louisiana, is presented in this thesis and an application of the classification system to precipitation variability in Louisiana is demonstrated. The automated classification presented here is a hybrid classification system that uses sea level pressure composites for each Muller weather type as seeds in a correlation procedure to classify daily NCEP/NCAR Reanalysis sea level pressure patterns. The resulting hybrid classification is automated, objective, and has value in describing the surface weather variability in Louisiana. In the second part of this research project, the newly developed hybrid classification system is used to establish relationships between synoptic weather types and precipitation variability in Louisiana. Weather types that produce precipitation in Louisiana are identified and, using linear regression models, the frequency of rainy weather types is used to predict seasonal rainfall for each of the nine Louisiana climate divisions. Averaged among all climate divisions, synoptic weather type frequency accounts for 25% of the interannual precipitation variability in winter, 14% in spring, 19% in summer, and 25% in fall. While the models are better at predicting the decadal scale variability and trends during fall and winter, these results indicate that synoptic frequency alone is insufficient to describe precipitation variability in Louisiana. Future work will need to identify additional predictors. However, the automated hybrid classification system presented in this study can be used for many additional applications in historical and future climate research for Louisiana.

CHAPTER 1. INTRODUCTION

1.1 Background

Louisiana is located in the Southeast United States, a region that is characterized by large shifts in weather conditions from year to year, especially in terms of precipitation. One common way to study weather variability for a location is using synoptic climatology. Synoptic climatology is a sub-field of climatology that focuses on establishing relationships between synoptic scale atmospheric circulation patterns and the surface environment (Yarnel 1993). The primary methodology of synoptic climatology is synoptic classification, or the grouping of similar circulation patterns into classes called synoptic types. In most contexts, a circulation pattern is a field of some atmospheric variable, often sea level pressure or geopotential height (Huth et al. 2008). There are a wide variety of different synoptic classification methodologies and schemes, which are discussed in more detail in Chapter 2. The choice of synoptic classification for use in a particular study is dependent on a variety of factors including study region, weather phenomena, research question, etc. Oftentimes, a researcher will develop their own unique classification scheme to match their research purposes.

Since there is a limited amount of synoptic climatological research in the south central United States, it is still unclear how much synoptic type variability contributes to surface climate variability and trends in Louisiana. Only one synoptic weather typing system exists exclusively for Louisiana climate related studies; the Muller weather typing system for Louisiana (Muller 1977). While this system has been successful for many applications, it is a manual system that is both subjective and time-consuming. The Muller system has limited applicability for studying long term and/or future climate impacts. This thesis will present an automated classification system for classifying synoptic weather typing system for Louisiana that attempts to capture the

essence of the Muller system. Automated classification systems open up many additional applications by providing a fast, objective way to produce long-term synoptic type catalogs for a region. Having the ability to produce large datasets broadens the scope of potential research to include applications that require long term data, such as establishing relationships between synoptic type frequency and surface phenomena. These applications are very important in climate change research and can serve as the basis for a relatively new area of research investigating synoptic types in future climates using general circulation models (GCMs), as well as synoptic-based statistical downscaling of GCM projections. In particular, the discovery of statistical relationships between variables that are less accurately portrayed by the GCMs, like precipitation, are of great interest for statistical downscaling (Lee 2012).

For Louisiana, the various GCM's disagree about the sign and magnitude of future precipitation changes (Keim et al. 2011, Kunkel et al. 2013), likely due to process-based errors in the models (Hope 2006, Finnis et al. 2009). As a result, until precipitation dynamics in the models are improved substantially, statistical downscaling based on more accurately predicted GCM variables is the only option to generate accurate precipitation predictions (Lee 2012). One type of statistical downscaling is synoptic-based statistical downscaling, where models use synoptic type frequency to predict surface variables. However, this is only a viable option if there is a strong relationship between synoptic type and the surface variable in question. There has yet to be a study investigating the statistical link between synoptic type frequency and precipitation in Louisiana. However, precipitation has been broadly linked to synoptic-scale controls (Muller 1977, Trewartha 1981, Keim 1996). By quantifying the relationship between synoptic types and precipitation in Louisiana, this study will serve as the first step in evaluating

the feasibility of developing a statistical downscaling model for the region. Therefore, the objectives of this thesis are:

1. Develop an automated synoptic classification system that will have wide reaching climate and weather applications for Louisiana.
2. Use the newly developed classification system to study the influence of synoptic scale weather variability on interannual to decadal scale precipitation variability in Louisiana.

1.2 Summary

The second chapter of this thesis presents a new method of synoptic classification for Louisiana. The requirements for the classification system are 1) that it has wide applicability to Louisiana weather and climate investigations and 2) that it is able to classify weather patterns both quickly and objectively. The proposed method is an objectification of the Muller Weather Typing system for Louisiana, a widely used manual classification system in the region for applications ranging from air quality research (Muller and Jackson 1985) to the quantifying the effect of El Niño-Southern Oscillation events on weather type frequencies (McCabe and Muller 2002). The goal of the procedure is not to recreate the Muller weather typing system, but to develop a new classification system that is able produce a synoptic type catalog that describes the synoptic variability of Louisiana in a way that is consistent with the manual Muller Weather Types, yet has the advantages of being both objective and automated. The third chapter of this thesis is an application of the newly developed classification system to study precipitation variability in Louisiana. In Chapter 3, regression models are developed using synoptic type frequency to predict seasonal rainfall for Louisiana's climate divisions. By investigating the statistical relationships between synoptic weather types and rainfall in Louisiana, this study is a first step toward creating improved climate change projections for precipitation in the Louisiana.

Lastly, Chapter 4 includes a summary of findings and a discussion of future work related to this project.

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CHAPTER 2. AN AUTOMATED PROCEDURE FOR CLASSIFYING SYNOPTIC TYPES FOR LOUISIANA, USA BASED ON THE MANUAL MULLER WEATHER TYPING SCHEME

2.1 Abstract

This study presents an automated hybrid synoptic classification procedure for classifying Louisiana weather types, based on the manual weather typing system devised by Robert Muller. The goal of the procedure is to produce a synoptic classification system for Louisiana that harnesses the strengths of both manual and automated classifications, while eliminating the weaknesses. The Muller weather types archive from 1981 – 2001 is used in conjunction with the NCEP/NCAR Reanalysis dataset to develop sea level pressure composites for each Muller weather type. The composites are used as seeds in an automated correlation-based algorithm to generate weather types from 1981-2001. Results of the automated procedure are compared to the Muller weather type catalog. Despite systematic differences between the two classifications, the automated procedure correctly matched the Muller weather type at one or more of the point locations for 57% of the days. In addition, the automated catalog captured the seasonal distribution and interannual variability of the Muller types remarkably well. The hybrid synoptic weather classification system applied to weather properties at Shreveport and New Orleans showed significant differences between weather types, demonstrating that although the automated procedure does not replicate the Muller weather type classification exactly, it is homogenous within itself and has value for describing the variability of surface weather in Louisiana. In fact, it is arguably advantageous for some applications, due to its objectivity, speed, and reproducibility.

2.2 Introduction

Synoptic classification is a commonly used approach within the field of climatology. It focuses on establishing relationships between synoptic scale atmospheric circulation patterns and the surface environment (Yarnel 1993). Synoptic scale features that make up the atmospheric circulation pattern are generally between 1000 to 2500 kilometers in size (Huschke 1959), and include ridges, troughs, cyclones, and anticyclones. The location and strength of synoptic features can be indicative of the occurrence of different surface meteorological phenomena. In fact, various sectors of cyclones and anticyclones can produce dramatically different weather conditions (Keim et al. 2005). To capture this variability, synoptic patterns reduce the complex atmosphere into a manageable number of discrete reoccurring patterns, or synoptic types (Yarnel 1993). Synoptic classification is a useful tool for climatological research, and has a wide range of applications. Examples of applications include studying the relationship of synoptic types to precipitation occurrence (Fragoso and Gomes 2008, Bettolli et al. 2010, Raziei et al. 2012), linking synoptic type frequency to Pacific teleconnection frequency (Coleman and Rogers 2007), investigating synoptic types in future climates using general circulation models (GCMs) (Hope 2006), and synoptic-based statistical downscaling of GCM projections (Wetterhall et al. 2009), among many others.

There are many different techniques used to perform synoptic classification. However, each classification follows the same general procedure of defining classification types and then assigning each individual map pattern to a type (Huth et al. 2008). The earliest classifications were done manually and are implicitly subjective (Hess and Brezowsky 1952, Lamb 1972, Muller 1977). These classifications depended greatly on the experience of the researcher to recognize important patterns (Huth et al. 2008, Yarnel 1993). While the development and

application of manual classifications are still found in recent synoptic climatology (Keim et al. 2005), the methods of synoptic classification have vastly evolved as computers have advanced to facilitate the analysis of large, complex datasets. A range of automated methods has emerged, including correlation-based methods (Lund 1962), cluster analysis (Kalkstein et al. 1987), principal component analysis (PCA) (Richman 1986), self-organizing maps (Hewitson and Crane 2002), and fuzzy clusters (Bardossy et al. 1995). Although automated techniques have not been found to be significantly more accurate than manual techniques, they have some important advantages (Yarnel 1993). In addition to being much faster than manual techniques, automated techniques are considered to be more objective and are often 100 percent reproducible. However, despite the advantages of automated techniques, there is very little control over the synoptic patterns that the computer defines, and often non-significant patterns emerge or patterns that are known to be important do not appear (Frakes and Yarnel 1997). The main advantage of manual techniques is that the user has control of the weather types chosen, thus can ensure the types represent the important patterns for the region (Keim et al. 2005).

In addition to manual and automated classifications, there are some weather type classifications in which the weather types are defined subjectively by the researcher, but the individual cases are assigned objectively using an automated procedure (Schwartz 1991, Jones et al. 1993, Kalkstein 1996, Frakes and Yarnel 1997, James 2007, Beck et al. 2007). These synoptic classifications are referred to as hybrid or mixed classifications (Huth et al. 2008, Frakes and Yarnel 1997). Hybrid classifications aim to harness the strengths of both manual and automated techniques, since they are both automated and reproducible, yet allow for the expertise of the researcher to be used to define the synoptic types. The methods of hybrid classifications vary. Some hybrid techniques classify synoptic types using subjectively defined thresholds of weather

variables for each type (Schwartz 1991, Kalkstein 1996). Other hybrid techniques are automated versions of manual classifications, such as the Bergen school mid-latitude cyclone model (Frakes and Yarnel 1997), the Hess and Brezowsky Grosswetterlagen for central Europe (James 2007), and the Lamb Weather Types for the British Isles (Beck et al. 2007, Jones et al. 1993). These types of hybrid classifications are created using pattern correlation between prototypes of each weather type and the individual cases (Huth et al. 2008). These classifications are useful because the manual classifications they are based on are well-known and are proven to describe atmospheric variability well for their prospective regions. In a comparison study of the ability of 74 weather type classifications to identify associations of weather types with drought in northwest Europe, the objectivized Grosswetterlagen (James 2007), a hybrid map pattern classification, outperformed all other classification methods, even the manual Grosswetterlagen (Fleig et al. 2010).

This paper centers on objectivizing a manual weather typing scheme for Louisiana that was developed in the 1970s by Muller (1977). The Muller weather types are a very unique synoptic type catalog and have a wide array of applications (Muller and Jackson 1985, McCabe and Muller 1987, Faiers 1988, Faiers 1993, Faiers et al. 1994, Rohli and Henderson 1997, McCabe and Muller 2002). The applications of the Muller weather range from studying the effect of the El Nino Southern Oscillation on synoptic type frequency and properties of winter precipitation in New Orleans (McCabe and Muller 2002), to evaluating air quality potential at Shreveport, LA (Muller and Jackson 1985), to creating an index of evaporation by weather type for Southern Louisiana (McCabe and Muller 1987). While the Muller weather type catalog is useful for climate studies, its temporal coverage is limited, and types have not been cataloged in over 10 years. This study aims to use a correlation-based hybrid synoptic classification

procedure, similar to that used by Frakes and Yarnel (1997), to blend the Muller Weather Typing scheme for Louisiana with an automated correlation based classification technique. Furthermore, this research will determine whether the hybrid procedure outlined below produces a synoptic type system that describes the synoptic variability of Louisiana in a way that is consistent with the manual Muller weather types. A successful automated hybrid procedure using the Muller weather types as prototypes could be used to generate a long-term weather type catalog for Louisiana, including intra-diurnal classifications of weather types. The resultant catalog will provide a baseline for studying climate trends and their impacts in the region. In addition, the hybrid method will be appropriate for studying climate model output and for further application in synoptic climatology, especially since the Muller catalog is no longer maintained.

2.3 Data

2.3.1 NCEP/NCAR Reanalysis Dataset

This study utilizes sea level pressure data from the National Center for Atmospheric Research (NCAR)/National Centers for Environmental Prediction (NCEP) Reanalysis I Dataset (Kalnay et al. 1996). This dataset was assembled from a variety of climate data sources, including land surface, satellite, aircraft, and rawinsonde data (Kalnay et al. 1996). There are many different atmospheric variables included in the dataset, including both surface and upper-air data. These data are available 4 times daily at six-hourly intervals (6Z, 12Z, 18Z, 00Z) from 1948 to present. The data are in the form of global grids, with 2.5 degree grid spacing. An example of the data grid overlaid on the continental United States can be found in Figure 2.1. All of the sea level pressure maps in this thesis show surfaces interpolated from gridded datasets.

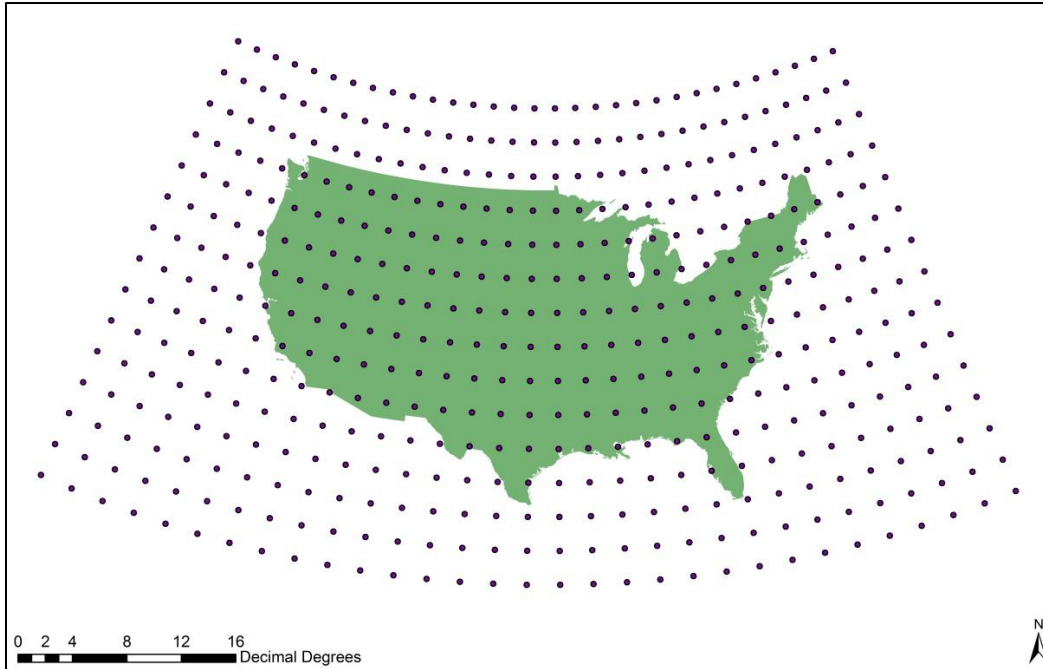


Figure 2.1. A 20°N –55°N by 60°W – 135°W subset of the NCAR/NCEP Reanalysis I dataset grid overlaid on the continental United States.

2.3.2 Muller Weather Type Catalog

The Muller weather typing scheme for Louisiana was developed in the 1970s by Robert Muller and maintained until mid-2002 by the Louisiana Office of State Climatology (LOSC). A manual synoptic classification was produced for 0600 and 1500 CST (12Z and 21Z) for New Orleans from January 1, 1961 – October 31, 2002 and for Shreveport, Monroe, Baton Rouge, and Lake Charles from January 1, 1981 – October 31, 2002. The Muller Weather Typing scheme is a subjective classification of surface maps, based primarily on pressure patterns and the location of fronts; however, the researcher also takes into account certain local climate parameters, including temperature, precipitation, clouds, relative humidity and winds, when assigning each surface map to a weather type. Therefore, there are instances in which the entire state is experiencing the same weather type and other times when 2 or more weather types are present within the state at the same time. For this reason, the weather types were determined separately for each individual

city or point location. The eight Muller Weather types are briefly described below as they were outlined in Muller and Willis (1983) with examples shown in Figure 2.2.

1. Continental High (CH): This weather type is characterized by surface high pressure over the central US extending down into Louisiana, which causes north to northeasterly winds over the region. The weather associated with this type is fair and cold.
2. Pacific High (PH): This weather type occurs in Louisiana after the passage of a Pacific cold front. Normally, a surface low pressure system is situated to the northwest of the region, causing west to northwest winds to usher in dry air over Louisiana. The typical weather associated with this type is fair and mild.
3. Gulf High (GH): This weather type occurs when a high pressure system is located south of Louisiana over the Gulf of Mexico. In these situations, the location of the high pressure system causes southwest surface winds and brings fair and warm weather to Louisiana.
4. Coastal Return (CR): This weather type occurs when a high pressure system is located to the northeast of the region. This pattern causes easterly winds and brings fair and mild weather to Louisiana.
5. Gulf Return (GR): This weather type occurs when a surface high pressure system moves far enough east of the region to cause the surface winds over Louisiana to shift to southeasterly, ushering in warm, moist air from the Gulf of Mexico. In addition, the pressure gradient is often enhanced by a developing low pressure system over Texas. The weather associated with this weather type in Louisiana is fair, warm, and humid.

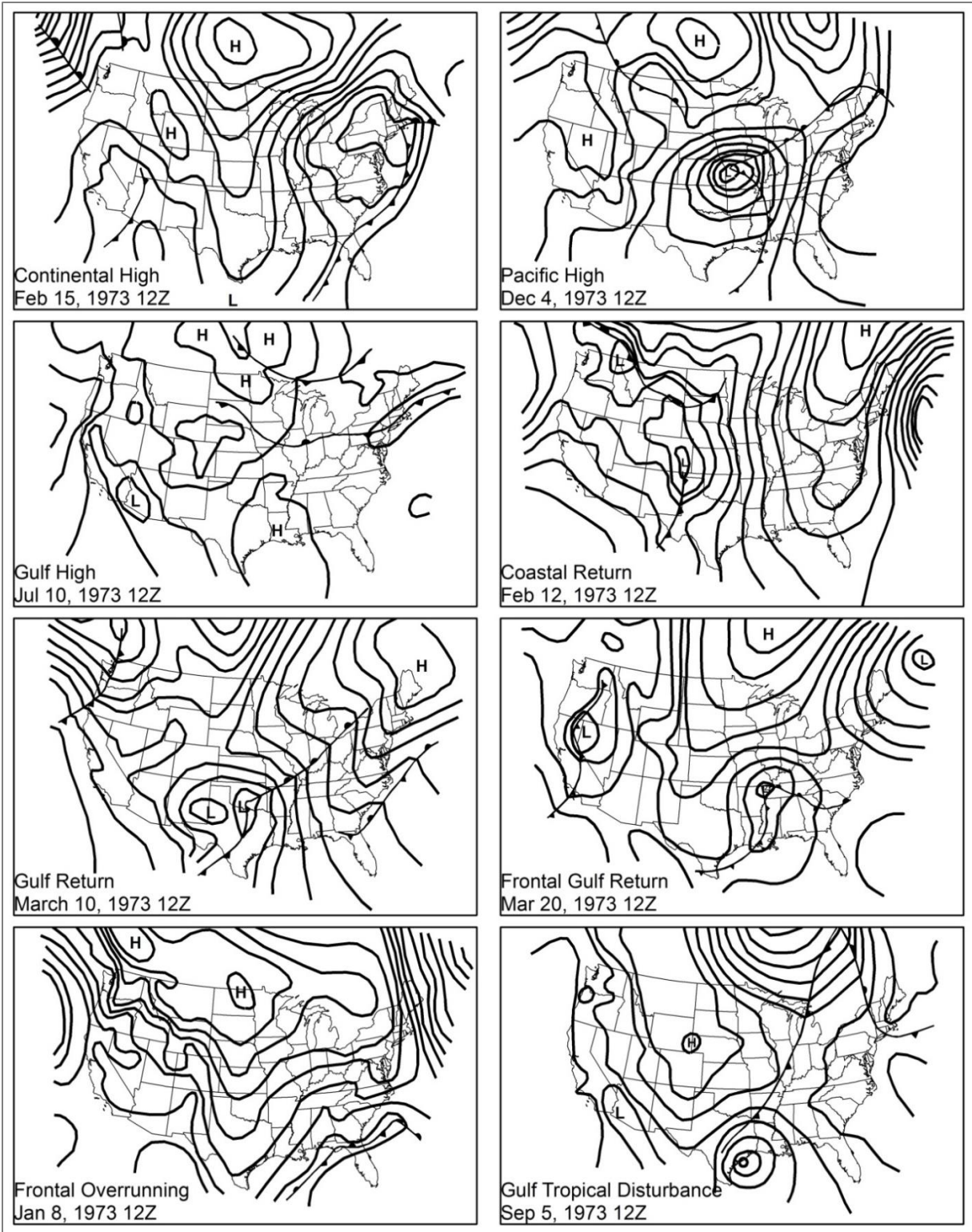


Figure 2.2. Examples of sea level pressure patterns showing isobars, high and low pressure centers, and fronts for each of the 8 original Muller Weather Types (From Muller and Willis 1983).

6. Frontal Gulf Return (FGR): This weather type is characterized by a frontal low pressure system that is close enough to the region to affect its weather. Normally, an approaching low pressure system causes south to southwest winds, and brings turbulent and stormy weather to Louisiana.
7. Frontal Overrunning (FOR): This weather type occurs when a front becomes stationary along the northern Gulf coast. Often during this kind of pattern, waves of low pressure form and move eastward along the front. Normally, this weather type brings northeasterly winds and rain to the region.
8. Gulf Tropical Disturbance (GTD): This weather type occurs when a tropical system, ranging from a tropical wave to a Category 5 hurricane, impacts Louisiana. This weather type brings strong, shifting winds and rainy weather to the region.

An archive of Muller weather types for Louisiana was created and maintained by Robert Muller and his students until early 2002. Dr. Muller originally began the classification in the 1970's. He later trained his students to use the system, and they extended the classification for New Orleans back to 1961. Additionally, in the late 1990's and early 2000's, Dr. Muller's students assisted in weather typing for all cities. The entire archive was utilized in this study.

2.4 Automated Muller Weather Typing Procedure

2.4.1 Muller Weather Types Sea Level Pressure Composites

A weakness of automated synoptic typing techniques is the loss of valuable climatological expertise in defining meaningful synoptic types for a region, inherent in manual classifications. By using composite sea level pressure grids for each Muller weather type as seeds in a correlation-based synoptic typing algorithm, we preserve the valuable researcher knowledge that was used to define the Muller synoptic types in the manual typing procedure.

Daily sea level pressure data were collected from the NCAR/NCEP Reanalysis dataset for the region from 20°N –50°N by 65°W – 125°W from 1948 to 2012. This area covers the entire continental United States, as well as the Gulf of Mexico. To create the composite sea level pressure grids for each Muller type, a 21-year subset of the 12Z Muller synoptic type catalog from 1981 to 2001, maintained in the Louisiana Office of the State Climatology and Southern Regional Climate Center, was used to assign each corresponding NCEP/NCAR Reanalysis I daily sea level pressure grid to the correct Muller weather type. This subset is referred to as the training dataset. The time period from 1981 to 2001 was chosen because the Muller weather type archive includes types for all five cities starting in 1981, with 2001 as the last full year of data available. The training dataset was then refined to include only “non-transition” days, or days on which the Muller synoptic type was the same at all 5 locations: Shreveport, Monroe, Lake Charles, Baton Rouge, and New Orleans. The choice to include only “non-transition” days in the calculation of the Muller weather type composites was made to ensure separation between the types by preventing the influence sea level pressure grids that were in transition between two weather type situations. Of the 7670 0600 CST sea level pressure grids from 1981 – 2001, 4202 of them were “non-transition”.

Using the grids from the training dataset, the average sea level pressure field for each Muller weather type was calculated. Since there are seasonal differences in sea level pressure pattern intensity, each sea level pressure grid was standardized before the seasonal means were calculated. According to the study of Yarnel (1993), standardization is necessary to remove the seasonal influences on absolute pressure patterns so that only the generalized map pattern remains, making seasonal pressure patterns from different seasons comparable. Each daily sea level pressure grid was standardized using the following formula known as the Z-transformation:

$$Z_i = \frac{x_i - \bar{X}}{s} \quad (\text{Equation 1})$$

where Z_i is the standardized grid point value, x_i is the original grid point value, \bar{X} is the mean value of all of the grid points, and S is the standard deviation of all of the grid point values (Yarnel 1993).

2.4.2 Hybrid Correlation Based Automated Procedure

There are several different methods that can be used to develop a hybrid weather type classification. The goal of the hybrid classification presented here is to automatically classify daily sea level pressure grids using the pre-defined Muller classification system. A correlation-based method was chosen for this study because it is ideal for performing a targeted classification using predefined types (Schoof and Pryor 2006). Correlation based methods for the synoptic classification of gridded data were first introduced by the study of Lund (1962). The study of Kirchhofer (1973) improved upon the Lund (1962) methodology of correlation-based classifications by introducing correlation thresholds for sub scale map patterns. The methodology of Kirchhofer (1973) is widely accepted and has been used extensively in synoptic classification studies (McKendry et al. 1995, Saunders and Byrne 1996, Saunders and Byrne 1999, Frakes and Yarnel 1997, Schoof and Pryor 2006, El-Kadi and Smithson 2000). The Kirchhofer classification scheme is based on the Kirchhofer score (SS), or the sum of squares value between the normalized grid point values of two map patterns (Yarnel 1993). To perform a classification, the SS is calculated for every possible pair of gridded map patterns. The researcher sets a SS threshold that represents a cut-off point at which two grids are considered similar. The observation day grid with the highest amount of threshold exceedances is selected as a keyday. The keyday can also be understood as the observation day that has the most number of

observational days with similar sea level pressure grids. Keydays represents typical synoptic patterns (Yarnel 1993). Next, the keydays and all similar days are removed from the dataset, and the process is repeated until there are no days left. Each observation is then assigned to the keyday for which it has the highest SS value above the chosen threshold. If an observation has no SS value above the threshold, it is considered unclassified (Yarnel 1993). The choice of correlation threshold impacts how many keydays are chosen, how many unclassified days there are in the classification, and the within and between group variance of the weather types (Yarnel 1993). An overview of a correlation based classification procedure in synoptic climatology is presented in Figure 2.3.

The classification performed in this study is a targeted Kirchhofer classification (Frakes and Yarnel 1997, Schoof and Pryor 2006). Instead of allowing the algorithm to define the keydays as in a traditional Kirchhofer classification, keydays were predefined as the Muller sea level pressure composites. Therefore, the choice of correlation threshold has no impact on the number of keydays chosen. Theoretically, the choice of correlation threshold is still important in a targeted Kirchhofer classification. Higher correlation thresholds should minimize within group variance, but result in a high number of unclassified days, whereas lower correlation thresholds result in higher within group variance with a lower number of unclassified days. However, the study of Frakes and Yarnel (1997) found no significant advantages in minimizing within group variance by choosing higher correlation thresholds over lower correlation thresholds with much higher percentages of days classified. In fact, they found that the within-group variance of the hybrid weather types with a correlation threshold of $r = 0.00$ was actually less than the within-group variance of the manual classification weather types. For this reason, I chose to eliminate

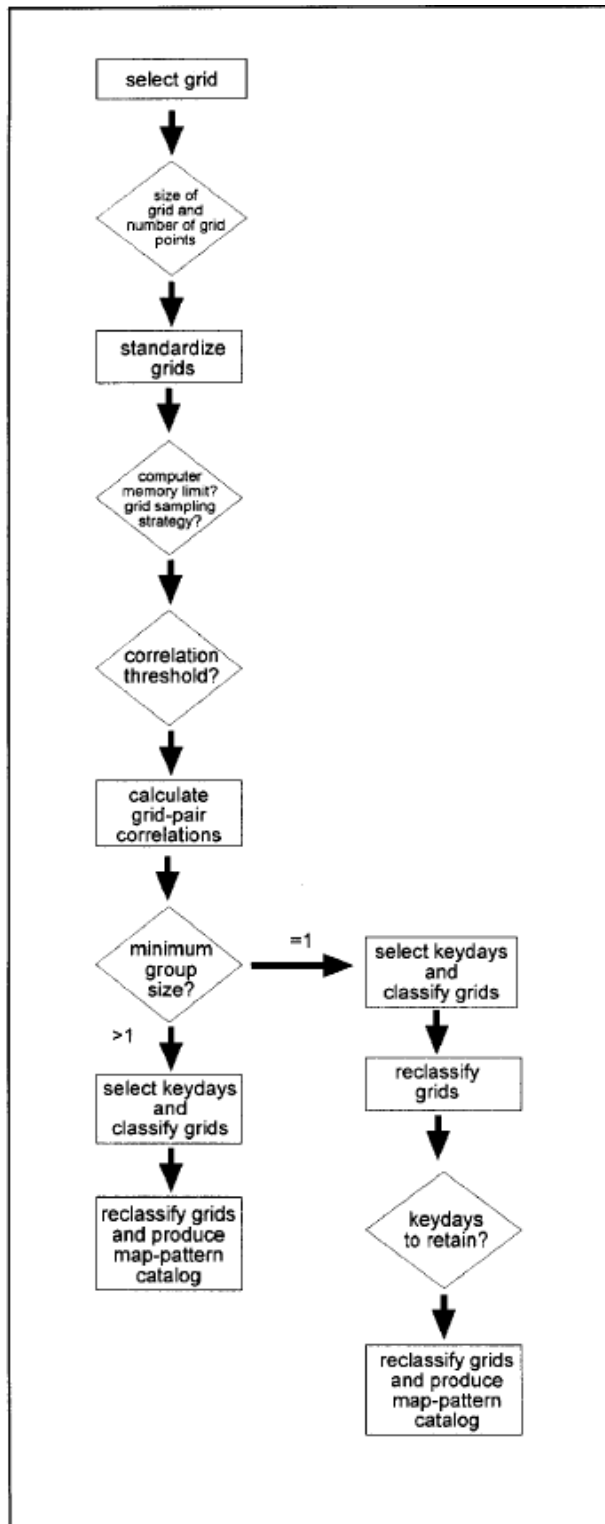


Figure 2.3. A flowchart of a correlation based classification of map patterns in synoptic climatology. (Figure from Frakes and Yarnel 1997).

the correlation thresholds from the classification procedure and simply assign each observation to the keyday that had the lowest SS value. To determine the most appropriate weather type, the SS was calculated between an individual sea level pressure grid and each Muller sea level pressure composite grid, using the formula:

$$SS = \sum_{i=1}^N (G_{xi} - M_{yi})^2 \quad (\text{Equation 2})$$

where **SS** is the Sum of Squares or Kirchhofer score, **N** is the number of grid points, **G_{xi}** is the normalized value of grid point **i** on sea level pressure grid **x**, and **M_{yi}** is the normalized value of grid point **i** on the Muller sea level pressure composite grid **y** (Yarnel 1993). Using this procedure, all sea level pressure grids are classified. A variety of different sized subsets of the gridded NCAR/NCEP Reanalysis data were experimented with for use in the sum of squares procedure (Figure 2.4). Using each of the grid sizes, daily weather types were produced using the procedure from 1981 to 2001 and compared with the Muller weather types. The table 2.1 reports the percentages of days that had an exact weather type match between the Muller and hybrid datasets for one or more of the point locations. It was found that when using gridded data that covered the large areas, many of the features that are significant to Louisiana weather got “washed out” by the variability of other synoptic features across the country, and fewer daily matches occurred. On the other hand, the small grid that centered on Louisiana (H in Figure 2.4) did not offer enough information about the synoptic conditions to produce a good classification.

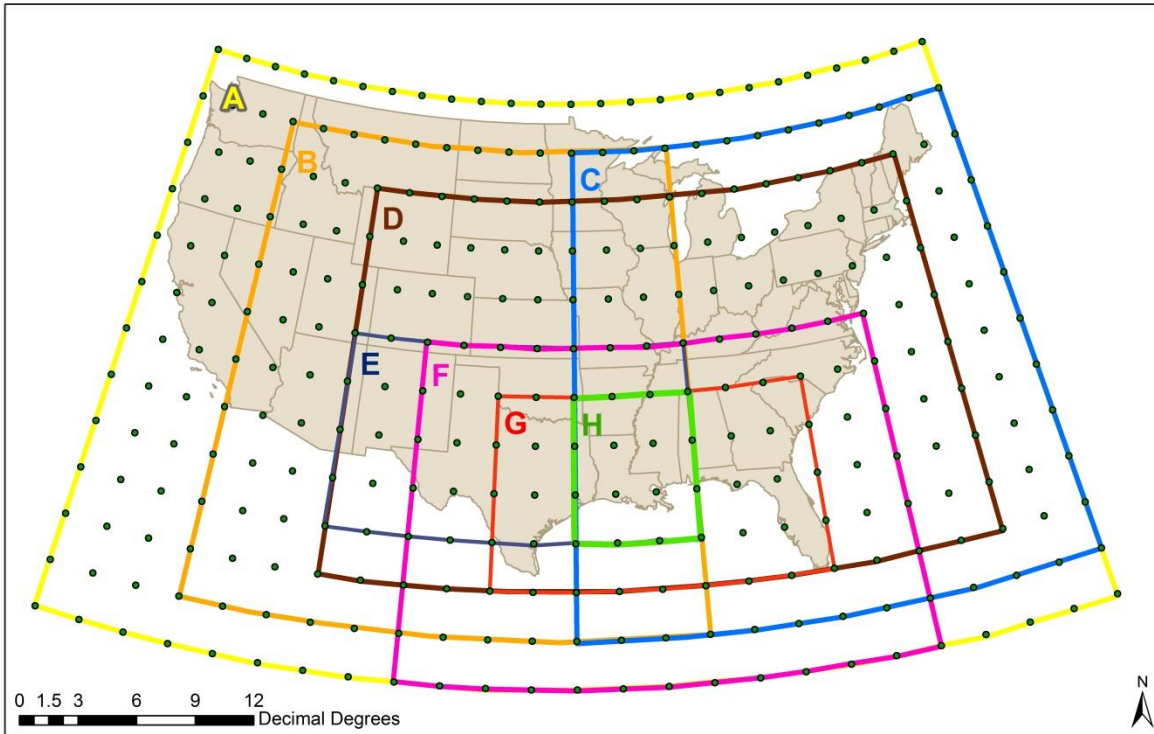


Figure 2.4. The subsets of the NCAR/NCEP reanalysis gridded dataset that were used in the correlation procedure.

Table 2.1. The coordinates and percentage of days that had an exact weather type match between the Muller and hybrid weather classification catalogs for the grids shown in Figure 2.4.

Grid	Upper Right Coordinates	Lower Left Coordinates	Daily Matches
A	50 N, -65 W	20 N, -125 W	55%
B	47.5 N, -87.5 W	22.5 N, -177.5 W	42%
C	47.5 N, -65 W	22.5 N, -95 W	43%
D	45 N, -70 W	25 N, -110 W	46%
E	37.5 N, -87.5 W	27.5 N, -110 W	50%
F	37.5 N, -75 W	20 N, -105 W	55%
G	35 N, -80 W	25 N, -100 W	57%
H	35 N, -87.5 W	27.5 N, -95 W	53%

Through trial and error, it was found that calculating the sum of squares between subsets of the grids from 25°N – 35°N by 80°W – 100°W (G in Figure 2.4) produced a classification that was the most similar to the manual Muller weather types on a daily time scale. This subset covers a 1000 x 2000 kilometer area centered on New Orleans, LA. The hybrid procedure was first used to classify only the sea level pressure grids in the training dataset, which includes all 12Z sea level pressure grids from 1981 – 2001. After the procedure was evaluated according the methods described below, all 12Z sea level pressure grids from 1948 – 2012 were classified using the hybrid procedure.

2.4.3 Evaluation of Hybrid Classification

The hybrid classification was first evaluated by comparing the automated and manual classifications for each sea level pressure grid in the training dataset on a daily basis to determine what percentage of the grids were classified as the same type using both methods. However, it is important to note that the automated hybrid procedure defines weather types for the entire state, whereas the Muller system defines weather types individually for each point location. This difference makes it somewhat challenging to compare the two classifications. Since only one classification was performed for the entire state in the hybrid procedure, results were compared to the manual Muller classification at each of the 5 cities to determine if the hybrid procedure performed better at some locations than at others. Monthly and annual frequencies of each weather type were compared and correlation coefficients were calculated between datasets to determine if the hybrid classification captured the same seasonal and annual distribution of weather types as the Muller classification. Finally, using the hybrid classification catalog from 1948 – 2012, mean weather properties at each city (wind speed and direction, visibility, cloud cover, temperature anomaly, dew point depression, and precipitation days) were calculated from

World Meteorological Organization (WMO) Surface Hourly Data for each hybrid weather type to evaluate whether the hybrid classification captures differences in observed weather between weather types. To further explore differences between the weather types, pairwise multivariate tests for equality were conducted on the mean weather properties for each type.

2.5 Results and Discussion

2.5.1 Muller Weather Types Sea Level Pressure Composites

Sea level pressure composites for the eight Muller Weather Types are shown in Figure 2.5. For the most part, the composites capture the main synoptic level features that are characteristic of each type and the wind flow over Louisiana is correct for most types. For example, the sea level pressure composite for the Pacific High type has high pressure system in the west and low pressure in the midwest, with northwesterly flow over Louisiana. This pattern is similar to that described by Muller and Willis (1983) for a typical Pacific High pattern. This holds true in most cases; however, one composite that does not have a very distinct pattern is the Frontal Overrunning composite. This is likely because the location of the surface cold front is important to delineating this weather type in the Muller classification, though these fronts are not included in the pressure patterns of the NCEP Reanalysis dataset. As such, it will be difficult for the automated procedure to distinguish it from some of the other weather types using pressure patterns alone. The Gulf Tropical Disturbance sea level pressure composite detects low pressure in the eastern Gulf, but the low pressure system is elongated and offset to the west of Louisiana. This is likely due to the fact that there is a large amount of variability in tropical patterns,

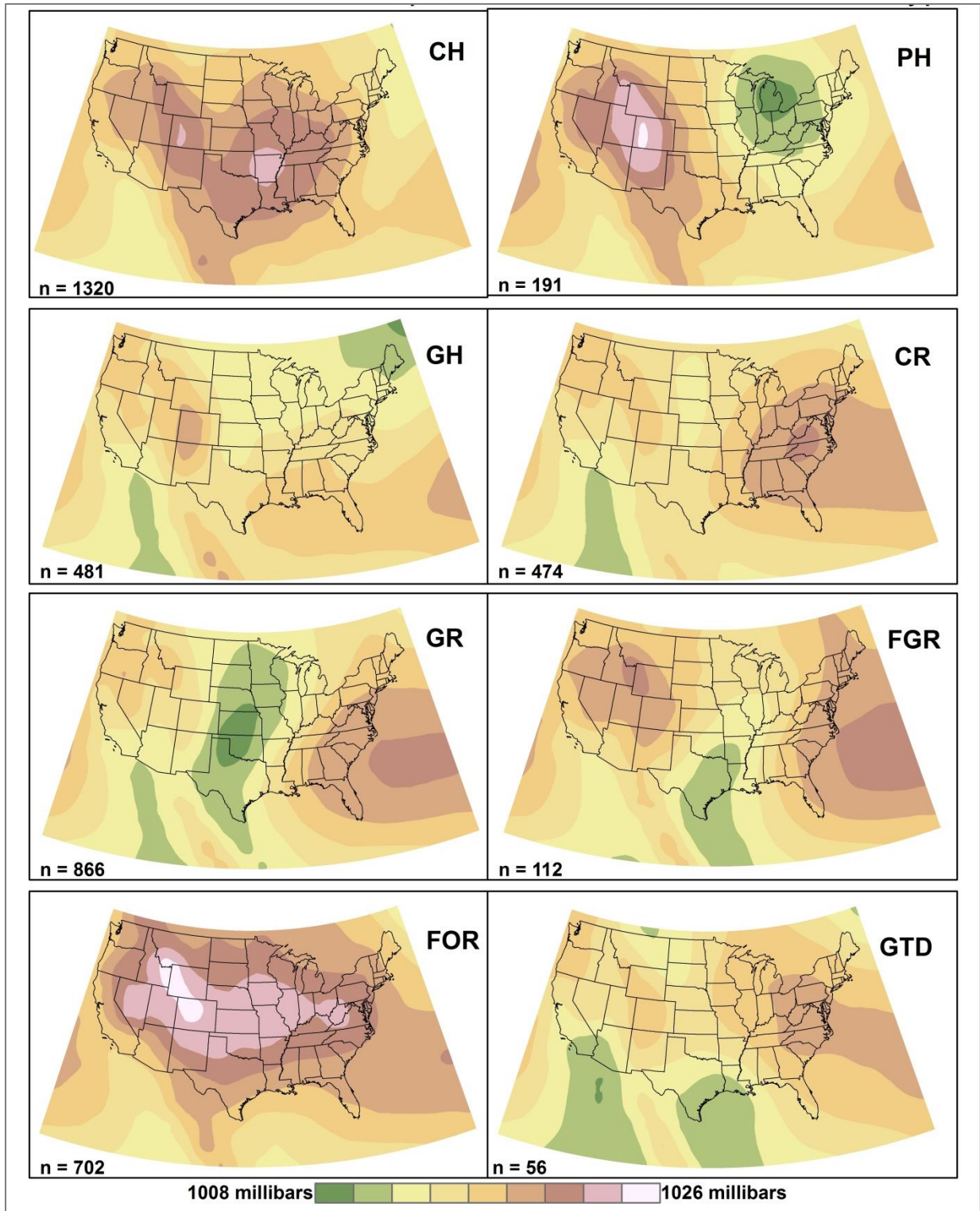


Figure 2.5. Muller Sea Level Pressure Composites created using grids from the testing dataset. (CH = Continental High, PH = Pacific High, GH = Gulf High, CR = Coastal Return, GR = Gulf Return, FGR = Frontal Gulf Return, FOR = Frontal Overrunning, GTD = Gulf Tropical Disturbance).

which range from weak tropical disturbances to major hurricanes, and can affect Louisiana from any position in the Gulf of Mexico under a variety of atmospheric conditions. While this composite should be able to identify most of the tropical systems in the automated classification, it will also classify extra-tropical Gulf lows, which commonly form off the coast of Texas in winter and spring (Hsu 1992), as Gulf Tropical Disturbances. Both of these weather patterns cause disturbed weather in Louisiana, so instead of eliminating the pattern from the automated classification, we chose to rename the class Gulf Low (GL) and accept that this will cause some disagreement between the two classification systems.

2.5.2 Evaluation of Hybrid Classification

The 1981 to 2001 sea level pressure composites for both the Muller and hybrid classifications are displayed in Figure 2.6. The red box indicates the grid that was used in the automated procedure. If the hybrid classification was a perfect replica of the Muller classification, the composites for each classification would be identical. While there are some minor differences, such as the strength of the high and low pressure systems, the main synoptic features are the same for both classifications. Most importantly, the orientation of the sea level pressure gradient over Louisiana is very similar between the two classifications for each weather type. This is important because the Muller classification relies heavily on wind direction, and the pressure gradient orientation largely determines wind direction. The similarity between the Muller and hybrid sea level pressure composites suggests that the hybrid system, while not replicating the Muller system, may serve as an acceptable surrogate.

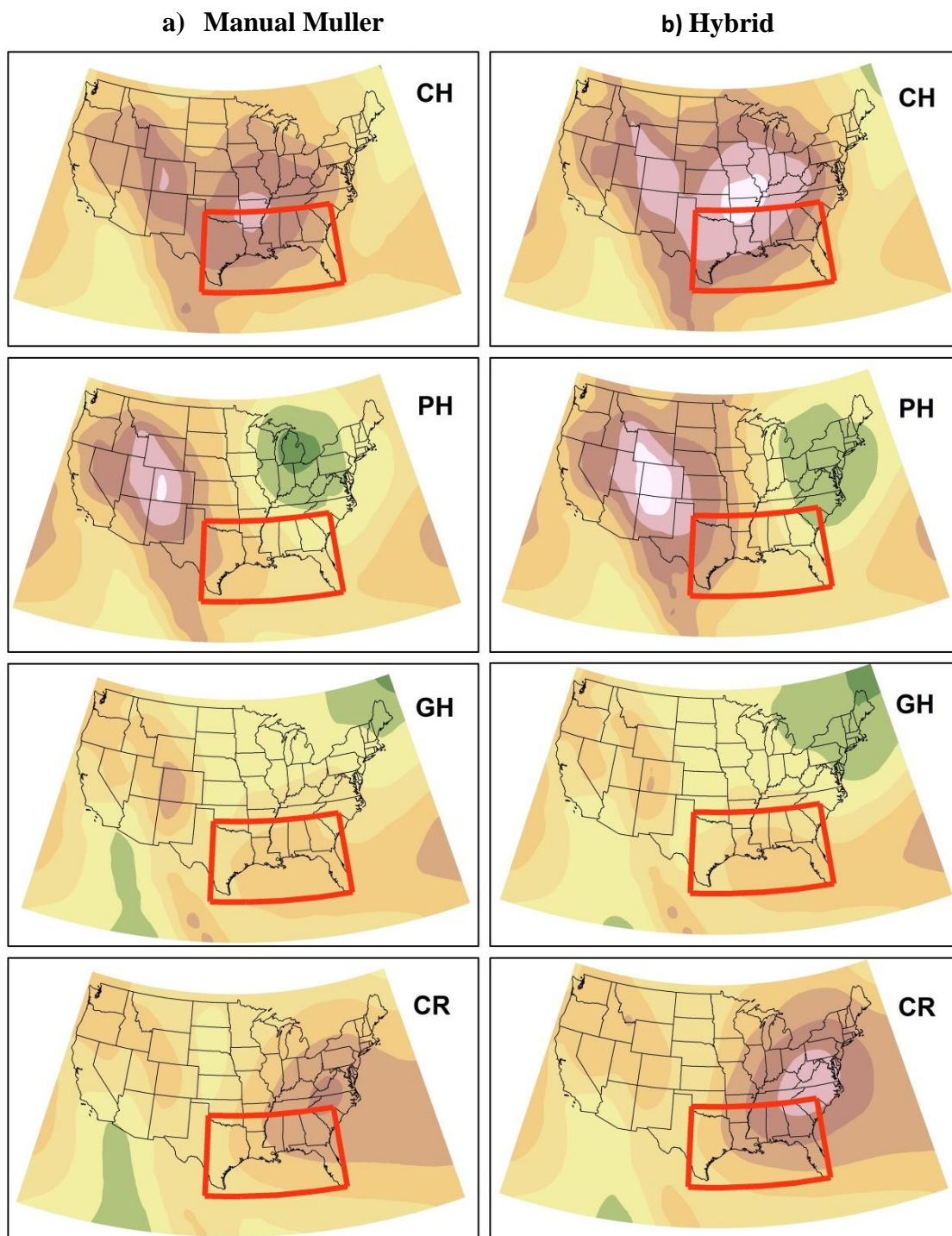
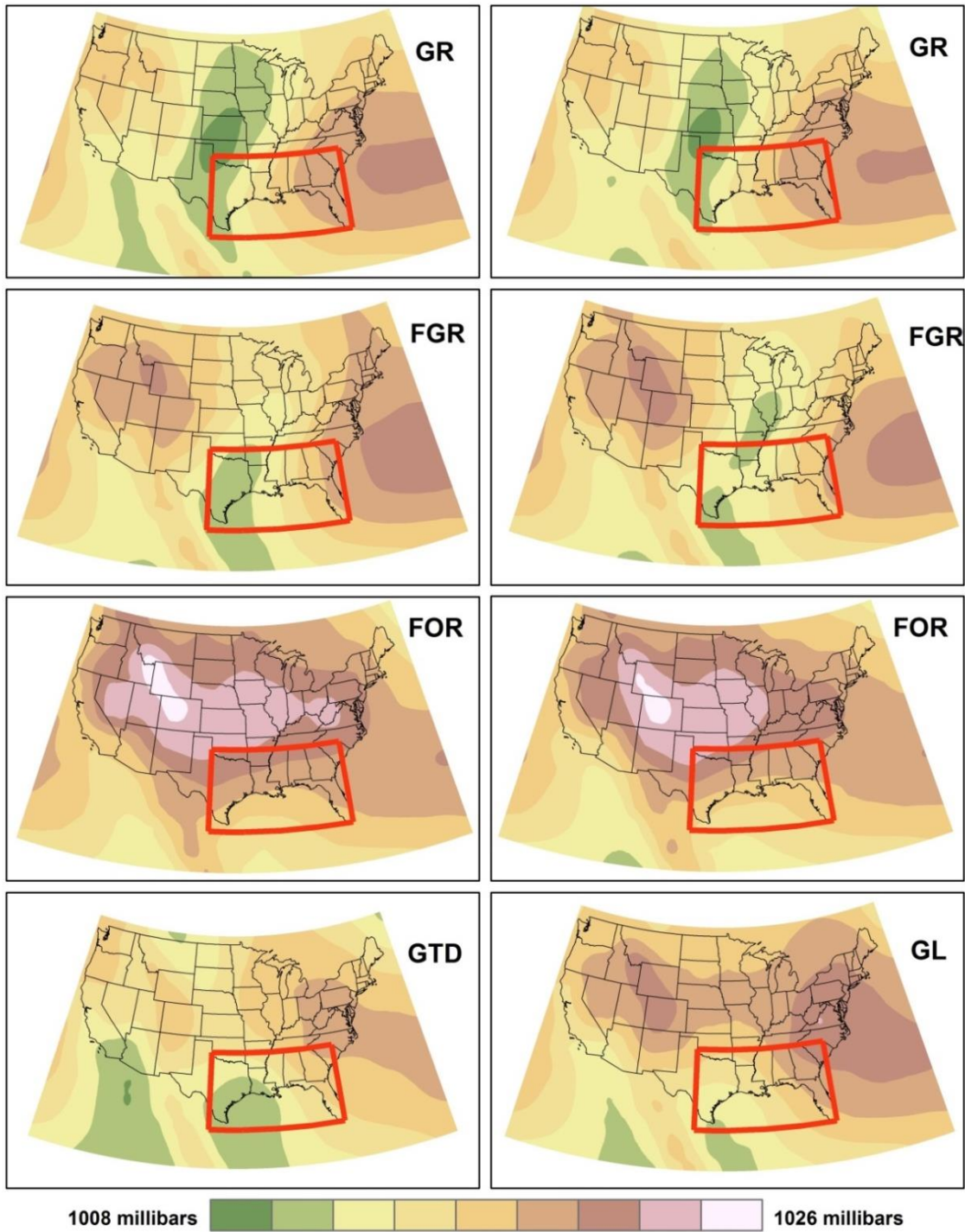


Figure 2.6. Sea level pressure composites by weather type for the a) Muller and b) hybrid classifications. The red bounding box shows the grid area used in the classification algorithm. (CH = Continental High, PH = Pacific High, GH = Gulf High, CR = Coastal Return, GR = Gulf Return, FGR = Frontal Gulf Return, FOR = Frontal Overrunning, GTD = Gulf Tropical Disturbance, GL = Gulf Low).

(Figure 2.6 continued)

a) Manual Muller

b) Hybrid



A comparison of the Muller and hybrid classifications on a daily basis revealed that the hybrid classification correctly matched the Muller weather type at one or more of the points. The hybrid classification correctly identified the Muller weather type in 41% of the cases (Table 2.2). The highest percentage classified correctly was 45 % at Lake Charles. At first consideration, these figures seem low. It is important to remember that the purpose of a hybrid classification is not to exactly replicate the original manual classification; instead, the goal is to provide an acceptable alternate that can be used for applications that benefit from using automated methodologies (Huth et al. 2008). In the hybrid classification literature, these results of this study are comparable to the results of other similar studies. For example, the objectivized Grosswetterlagen classification had a 39.1 % daily correspondence with the manual Grosswetterlagen classification (James 2007). However, the classification is considered highly successful. In fact, it outperformed over 70 other classifications in an inter-comparison study of their power to analyze drought in north-western Europe. Other daily correspondence values between manual classifications and their objectivized versions are 42 % in Frakes and Yarnel (1997) and 34.7 % in Kruger (2002). Compared to these previous studies, the objectivized Muller classification had slightly better success on the daily timescale at each point location.

Figure 2.7 shows the total number of days from the testing dataset assigned to each weather type for each classification, with the number of Muller days presented as the average of the number of days classified as each weather type at the five Louisiana cities. This figure shows that the hybrid classification under classifies the Continental High and Frontal Overrunning types, and over classifies the Pacific High and Gulf Disturbance types. Yet, the total number of days classified as Gulf High, Coastal Return, Gulf Return, and Frontal Gulf Return types is similar for both the Muller and hybrid Classifications.

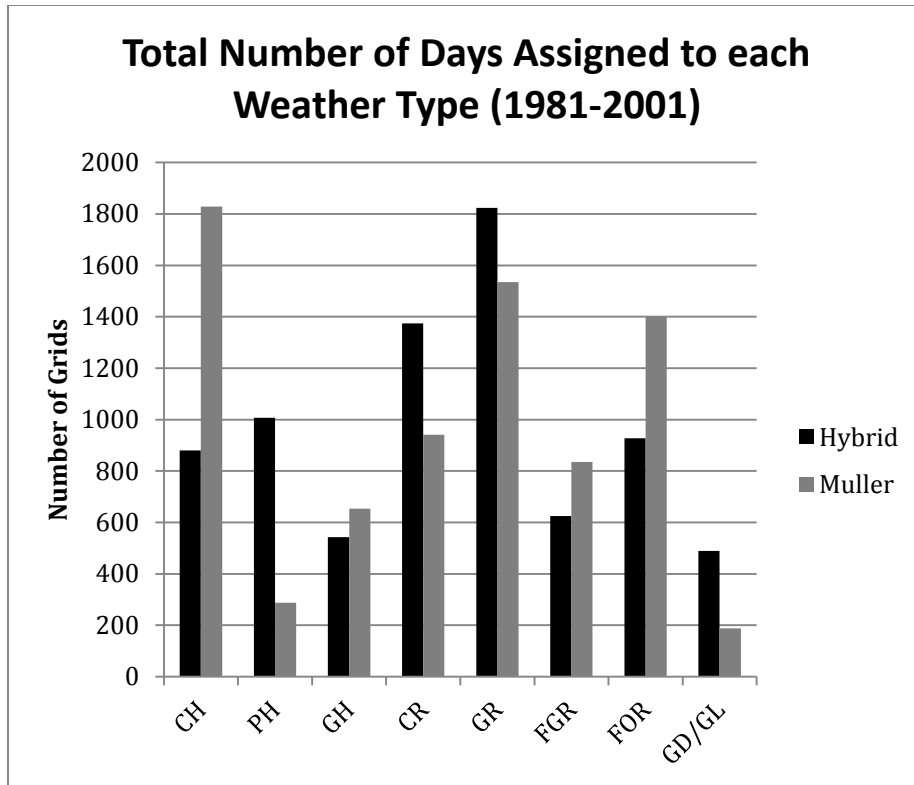


Figure 2.7. Chart comparing the total number of days from the testing dataset classified as each weather type between the Muller manual typing scheme and the hybrid typing procedure from 1981 - 2001.

A more detailed look at the performance of the hybrid classification can be seen in Table 2.2, which shows the percentage of the Muller weather types that were matched in the hybrid classification by weather type for each of the five Louisiana cities. The comparison of the two classifications by weather type reveals that the hybrid procedure is better at identifying some of the Muller weather types than others. For instance, at Shreveport, 72% of the Gulf Return grids were classified correctly using the hybrid procedure, whereas only 32% of the Frontal Overrunning grids were identified correctly. The various disagreements between the Muller and hybrid classifications can likely be attributed to one of two sources: the subjectivity of the Muller classification system or the limitations of the correlation algorithm in identifying certain weather patterns.

Table 2.2. A) The percentages of Muller classification grids by type from the testing dataset that were classified as each of the weather types in the hybrid classification from 1981 – 2001 for Shreveport, Monroe, Lake Charles, LA. B) Same, but for Baton Rouge, and New Orleans, LA.

A) Hybrid Classification	CH	PH	GH	CR	GR	FGR	FOR	GD
Shreveport								
CH	34%	7%	6%	4%	1%	1%	7%	1%
PH	24%	55%	15%	1%	0%	4%	14%	1%
GH	4%	6%	43%	3%	6%	7%	2%	2%
CR	18%	3%	9%	51%	15%	9%	14%	13%
GR	2%	4%	21%	23%	72%	31%	8%	23%
FGR	1%	14%	3%	2%	4%	32%	10%	6%
FOR	15%	7%	2%	8%	0%	5%	32%	7%
GL	2%	3%	1%	8%	2%	10%	13%	46%
Total Agreement = 44%								
Monroe								
CH	33%	7%	5%	3%	0%	1%	7%	0%
PH	20%	58%	14%	1%	1%	5%	18%	1%
GH	4%	7%	43%	2%	5%	8%	2%	3%
CR	22%	4%	8%	47%	11%	8%	12%	8%
GR	4%	6%	25%	30%	72%	23%	8%	20%
FGR	1%	11%	3%	1%	8%	36%	8%	8%
FOR	13%	6%	2%	8%	0%	7%	33%	6%
GL	2%	1%	1%	8%	3%	12%	12%	53%
Total Agreement = 44%								
Lake Charles								
CH	36%	6%	5%	5%	1%	2%	11%	1%
PH	23%	63%	16%	1%	1%	7%	17%	1%
GH	4%	5%	41%	3%	5%	3%	1%	3%
CR	20%	3%	9%	48%	20%	8%	16%	22%
GR	2%	4%	21%	26%	63%	17%	7%	20%
FGR	1%	10%	4%	2%	6%	36%	4%	6%
FOR	12%	5%	3%	9%	1%	13%	34%	9%
GL	2%	2%	1%	6%	3%	15%	9%	38%
Total Agreement = 45%								

(Table 2.2 continued)

B) Hybrid Classification	CH	PH	GH	CR	GR	FGR	FOR	GD
Baton Rouge								
CH	34%	8%	5%	4%	0%	2%	12%	1%
PH	19%	65%	15%	1%	1%	12%	21%	2%
GH	4%	6%	40%	2%	5%	4%	2%	3%
CR	25%	3%	8%	44%	10%	5%	14%	17%
GR	5%	5%	25%	33%	61%	10%	7%	22%
FGR	1%	9%	3%	2%	16%	32%	3%	8%
FOR	11%	4%	2%	8%	2%	18%	33%	8%
GL	1%	1%	1%	5%	5%	17%	8%	39%
Total Agreement = 42%								
New Orleans								
CH	35%	8%	4%	4%	0%	2%	14%	1%
PH	18%	65%	16%	1%	1%	15%	21%	1%
GH	5%	6%	40%	3%	5%	3%	2%	3%
CR	25%	3%	8%	43%	9%	5%	15%	18%
GR	6%	6%	25%	34%	60%	9%	7%	22%
FGR	0%	7%	3%	2%	17%	28%	2%	9%
FOR	10%	3%	2%	8%	2%	22%	32%	9%
GL	1%	1%	1%	5%	5%	16%	7%	37%
Total Agreement = 41%								

The seasonal frequency of the weather types was compared between the two classifications (Figure 2.8). The Muller seasonal frequency values were computed as the average of the seasonal frequency of each weather type at the five Louisiana cities. Similar to the daily comparison, the seasonality of some of the weather types was captured better by the hybrid procedure than others. However, considering the daily alliance of the Muller and hybrid classifications was less than 60%, the seasonal distribution of the Muller weather types was reproduced remarkably well in the hybrid classification. The Pearson's correlation coefficient

was calculated between the Muller and hybrid seasonal frequencies for each weather type (Table 2.3). The seasonal frequencies of all weather types, except for Frontal Overrunning and Gulf Tropical Disturbance/Gulf Low, for the Muller and hybrid classifications are significantly correlated at the 95 % confidence level. This result could indicate that a large number of the misclassified grids are assigned to a weather type with a similar sea level pressure pattern that is just as likely to occur during a particular season. For example, while 40% of the Coastal Return grids were classified correctly by the hybrid procedure at New Orleans, 25% of them were assigned to the Gulf Return type (see Table 2.2). This is not that surprising, since the Coastal Return Type often transitions into the Gulf Return Type when the high pressure system shifts farther east of Louisiana. It is likely that some of the Coastal Return types in the Muller Classification that were “mistyped” in the hybrid classification were in transition between Coastal Return and Gulf Return. Since the Coastal Return and Gulf Return Types cause very similar types of weather for Louisiana, this error is not really detrimental to the hybrid classification. The major differences in seasonality between the two classifications are associated with the Gulf Tropical Disturbance/Gulf Low and Frontal Overrunning weather types. In the Muller classification, the seasonal frequency of the Gulf Tropical Disturbance type is centered on the hurricane season. However, in the hybrid classification, there are also baroclinic low pressure systems included in this type, which occur from late fall to spring (Hsu 1992). This helps to explain the double peak in the seasonality of the Gulf Low weather type in the hybrid classification, one in spring and one in summer.

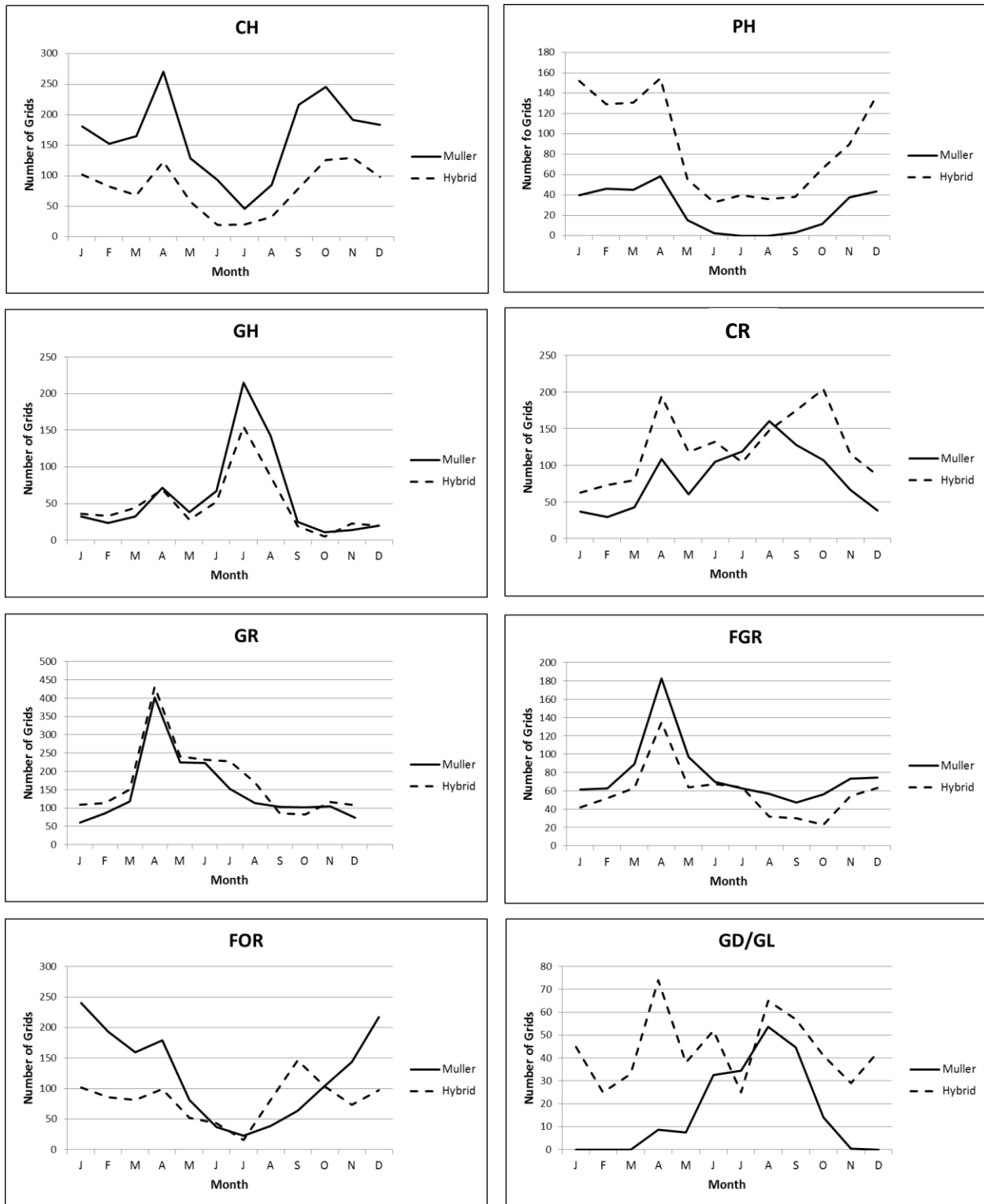


Figure 2.8. Graphs comparing the seasonal frequency of the Muller and hybrid classifications from 1981-2001. (CH = Continental High, PH = Pacific High, GH = Gulf High, CR = Coastal Return, GR = Gulf Return, FGR = Frontal Gulf Return, FOR = Frontal Overrunning, GD = Gulf Tropical Disturbance, GL = Gulf Low).

Table 2.3. Pearson correlation coefficients (* = significant at 95% confidence level) between the seasonal frequency of the Muller and hybrid classification weather types from 1981 – 2001 for the State of Louisiana. (CH = Continental High, PH = Pacific High, GH = Gulf High, CR = Coastal Return, GR = Gulf Return, FGR = Frontal Gulf Return. FOR = Frontal Overrunning, GD = Gulf Tropical Disturbance, GL = Gulf Low).

Hybrid Classification	Manual Muller Classification							
	CH	PH	GH	CR	GR	FGR	FOR	GD
CH	0.90 *	--	--	--	--	--	--	--
PH	--	0.96 *	--	--	--	--	--	--
GH	--	--	0.97 *	--	--	--	--	--
CR	--	--	--	0.74 *	--	--	--	--
GR	--	--	--	--	0.93 *	--	--	--
FGR	--	--	--	--	--	0.93 *	--	--
FOR	--	--	--	--	--	--	0.43	--
GL	--	--	--	--	--	--	--	0.44

The interannual variability of the weather types in the two classifications was evaluated (Figure 2.9). The Muller annual frequency values were computed as the average of the interannual frequency of each weather type at the five Louisiana cities. Similar to the previous results reported, the interannual variability was captured by the hybrid procedure more accurately for some weather types than for others; however, the annual comparisons showed less covariability than the seasonal comparisons. The Pearson’s correlation coefficient was calculated between the Muller and hybrid seasonal frequencies for each weather type (Table 2.4). Although the correlations are not as strong for interannual variability as they are for seasonality, six of the eight weather types have significant correlations at the 95 % confidence level. While the annual hybrid time series captures most of the annual rainfall peaks in the Muller classification, it does not always capture the same trends. For example, in the Muller classification, there is an increasing precipitation trend in the Gulf Return type. This same trend is not evident in the hybrid classification.

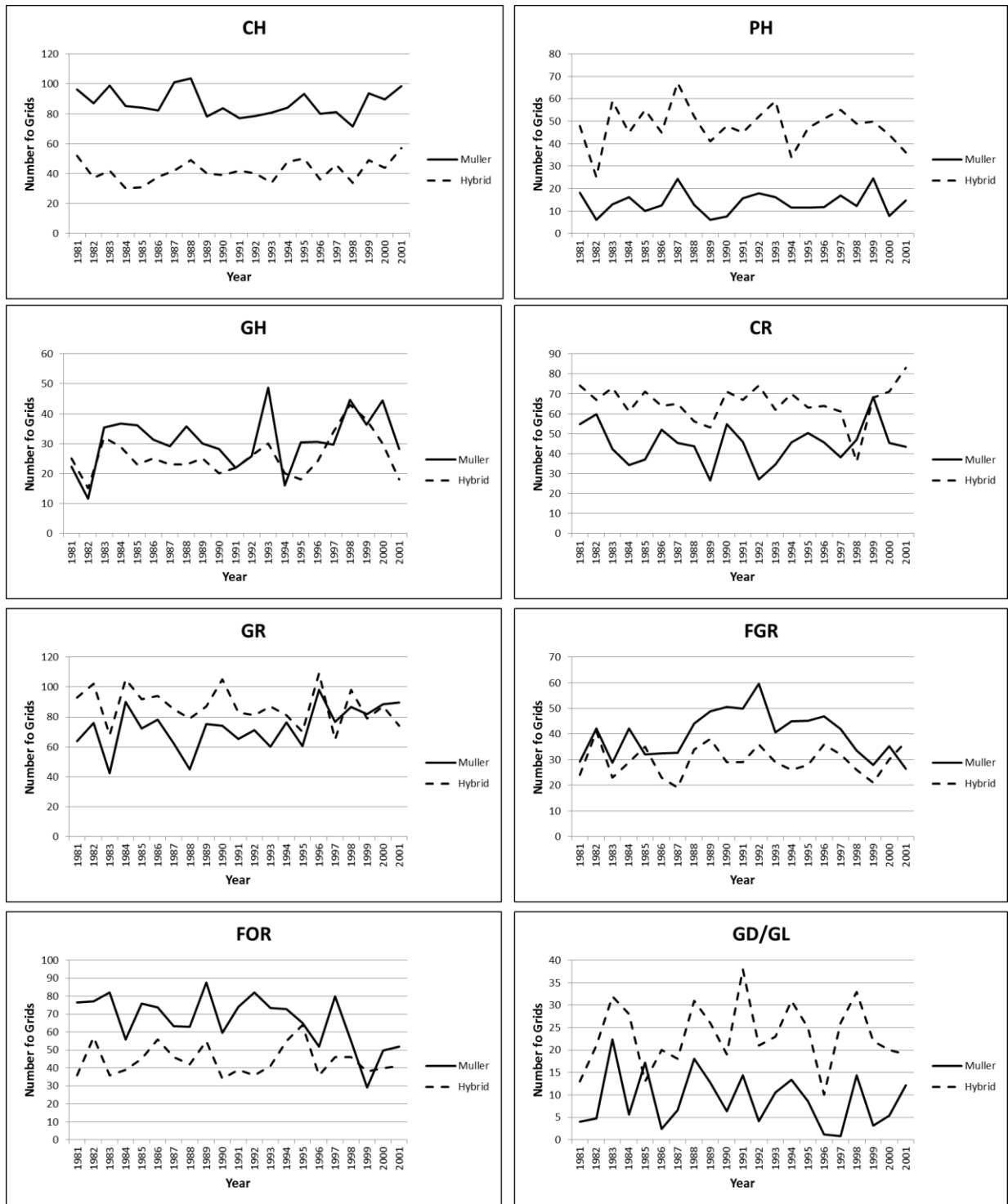


Figure 2.9. Graphs comparing the annual frequency of the Muller and hybrid classifications from 1981-2001. (CH = Continental High, PH = Pacific High, GH = Gulf High, CR = Coastal Return, GR = Gulf Return, FGR = Frontal Gulf Return. FOR = Frontal Overrunning, GD = Gulf Tropical Disturbance, GL = Gulf Low).

Table 2.4. Pearson correlation coefficients (* = significant at 95% confidence level) between the annual frequency of the Muller and hybrid classification weather types from 1981-2001 for the State of Louisiana. (CH = Continental High, PH = Pacific High, GH = Gulf High, CR = Coastal Return, GR = Gulf Return, FGR = Frontal Gulf Return, FOR = Frontal Overrunning, GD = Gulf Tropical Disturbance, GL = Gulf Low).

Hybrid Classification	Manual Muller Classification							
	CH	PH	GH	CR	GR	FGR	FOR	GD
CH	0.60 *	--	--	--	--	--	--	--
PH	--	0.54 *	--	--	--	--	--	--
GH	--	--	0.67 *	--	--	--	--	--
CR	--	--	--	0.13	--	--	--	--
GR	--	--	--	--	0.49 *	--	--	--
FGR	--	--	--	--	--	0.46 *	--	--
FOR	--	--	--	--	--	--	0.29	--
GL	--	--	--	--	--	--	--	0.53 *

Despite the observed differences between the two classifications, the hybrid procedure was used to classify all sea level pressure grids from 1948 – 2012. Hourly meteorological data from the World Meteorological Organization were collected for New Orleans and Shreveport, LA from 1948 – 2012 and averaged for each hybrid weather type (Tables 2.5 and 2.6). These two locations were chosen for the analysis to provide a comparison between two different parts of the state, as New Orleans is located in extreme southeast Louisiana and Shreveport in located in extreme northwest Louisiana. Differences in observed weather between the hybrid weather types are evident at both New Orleans and Shreveport. One-way multivariate analysis of variance (MANOVA) tests were used on the data to determine if the differences in the mean weather properties among the hybrid weather types are significant. The number of rainfall hours, sky cover, and wind direction were excluded from the analysis because they are not continuous variables, and therefore violate one of the assumptions for a MANOVA test. For both New Orleans and Shreveport, the MANOVA results indicated significant differences in mean weather properties between the weather types. To discern the nature of the differences, multiple pairwise

tests were applied to the data at New Orleans and Shreveport. All of the multivariate pairwise mean comparisons for the weather types at New Orleans and Shreveport were found to be significantly different from each other at the 95% confidence level. The results illustrates that, although the hybrid procedure does not produce an identical Muller weather type classification, it still has value in describing the variability of surface weather in Louisiana.

Table 2.5. Mean weather properties from 1948-2012 by hybrid weather type for New Orleans, LA. (CH = Continental High, PH = Pacific High, GH = Gulf High, CR = Coastal Return, GR = Gulf Return, FGR = Frontal Gulf Return. FOR = Frontal Overrunning, GD = Gulf Tropical Disturbance, GL = Gulf Low).

New Orleans	N	Wind Direction (degrees)	Wind Speed (mph)	Sky Cover (%)	Visibility (mi)	Dewpoint Depression (°F)	Temperature Anomaly (°F)	Rainfall Hours
CH	2726	126	8.46	39	9.19	7.56	-5.61	44
PH	3079	256	8.72	54	8.40	5.28	-1.55	132
GH	1609	236	4.07	43	7.47	3.37	-1.80	16
CR	4212	114	4.36	48	7.17	3.98	-1.54	72
GR	5713	152	4.28	54	6.70	2.96	1.41	92
FGR	1880	178	6.74	71	6.59	2.74	5.90	128
FOR	2913	133	7.27	70	7.01	4.19	1.64	247
GL	1610	127	6.71	76	6.72	3.15	3.44	203

Table 2.6. Mean weather properties from 1948-2012 by hybrid weather type for Shreveport, LA as in Table 2.5.

Shreveport	N	Wind Direction (degrees)	Wind Speed (mph)	Sky Cover (%)	Visibility (mi)	Dewpoint Depression (°F)	Temperature Anomaly (°F)	Rainfall Hours
CH	2688	151	4.47	30	10.93	5.14	-12.71	13
PH	3044	272	7.79	35	11.41	5.85	-11.42	49
GH	1595	194	5.02	40	9.90	4.02	5.04	12
CR	4160	139	4.10	54	8.92	3.69	2.43	110
GR	5614	166	7.37	70	8.38	2.96	7.61	230
FGR	1852	212	7.32	74	8.29	2.93	4.87	223
FOR	2838	157	7.40	65	9.23	4.65	-3.21	217
GL	1585	141	6.29	79	7.43	2.86	5.13	262

2.5.3 Limitations

One of the main limitations involved in automating a manual classification system is the subjectivity of the original system, which causes a certain amount of variability within the weather types. Although the Muller system had guidelines for assigning weather patterns to particular weather types, the decision was ultimately up to the researcher. Sometimes, the choice of one weather type over another in a particular situation was not distinct. It is also likely that the researcher introduced slight changes to his technique over the years. To complicate matters, various researchers were responsible for weather typing during certain time periods. One example of subjectivity in the Muller classification system was the distinction between Pacific and Continental High types. Patterns dominated by high pressure systems with Pacific origin were classified as Pacific High weather types. Often, once these high pressure systems moved eastward over the central US, the patterns that were originally Pacific High were then classified as Continental High. Dr. Muller considered this change from Pacific High to Continental High to occur when the wind at New Orleans shifted to the north (Rohli and Henderson 1997). Yet, this distinction was very subjective. This particular example explains why a high percentage of the Muller Continental High patterns are classified as Pacific High patterns in the Hybrid procedure (see Table 2.2). One way to quantify the subjectivity of the original Muller system is to calculate the within type variability for each weather type. Future work could investigate if the within type variability varies between different time periods. For instance, is the within type variability higher during periods when researchers other than Dr. Muller performed the classifications? Or, does the within type variability decrease with time as Dr. Muller refines his technique? This type of analysis could help refine the training dataset to only include a time period with low within type variability, perhaps minimizing some of the error introduced into the hybrid procedure.

Another limitation in this study was the restriction of the correlation algorithm used to perform the hybrid classification. Whereas the Muller system takes into account the local observed weather properties and the placement of fronts, the hybrid system relies simply on the sea level pressure pattern to assign types. This difference limits the ability of the correlation algorithm to detect certain weather types. For example, there is a large disparity between the Muller and hybrid systems for the Frontal Overrunning pattern, since the Muller system relied on frontal placement to assign this type and there is no distinct pressure pattern for the correlation algorithm to detect. Future research could incorporate different levels of the atmosphere into the hybrid classification to help identify weather types. Specifically, for the Frontal Overrunning type, there are some distinguishing features at 500 millibar geopotential height layer, such as shortwave troughs that, in addition to the sea level pressure pattern, could help a correlation algorithm identify the type correctly.

2.6 Summary and Conclusions

This study achieved the goal of producing a synoptic classification system for Louisiana that harnesses the strengths of both manual and automated classifications. The objective Muller weather typing system was used to classify daily 12Z NCEP/NCAR sea level pressure grids, and sea level pressure composites were generated for each Muller weather type. These composites were used as seeds in an automated correlation-based procedure to produce hybrid weather types for Louisiana. Compared on a daily basis, the Muller weather types and the hybrid weather types matched at one or more point locations on 57 % of the days in question. The hybrid classification developed in this study performed slightly better than other similar hybrid classification efforts on a daily time scale (Frakes and Yarnel 1997, James 2007). The hybrid classification was also successful at reproducing the seasonal and annual variability of most of the Muller weather

types. The hybrid classification was applied to weather properties at New Orleans and Shreveport, and significant differences were found between the mean weather properties of different hybrid weather types, illustrating the classification has some ability to describe surface weather variability in Louisiana.

While I consider the hybrid classification successful, it is important to note that it should not be considered synonymous with the manual Muller classification. The inherent subjectivity of the manual Muller classification system, as well as limitations of the correlation-based procedure, prevented the hybrid procedure from directly replicating the Muller classification system exactly. The most fundamental difference between the two classifications is that the Muller classification is performed separately for individual point locations, so at any instance different locations in the state can have different weather types than each other, while the hybrid classification assigns a single weather type to the entire state. While the hybrid classification catalog is homogeneous within itself, it is not recommended that it should be used to extend the Muller weather type catalog. The capabilities of each classification are unique, and both are valuable tools for studying the synoptic climatology of Louisiana. Unlike the manual Muller weather typing scheme, the hybrid procedure can be used to classify thousands of sea level pressure patterns in a matter of minutes, making it feasible to use this classification procedure to study the long term, and even the future, climate. While other automated synoptic classification methods have similar advantages, they lack any control over the definition of synoptic types. Yet, the procedure outlined in this study captures the intent Dr. Robert Muller had about classifying the weather patterns of Louisiana; therefore in this researcher's opinion, provides a better description of weather variability for the region than other automated techniques could offer.

The hybrid classification system and the daily synoptic type catalog generated in this study could be used for a wide range of climate related applications in Louisiana. These include, but are not limited to, analyzing the frequency and variability of weather types, studying the variability of surface weather phenomena, and investigating the effect of synoptic type variability on ecological and biological processes. The hybrid classification is also well suited to adaptation for use with GCM output. This opens up a whole suite of additional applications for studying future climate in Louisiana. Establishing relationships between synoptic type frequency and trends in surface phenomena is very important in climate change research and can serve as the basis for a relatively new area of research investigating synoptic types in future climates using GCMs. These relationships can be used to develop synoptic-based statistical downscaling of GCM projections, which can provide more accurate projections for certain weather variables than general GCM output (Lee 2012).

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CHAPTER 3. A SYNOPTIC CLIMATOLOGICAL INVESTIGATION OF PRECIPITATION VARIABILITY IN LOUISIANA, USA

3.1 Abstract

Variability in daily and seasonal rainfall occurrence has a profound effect on many economic sectors in Louisiana, including agriculture, transportation, and industry. Links between synoptic atmospheric circulation and precipitation occurrence in this region suggest that variability in synoptic type frequency contributes, in some degree, to precipitation variability in Louisiana. The goal of this study is to establish relationships between rainfall and synoptic types to serve as a basis for developing a precipitation statistical downscaling model for Louisiana from Global Climate Models (GCMs). Sea level pressure grids from 1948 to 2012 were objectively classified according to a hybrid classification system based off of the subjective Muller weather typing system for Louisiana. Linear regression models, with synoptic frequency as the predictors and seasonal rainfall as the predictands, were used to determine how much of the precipitation variability in Louisiana can be explained by synoptic type variability. The results show that, although models based on synoptic variability cannot sufficiently explain the interannual variability of precipitation in Louisiana in any season, they are able to predict longer-term precipitation variability and trends in winter and fall. This study is an important first step to developing a precipitation downscaling model for Louisiana, yet it has been determined that additional predictors are necessary to accurately model long-term precipitation variations in spring and summer that could improve interannual predications for all seasons.

3.2 Introduction

Precipitation in Louisiana, as in the rest of the Southeast United States, varies considerably from year to year. For most of 2010 and 2011, the entire state of Louisiana was in a severe or extreme drought (USDM 2012). In 2012, Louisiana received above normal precipitation and experienced one of its ten wettest summers on record (NOAA 2012). The interannual and decadal variability of precipitation has a sizable hydrologic impact in this region, as even small shifts in seasonal precipitation timing and amounts directly affect the hydrologic cycle, altering runoff, soil moisture, and crop yields (Karl and Riebsame 1989). As a result, variability in daily and seasonal rainfall occurrence has a profound effect on many economic sectors in Louisiana, including agriculture, transportation, and industry (Keim et al. 2011). A better understanding of the controls of precipitation variability in Louisiana could assist in short and long-term forecasting for this region, as well as provide valuable insight into future precipitation changes that may occur due to climate change.

Synoptic scale systems have been identified as one of the primary controls of precipitation in Louisiana and the rest of the Southeast United States (Keim 1996, Muller 1977, Trewartha 1981). Most heavy precipitation events in the region are associated with synoptic-scale systems, including frontal and tropical weather systems (Keim and Faiers 1996). The study of Muller (1977) describes three synoptic situations that typically produce “stormy” weather in Louisiana. These synoptic types are Frontal Gulf Return, which occurs when a frontal boundary moves across the state, Frontal Overrunning, which occurs when a front becomes stationary in the Gulf of Mexico, and Gulf Tropical Disturbance, which occurs when a tropical system moves over the state. There is some indication that the influence of synoptic-scale atmospheric circulation patterns Louisiana precipitation occurrence varies seasonally. The study of Faiers

(1988) found that the occurrence of winter precipitation at Lake Charles, Louisiana is strongly linked to the prevailing synoptic type. On the other hand, another study found that precipitation occurs in Louisiana under all synoptic weather types in July and August, possibly indicating less synoptic influence during summer (Muller 1977). Synoptic-scale atmospheric circulation patterns have been shown to have a strong impact on summer precipitation occurrence in certain other parts of the Southeast United States, such as Atlanta, Georgia (Diem 2012). Due to the linkage between synoptic atmospheric circulation and precipitation in the region, it is hypothesized that variability in the seasonal occurrence of synoptic scale systems contributes, in some degree, to precipitation variability in Louisiana.

The goal of this study is to increase the knowledge of rainfall variability in Louisiana by identifying daily synoptic circulation patterns and associating them with different rainfall conditions. This approach, called synoptic classification, is commonly used within the field of synoptic climatology. Synoptic classification helps to increase our understanding of environmental systems by reducing the complexity into a manageable number of discrete reoccurring patterns, or synoptic types (Yarnel 1993). Although it is acknowledged that many small-scale processes play a large role in generating rainfall in Louisiana, it is the intent of this research to identify the synoptic scale processes that help to organize the micro-and meso-scale rainfall processes that generate precipitation.

The discovery of statistical relationships between observed precipitation and synoptic types will be useful for creating improved climate change projections for precipitation in Louisiana. The current precipitation projections from various general circulation models (GCMs) are in disagreement about the sign and magnitude of precipitation changes for the majority of the southeast United States (Keim et al. 2011, Kunkel et al. 2013). Studies comparing GCM

projections with observed precipitation in other regions have found that precipitation errors in the models are largely process-based and that the errors in projecting general circulation patterns are relatively small (Hope 2006, Finnis et al. 2009). The 2007 IPCC report stated that the GCMs have shown a significant improvement in projecting general atmospheric circulation since 2001 (IPCC 2007). Statistical downscaling based on synoptic methods are useful in climate change research because they take advantage of the more accurate GCM variables, such as general circulation, temperature, and pressure patterns, to predict variables that are less accurately portrayed by the GCMs, like precipitation (Lee 2012). Relationships between rainfall and general circulation patterns, or synoptic types, found in this study could serve as a basis for developing a precipitation statistical downscaling model for Louisiana, and perhaps the Southeastern U.S. The objectives of this study are to:

1. Identify the synoptic weather types that are associated with rainy conditions in Louisiana.
2. Determine if the variability of synoptic type frequency can describe precipitation variability in Louisiana.

3.3 Data

3.3.1 Daily U.S. Unified Precipitation Gridded Dataset

The precipitation data used in this study was taken from the Daily U.S. Unified Precipitation dataset from the Climate Prediction Center (CPC). The daily dataset was compiled from two main rain gauge data sources: the Climate Prediction Center dataset, which includes River Forecast Center data and 1st order stations that report precipitation accumulations from 12Z to 12Z, and the National Oceanic and Atmospheric Administration (NOAA)/National Climatic Data Center (CDC) hourly precipitation dataset that was aggregated into a 12Z to 12Z

window for each day (Higgins et al. 1996). The dataset reported daily precipitation as the 24-hr accumulation from 12Z the day before to 12Z of the reporting day. The precipitation data were subject to standard quality control procedures, including standard deviation and buddy checks. The data were gridded onto a 0.25 x 0.25 degree grid using a Cressman scheme (Higgins et al. 1996). Daily precipitation values were reported as the precipitation accumulation from 12Z on the previous day to 12Z of the day in question.

3.3.2 Sea Level Pressure Dataset

This study utilized sea level pressure data from the National Center for Atmospheric Research (NCAR)/National Centers for Environmental Prediction (NCEP) Reanalysis I Dataset. This dataset was assembled from a variety of climate data sources, including land surface, satellite, aircraft, and rawinsonde data (Kalnay et al. 1996). There are many different atmospheric variables included in the dataset, including both surface and upper-air data. The data are available four times daily at six-hourly intervals (6Z, 12Z, 18Z, and 00Z) from 1948 to present. The data are in the form of global grids, with 2.5 degree grid spacing.

3.4 Methods

3.4.1 Creation of a Climate Division Daily Precipitation Dataset

To investigate the statistical relationship between precipitation and synoptic types, a daily precipitation dataset is necessary for comparison with daily synoptic types. Rather than using individual station data, which would be applicable to a limited number of points where long-term station data are available, or raw gridded data, which would require the development of hundreds of separate statistical models, the U.S. Unified Precipitation Dataset was aggregated to produce daily precipitation values for each of the nine Louisiana climate divisions (see Figure 3.1).



Figure 3.1. NCDC Climate Divisions of Louisiana. (Image courtesy of the Louisiana Office of State Climatology).

Climate divisions are defined by the National Climatic Data Center (NCDC) as regions of nearly homogenized climate (Guttman and Quayle 1996). The climate division dataset provided by NCDC was made up of monthly temperature and precipitation, as well a variety of other monthly climate variables and indices; however, daily climate variables were not included in the dataset. Since it is assumed the climate divisions represent areas in Louisiana with similar precipitation characteristics, a daily climate division precipitation dataset would be ideal to establish sub-

regional relationships between synoptic types and precipitation. Therefore, a daily climate division precipitation dataset was generated from the US Unified Precipitation Dataset using the climate division boundaries. Using a Geographic Information Systems (GIS) technique called zonal statistics (ESRI 2008), the arithmetic average of all of the grid cell values that fell within a particular climate division is taken as the daily precipitation for that division.

3.4.2 Synoptic Type Classifications

The synoptic classification system used in this study was a hybrid classification system based on the subjective Muller weather typing system for Louisiana presented in Chapter 2. The objectification of well-known subjective weather typing systems are useful for historical and future climate applications because they are able to classify large datasets, including GCM output, efficiently and are based on classifications that are widely used and accepted in the scientific community (Huth et al. 2008). The Muller weather types have been used successfully for a variety of research investigations in Louisiana (Muller and Jackson 1985, McCabe and Muller 1987, Faiers 1988, Faiers 1993, Faiers et al. 1994, Rohli and Henderson 1997, McCabe and Muller 2002).

While the hybrid classification system implemented here is not an exact replication of the Muller weather typing system for Louisiana, it is an objective alternative that represents the main features of the Muller system and has the ability to classify thousands of sea level pressure patterns in a matter of minutes. For this study, daily 00Z and 12Z synoptic classifications were performed on the NCEP/NCAR sea level pressure grids for the period from 1948 to 2012. Each sea level pressure grid was assigned to one of the eight synoptic types: Continental High (CH), Pacific High (PH), Gulf High (GH), Coastal Return (CR), Gulf Return (GH), Frontal Gulf Return (FGR), Frontal Overrunning (FOR), or Gulf Low (GL) (see Figure 2.2 from Chapter 2).

3.4.3 Identification of Wet Synoptic Types

From preliminary investigations, it was found that some rainfall occurs during all of the hybrid synoptic weather types, making it difficult to distinguish which types were relatively wet by just looking at rainfall totals associated with each type. Instead, daily precipitation anomalies were calculated for each synoptic type from the climate division daily precipitation dataset to determine if a particular weather type is associated with above or below average rainfall. Four sets of precipitation anomalies were produced, one for each season, since it has been suggested that there may be seasonal variation in the synoptic types associated with precipitation processes (Muller 1977). The seasons were defined as winter (December, January, and February), spring (March, April, and May), summer (June, July, and August), and fall (September, October, and November). The precipitation anomalies were calculated by subtracting the average daily precipitation for all days in a season from the average daily precipitation for only the days that belong to each synoptic type. A day was considered to belong to the synoptic type of its 00Z sea level pressure pattern. It was assumed that the 00Z synoptic type would best represent the synoptic conditions that produced precipitation over the 24-hr period from 12Z to 12Z. A synoptic type that has positive rainfall anomaly for a particular climate division was considered a “wet” pattern for that division and season.

3.4.4 Linear Regression Models

Linear regression models were used to determine how much of the precipitation variability in Louisiana can be explained by synoptic type variability. This approach has been used in multiple studies to determine the relationship between atmospheric circulation and precipitation (Goodess and Jones 2002, Brisson et al. 2011, Hanssen-Bauer and Forland 1998). Before the regression analysis could be performed, the monthly frequency of each synoptic type

was calculated by counting the number of 00Z occurrences of each synoptic type. Time series of the seasonal frequency of each type from 1948-2012 for winter, spring, summer, and fall were generated. The frequencies of the “wet” synoptic types were used as predictor variables in a multiple linear regression analysis, with monthly rainfall as the predictand. The choice of “wet” synoptic types for each climate division and season was based on the precipitation anomaly analysis. Regression analyses were performed for each season and climate division separately, yielding 36 regression models. To increase the sample size, three separate monthly precipitation values were used for each season rather than the seasonal mean (Goodess and Jones 2002). The regression model for any season/division can be expressed as:

$$P = \beta_0 + \sum_{i=1}^n (\beta_i \times ST_i) \quad (\text{Equation 3})$$

where P is the modeled monthly precipitation, ST_i is the i^{th} “wet” synoptic type monthly frequency, β_0 is the regression intercept and β_i is the regression coefficient for the i^{th} ST (Montgomery and Peck 1982). The models were calibrated using monthly data from 1948 – 2012.

3.4.5 Contribution to Observed Rainfall Variability and Trends

The ultimate goal of the regression analysis was to determine if models developed from synoptic type frequencies have enough skill for precipitation downscaling in this region. To investigate, the models were used to generate seasonal precipitation for the entire study period from 1948 to 2012. In addition to a yearly comparison of data, which is very noisy, the modeled values were smoothed using a low-pass Gaussian filter (standard deviation = 3 years) to remove high frequency noise and better represent the ability of the model to reproduce long-term variability and trends (Hanssen-Bauer and Forland 1998). While it allows for the analysis of decadal scale variability, this process comes at the expense of any shorter term modes of

variability that may be present in the data, such as the El Nino Southern Oscillation. Modeled data were then compared to the observed data to determine if the models, dependent solely on synoptic type frequency, can sufficiently reproduce the observed variability and trends.

3.5 Results and Discussion

3.5.1 Seasonal Daily Synoptic Type Precipitation Anomalies

The mean daily rainfall, as well as the synoptic type average daily rainfall anomalies, for each of the climate divisions and seasons can be found in Figure 3.2 to Figure 3.5. The FGR, FOR, and GL synoptic types were most commonly associated with positive rainfall anomalies. This is consistent with the original Muller weather typing scheme, in which the aforementioned types are associated with stormy weather in Louisiana (Muller 1977). All three of these types are characterized by some sort of synoptic forcing mechanism, whether baroclinic or barotropic, that can generate widespread rainfall in the region. In addition to the expected types, there were some other types that were associated with positive rainfall anomalies in some seasons and climate divisions. The GR type was associated with small positive rainfall anomalies during summer for all of the climate divisions, and during the fall in the Northwest climate division (See Figure 3.4 and Figure 3.5). In regards to the summer, the moisture flux associated with the GR type, which funnels warm, moist air northward over the state, likely fuels thunderstorm development in summer even without the upper-level forcing to initiate widespread precipitation. It is noted by Muller (1977) that precipitation can occur under all weather types during the summer, so this result is not unexpected. During fall, the GR type is often associated with upper-level low pressure development over the Texas panhandle, which is close enough to provide precipitation forcing in the Northwest climate division. The only other synoptic type that is ever associated with positive precipitation anomalies is the PH type.

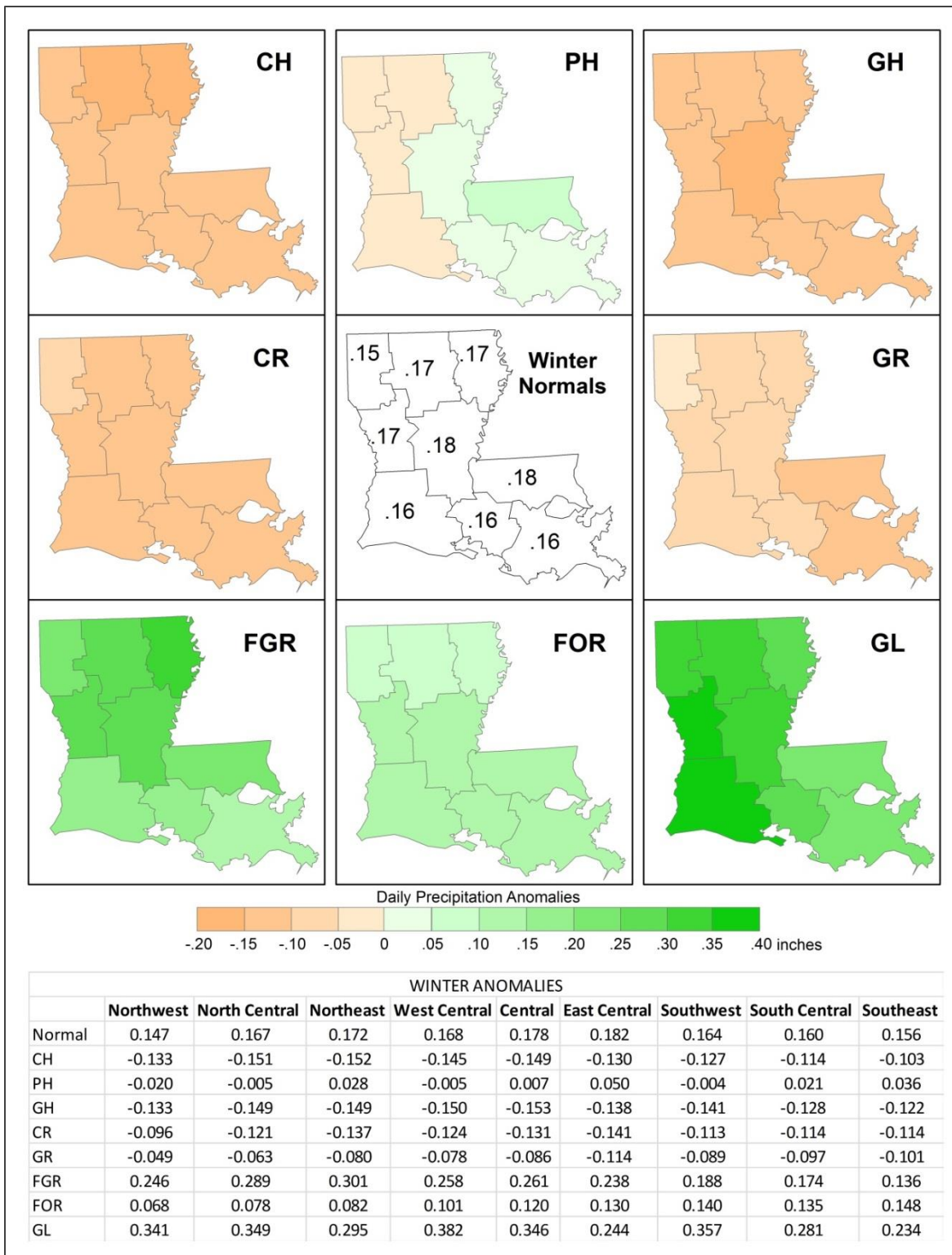


Figure 3.2. Winter normals and daily precipitation anomalies for Continental High(CH), Pacific High(PH), Gulf High(GH), Coastal Return(CR), Gulf Return(GR), Frontal Gulf Return(FGR), Frontal Overrunning(FOR), and Gulf Low(GL) weather types from 1948 - 2012.

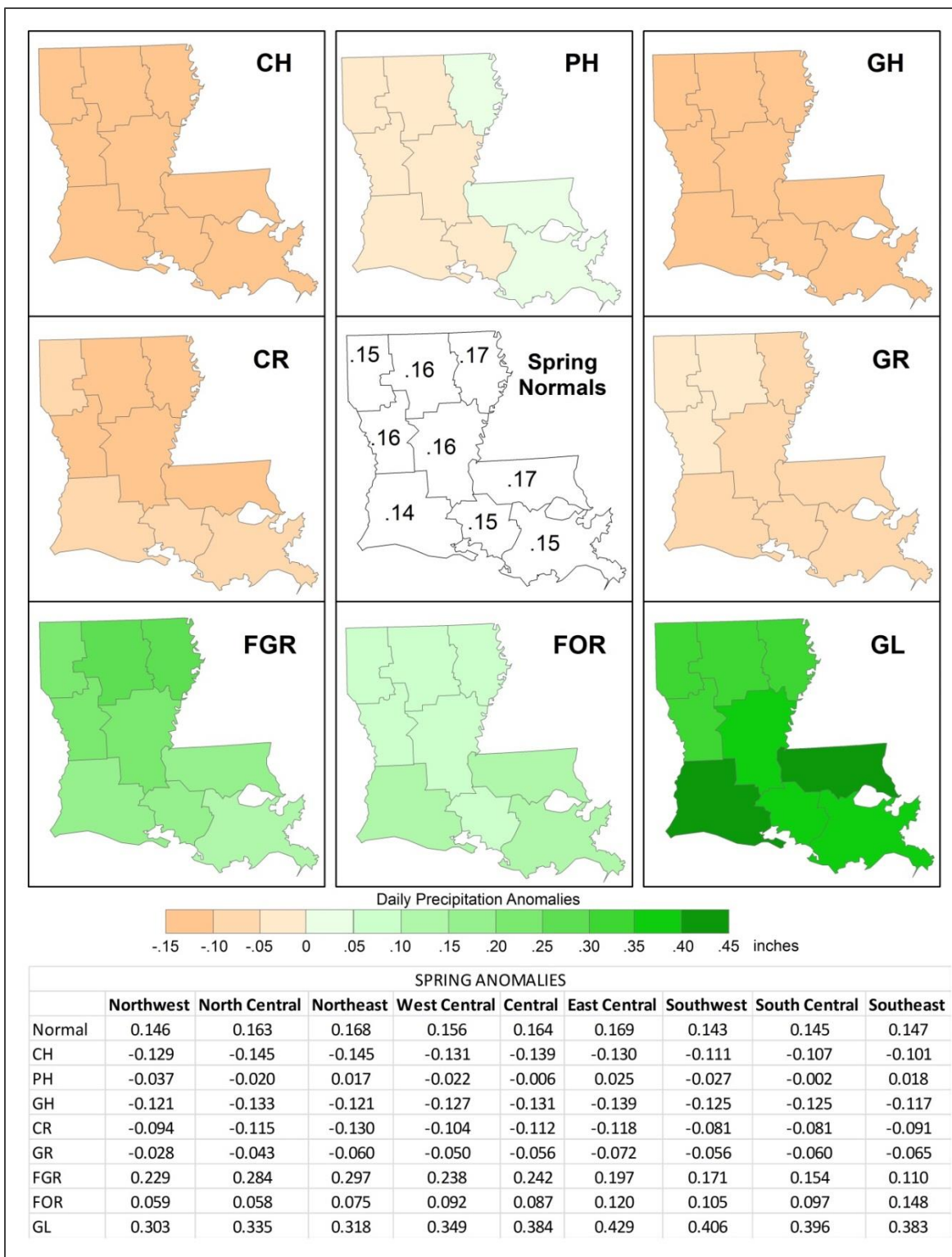


Figure 3.3. Spring normals and daily precipitation anomalies as in Figure 3.2.

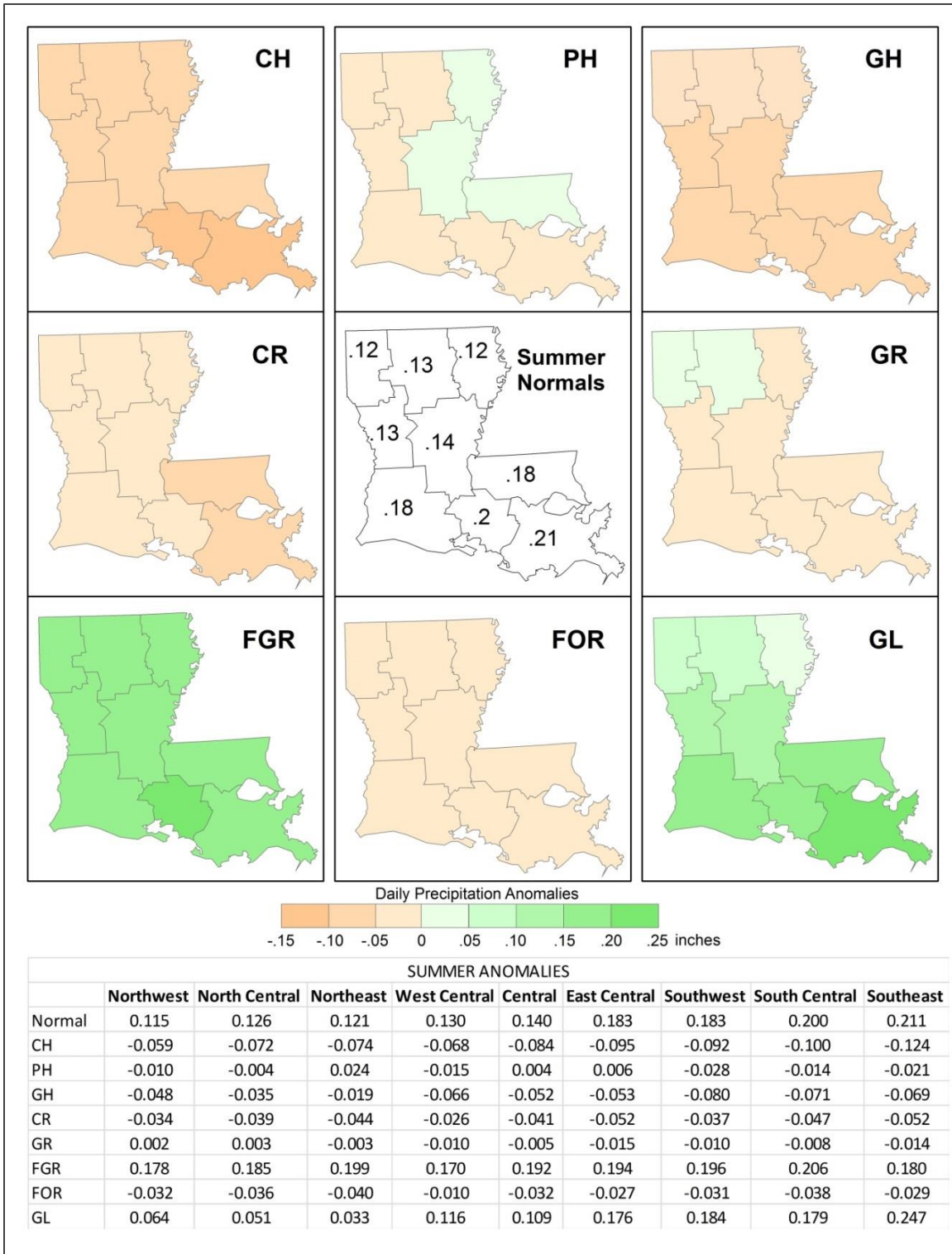


Figure 3.4. Summer normals and daily precipitation anomalies as in Figure 3.2.

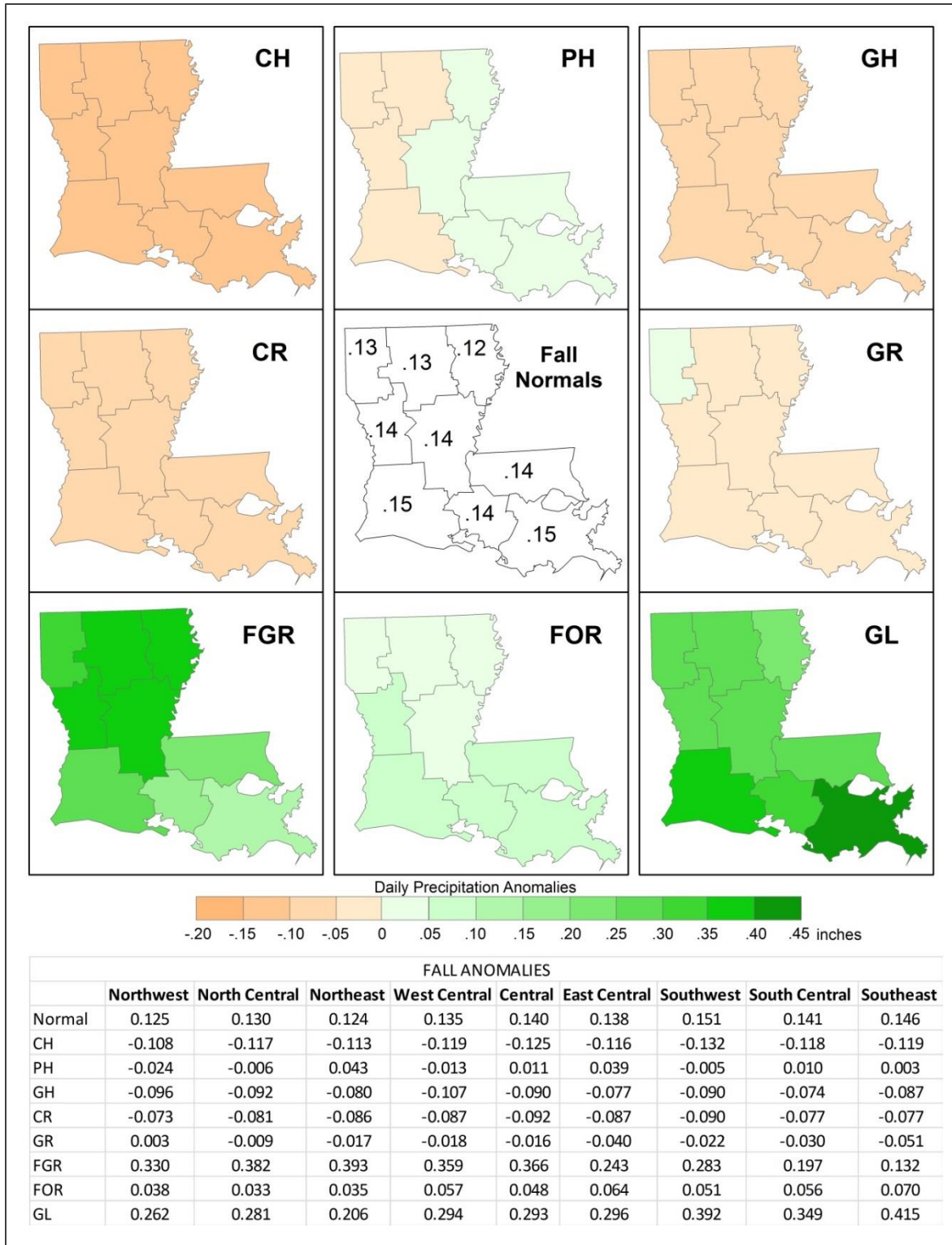


Figure 3.5. Fall normals and daily precipitation anomalies as in Figure 3.2.

Table 3.1. The amount of precipitation variance (R^2) explained by synoptic frequency for the nine Louisiana climate divisions for winter, spring, summer, and fall determined using regression models. The data is expressed as percentages.

	Winter	Spring	Summer	Fall
Northwest	26.9	12.1	11.2	15.1
North Central	28.9	12.9	18.1	19.5
Northeast	29.1	15.4	14.0	19.1
West Central	28.4	10.0	12.2	17.2
Central	29.2	12.6	24.5	19.1
East Central	17.2	19.7	23.1	31.2
Southwest	25.1	13.1	18.8	26.7
South Central	21.3	15.7	21.1	31.8
Southeast	17.0	17.1	25.7	44.2

This is not consistent with the original Muller weather types. However, the positive anomalies only appear in the eastern part of the state because PH patterns often follow FGR patterns. Since I am classifying the weather types for the entire state, the influence of the frontal system is still causing rainfall in the eastern climate divisions, even though it has cleared in the western divisions and Pacific High pressure is building into the state from the northwest. In addition, the hybrid procedure has been shown to sometimes assign sea level pressure patterns to the PH type that would usually be associated with the FOR type in the Muller system. This is likely contributed to the positive rainfall anomalies associated with the PH type. This result is an artifact of not having the frontal boundaries included in the analysis of the pressure patterns.

3.5.2 Linear Regression Models

Multiple linear regression models were calibrated using data from years of 1948 to 2012 for each of the 9 climate divisions for all 4 seasons, resulting in 36 regression models. The

adjusted R-squared of each multiple linear regression model measures the proportion of the precipitation variance that can be explained by the predictor variables (the frequency of each “wet” synoptic type). The explained variance ranges from 10% at the West Central climate division in spring to 44.2% at the Southeast climate division in fall (Table 3.1). Averaged over all climate divisions, the explained variance is approximately 25% for winter, 14% for spring, 19% for summer, and 25% for fall.

A residual analysis was applied to the regression models to test the assumptions of linear regression. Normality was tested by plotting a histogram of the residuals for each model. The residuals of each model appear approximately normal by visual inspection of the data plots; however, they fail the Shapiro-Wilk test for normality. Small errors in normality do not greatly affect the models, but large deviations from normality can affect confidence intervals (Montgomery and Peck 1982). For the purposes of this analysis, we assume normality. Regression is robust to normality errors and plots of the residuals ranked in increasing order resemble straight lines, indicating approximate normality (Montgomery and Peck 1982). The next assumption tested was heteroscedasticity. Visual examination of plots of the model residuals vs. the precipitation estimates revealed some non-linearity in the models (Montgomery and Peck 1982). For the purpose of this exploratory analysis, we assumed homoscedasticity, but acknowledge that future work may need to incorporate non-linear models or attempt data transformations to make the relationship between precipitation and synoptic type linear. The normality and homoscedasticity plots can be found in Appendix B. The final assumption tested was independence. The Durbin-Watson (D-W) test determined that the data were independent, as each D-W statistic is near 2 (Table 3.1.).

Table 3.2. The Durbin-Watson Statistic for the multiple linear regression models for each season and climate division.

Climate Division	Winter	Summer
Northwest	1.93	1.94
North Central	2.12	1.92
Northeast	2.05	1.97
West Central	2.03	2.04
Central	2.24	1.84
East Central	2.10	2.02
Southwest	1.90	2.04
South Central	2.02	1.82
Southeast	1.77	1.76
	Spring	Fall
Northwest	2.02	1.86
North Central	1.94	1.83
Northeast	1.86	1.90
West Central	1.90	1.93
Central	1.91	1.94
East Central	1.96	1.84
Southwest	1.91	2.13
South Central	1.97	2.16
Southeast	1.84	2.21

3.5.3. Ability of Models to Explain Variability and Trends

Despite the fact that the precipitation models developed from synoptic frequency only account for 10 to 44% of the interannual variability of precipitation, it is possible that they may

still be able to reasonably reproduce long-term (decadal-scale) variability and trends (Hanssen-Bauer and Forland 1998). This is because, although the precipitation causes is irregularly distributed, over longer time scales, the randomness of precipitation is smoothed out (Hanssen-Bauer and Forland 1998). The smoothed regression modeled results versus observed precipitation for each season and climate division can be found in Figure 3.6 – Figure 3.9. The smoothed results represent decadal scale variability in the data.

The smoothed modeled versus precipitation series show, that during the winter and, especially, the fall, the models account for most of the observed long-term precipitation features in the Southeast climate division. However, during spring and summer, the models do not adequately capture the observed variability and trends. In summer, weak pressure patterns set up over the area, making it hard to distinguish between weather types. In addition, convective rainfall often occurs during non-stormy weather types due to the intense surface heating that is received during summer in this region. While the spring results are somewhat surprising and deserve further investigation, the poor performance of the models is likely due to large amounts of variability in precipitation amounts during stormy weather types in spring. Overall, the results suggest that the models based on synoptic variability cannot sufficiently explain the interannual variability of precipitation in Louisiana; however, they have the skills necessary to predict longer-term variability and trends in winter and fall. It is likely that additional predictors are necessary to model long-term precipitation variations in the spring and summer, and could improve predictions in winter and fall as well.

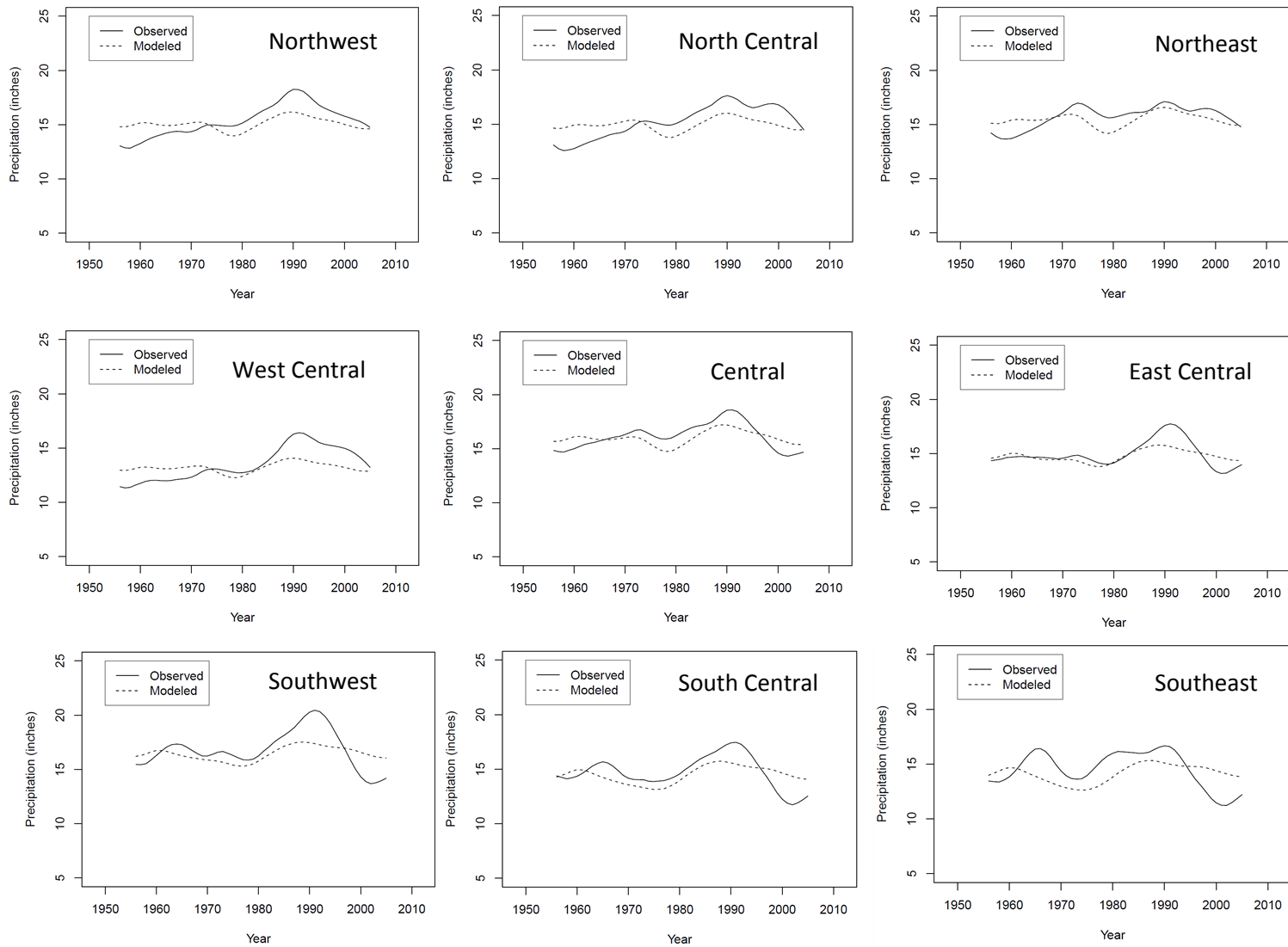


Figure 3.6. Smoothed winter modeled and observed precipitation for each climate division from 1956 to 2005.

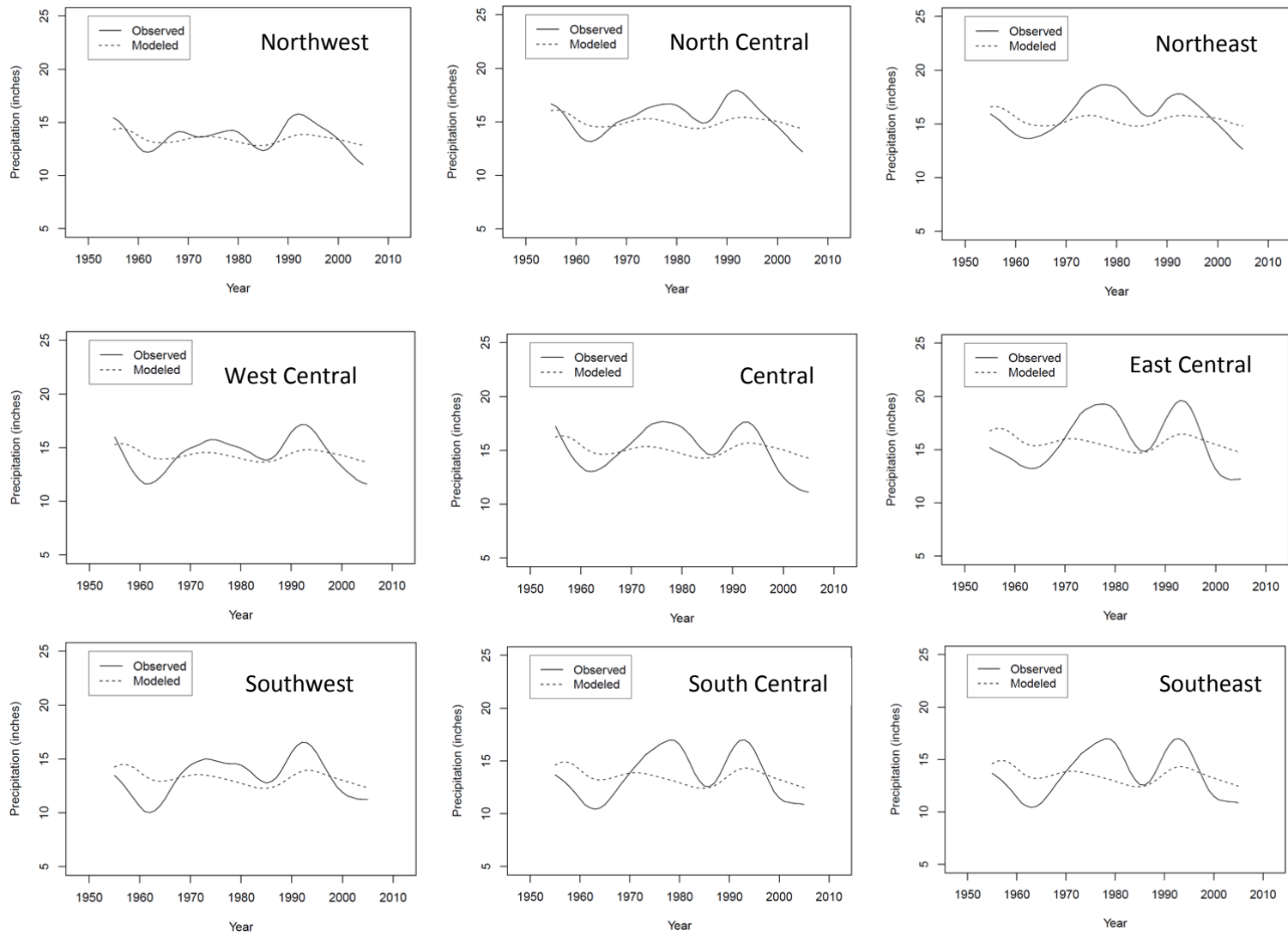


Figure 3.7. Smoothed spring modeled and observed precipitation for each climate division from 1955 to 2005.

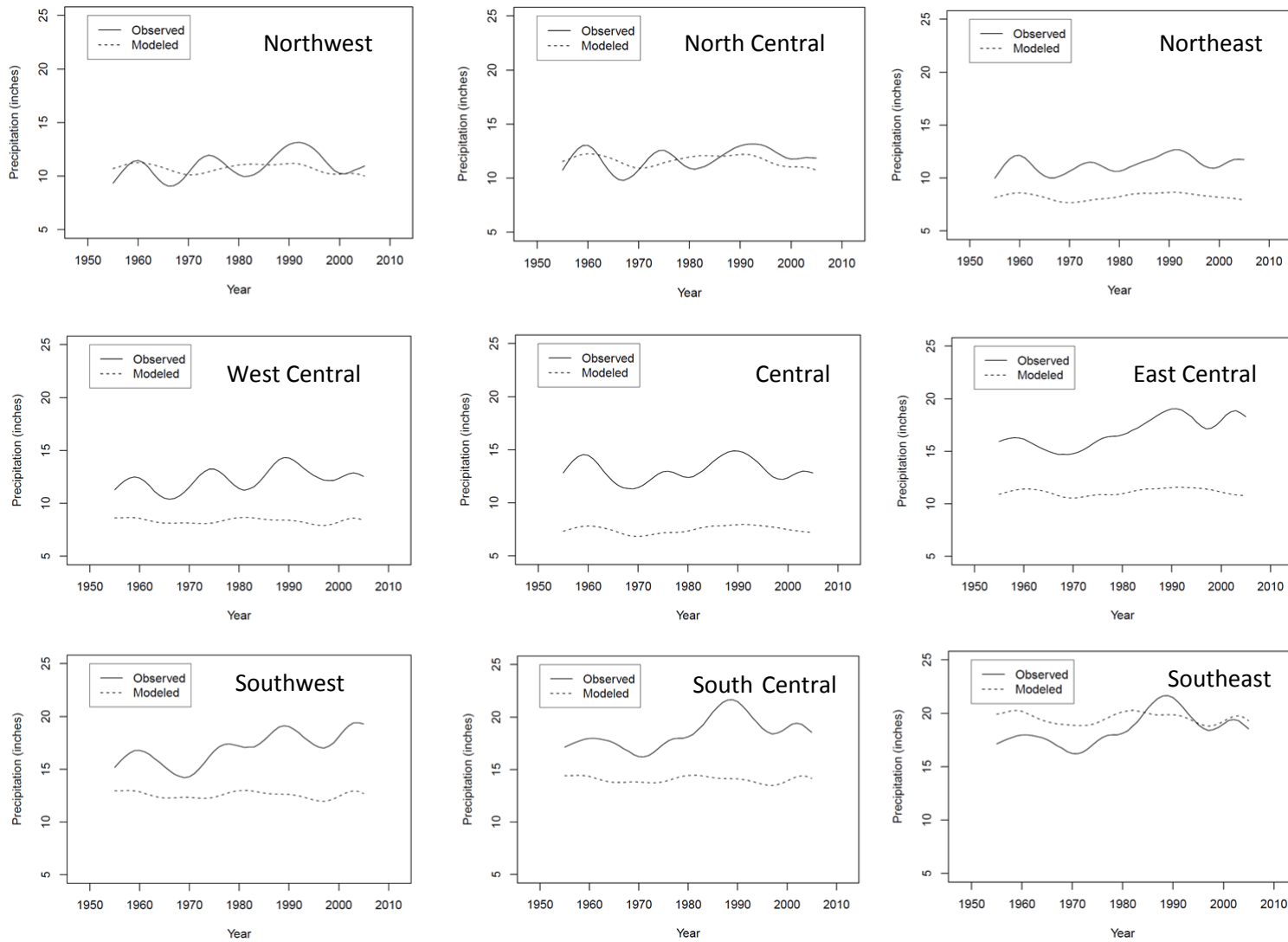


Figure 3.8. Smoothed summer modeled and observed precipitation for each climate division from 1955-2005.

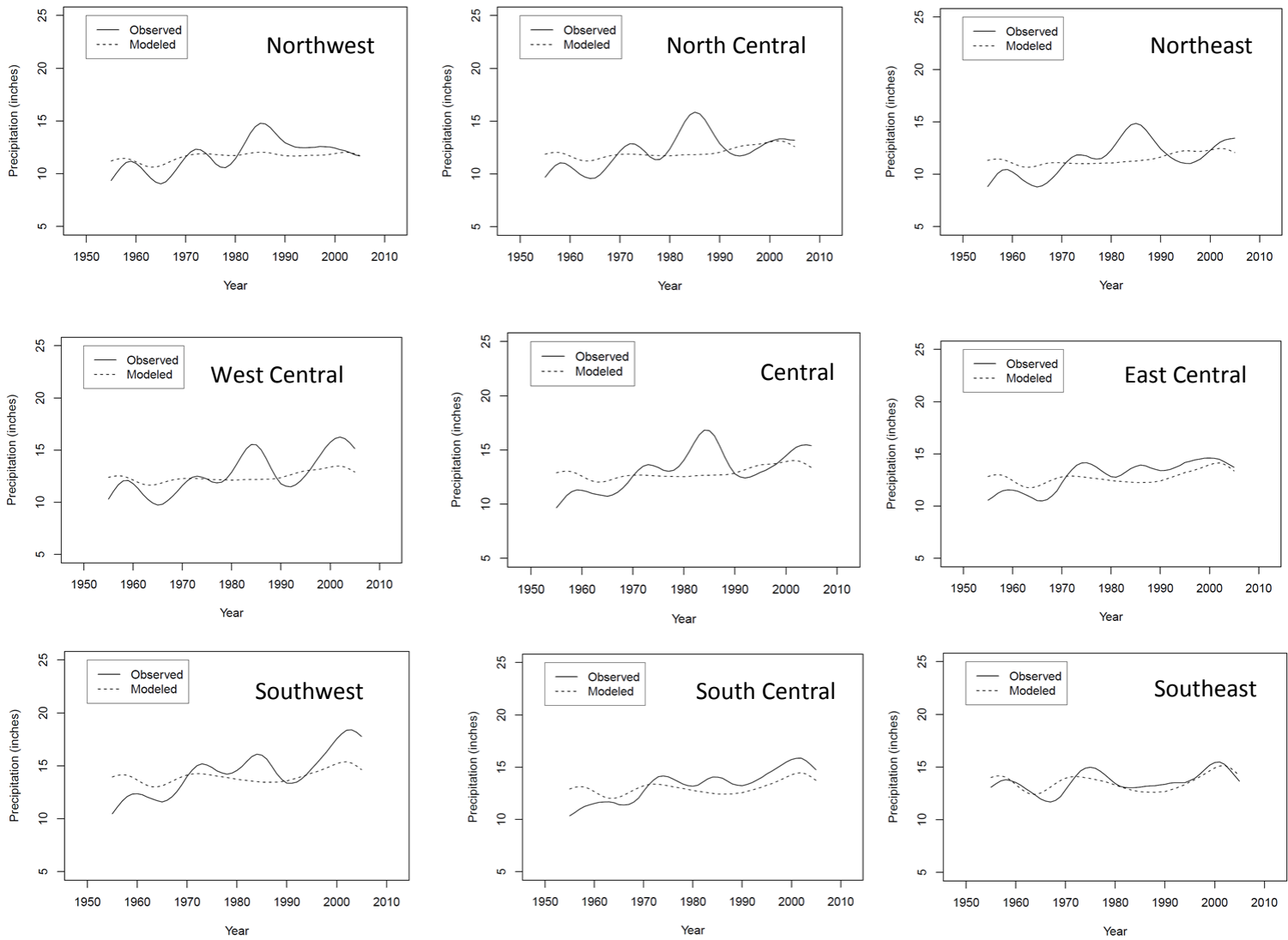


Figure 3.9. Smoothed fall modeled and observed precipitation for each climate division from 1955 to 2005.

3.5.4 Limitations

This study is limited by a few different factors. First, and most importantly, the multiple linear regression models used in the study depend on a linear relationship between each input variable and the predictand. As determined in the residual analysis, this is not always the case with the data used in this study. Future work should focus on finding a remedy for this weakness by using data transformations or non-linear models. Additionally, this type of analysis is limited by the irregularity of precipitation, making it hard to predict using a simple model. Additional analyses could use models with more predictors or try use different Gaussian filters to detect sources of regular variability in the region, such as the El Nino Southern Oscillation. Finally, the models based on synoptic frequency are limited by the power of the synoptic classification system to capture rainfall variability. There are some weaknesses in the hybrid classification system, which are discussed in Chapter 2. Future improvements to the synoptic classification system could improve the results of this study.

3.6 Summary and Conclusions

Precipitation in Louisiana varies considerably from year to year. To predict the future effects of climate change, there is a need to better understand the controls of rainfall processes in this region. This study was successful in identifying the synoptic patterns that are important to precipitation generation in Louisiana, and the results were mostly consistent with the original Muller weather typing system for Louisiana. However, it was determined that the variability of synoptic types can only account for a small portion of the interannual rainfall variability in Louisiana. This is likely due to a combination of reasons. The first is that precipitation is irregularly distributed in time and space, and is therefore very difficult to predict on short time scales. The second is that, in addition to synoptic atmospheric circulation, there are likely other

factors controlling rainfall in this region. Some possible additional predictors that could be included in a precipitation model for this region are air temperature, sea surface temperature (SST) and aerosol forcing.

On longer time scales, however, the predictability of the models improved for some seasons. In winter and fall, the synoptic-based models do an adequate job of reproducing the observed decadal variability and long-term precipitation trends. Therefore, synoptic-based models may be a good candidate for determining future decadal precipitation variability and trends from GCM outputs for these seasons. However, this does not provide any solutions for spring and summer. While this study was an important first step to developing a statistical downscaling model for Louisiana, additional research must be conducted to identify predictors that can improve the predictability of the models for Louisiana precipitation.

3.7 References

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CHAPTER 4. SUMMARY AND CONCLUSIONS

Automated synoptic classification has many applications for studying current and future climate variability in a region. Louisiana is located in the South Central United States, a region that is known for exhibiting large amounts of variability in surface weather, especially precipitation. However, there are currently no widely accepted automated synoptic weather classification systems for this region. The primary goals of this thesis were to 1) present an automated synoptic weather type classification system for climate related studies in Louisiana and 2) use the newly created synoptic classification system to determine the relationship between synoptic type frequency and precipitation variability in Louisiana.

A new method of synoptic weather classification for Louisiana was presented in Chapter 2. The main objective of the new classification system was to avoid the weaknesses of both manual and automated classification systems by creating a hybrid classification system based on the Muller weather typing scheme for Louisiana. NCEP/NCAR Reanalysis sea level pressure data from 12Z each day from 1981 – 2001 were typed using the Muller weather type archive, and sea level pressure composites were generated for each Muller weather type. For the hybrid procedure, these composites were used as seeds in a correlation algorithm to determine the most appropriate weather type for each day. The Muller and hybrid types from 1981 – 2001 were compared at daily, seasonal, and annual resolution. At a daily resolution, the hybrid types match the Muller weather types at one or more location on 57 % of the days. For most of the weather types there is significant agreement at the seasonal and annual resolutions. One source of discrepancy between the Muller and hybrid types was the inability of the hybrid procedure to distinguish between tropical and baroclinic low pressure systems. The hybrid system also had difficulty identifying the Muller FOR type because it does not have a strong surface pressure

signature. However, the goal of the procedure was not to replicate the Muller classification system, but to create a new system that was automated and captured the essence of the Muller weather types. The hybrid classification is homogenous within itself, and preliminary investigations show it has value in describing the variability of surface weather in Louisiana. The strengths of the automated hybrid system are its objectivity, speed, and reproducibility, making it an advantageous candidate for long-term climate studies. It is also easily adaptable to GCM output, opening up new applications for studying future synoptic climatology in the region.

The automated hybrid classification system presented in this study can be used for seemingly endless applications in climate and climate impact research for Louisiana. This could include updates to older studies that used the Muller classification systems (Muller and Jackson 1985, Faiers 1988, Faiers 1993, Faiers et al. 1994, Keim and Faiers 1996, McCabe and Muller 2002), as well as completely new studies, such as synoptic climatological investigations of future climates using GCMs. In addition, future work related to this project could include developing hybrid classification systems for other regions using the methodology presented in this study or even expanding the classification developed here to include other parts of the South Central U.S., since the entire region experiences the similar synoptic patterns.

The newly developed automated classification system was used to study Louisiana precipitation variability in Chapter 3. Using the hybrid weather classification system and gridded daily precipitation data, wet synoptic types, or synoptic types that are associated with above average daily rainfall, were identified for each climate division and season. The frequency of the wet synoptic types was used to create a regression model to predict seasonal precipitation for each climate division. The models developed from synoptic frequency only account for 10 – 44% of the interannual variability of precipitation in Louisiana. Averaged among all climate

divisions, the explained variance is 25% for winter, 14% for spring, 19% for summer, and 25% for fall. Applying a smoothing technique to the modeled and observed rainfall data shows that the predictability of the models is slightly improved on decadal time scales. However, more research must be done to identify additional predictors before we can move forward with the development of a statistical downscaling model for Louisiana. While the research presented in this thesis was an important first step, the results suggest that a model based solely on synoptic frequency cannot adequately describe the variability and trends in observed precipitation data for all seasons. Therefore, the next step for this project will be to investigate other variables that will improve the predictability of the models so that the project can move forward.

4.1 References

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APPENDIX A. R PROGRAM FOR HYBRID CLASSIFICATION

Create a Function to Subset NetCDF Data

```
nnrsubset = function (datapath, type, mode,level,lat1, lat2, lon1, lon2, startyear, endyear, startmonth,
endmonth, obstime){
```

```
  library(ncdf)
  library(mapproj)
  library(maps)
  library(fields)
  library(RColorBrewer)
  library(chron)
```

```
  path1 = datapath
  path2 = type
  path3 = endyear
  ncFile = ncFile <- paste(path1,path2,".",path3,".nc", sep="")
  nc <- open.ncdf(ncFile)
  print(nc)
```

get attributes (not data) of variable

```
att.get.ncdf(nc,type,"long_name")
att.get.ncdf(nc,type,"_FillValue")
```

#Read in Lat and Lon

```
lat <- get.var.ncdf(nc,"lat",verbose=F)
nlat <- dim(lat)
lon <- get.var.ncdf(nc,"lon")
nlon <- dim(lon)
```

get index for lat lon subset

```
wherenearest = function(val, matrix){
  dist = abs(matrix-val)
  index = which.min(dist)
  return(index)}
```

```
lower_left_lon_lat = c(lon2,lat2)
upper_right_lon_lat = c(lon1,lat1)
```

```
ix0 = wherenearest( lower_left_lon_lat[1], lon )
ix1 = wherenearest( upper_right_lon_lat[1], lon )
```

```

iy0 = wherenearest( lower_left_lon_lat[2], lat )
iy1 = wherenearest( upper_right_lon_lat[2], lat )

countx = ix1 - ix0 + 1
county = iy0 - iy1 + 1

# get time dimension

t <- get.var.ncdf(nc,"time")
tunits <- att.get.ncdf(nc,"time","units")

# print t and tunits

head(t)
tunits$value

# get "real" times

chron((t/24)-2,origin=c(month=1, day=1, year=0001))
time = chron((t/24)-2,origin=c(month=1, day=1, year=0001))

# get data subset

if (type == "hgt"){
  x = length(t)
  subset = get.var.ncdf(nc,type, start = c(ix0,iy1,level,1), count = c(countx,county,1,x))
  dim(subset)} else
if (type == "slp"){x = length(t)
  subset = get.var.ncdf(nc,type, start = c(ix0,iy1,1), count = c(countx,county,x))
  dim(subset)}

#####

# Create a matrix of Lat/Lon

lon = rep(seq(lon2, lon1, by = 2.5), each = county)
lat = rev(rep(seq(lat2,lat1,by = 2.5), countx))
tMat <- matrix(c(lon,lat),nrow=length(lat),ncol=2)

# Put data in Loc Dataframe

names = time
colnames = c("hours", "month", "year", seq(1, length(lat)))
Loc = data.frame(row.names = names, hours(time), months(time), years(time))

```

```

for (j in 1:countx){
  for (k in 1:county){
    Loc = cbind(Loc,subset[j,k,])}}

names(Loc) = colnames

#####

# Subset the remaining data

y = c(startyear:(endyear-1))
y = rev(y)
y = as.numeric(y)
path1 = datapath
path2 = type

nc <- open.ncdf(ncFile)
print(nc)

for (i in y){

  ncFile = ncFile <- paste(path1,path2,".",i,".nc", sep="")
  nc <- open.ncdf(ncFile)
  print(nc)

  # get attributes (not data) of slp

  att.get.ncdf(nc,type,"long_name")
  att.get.ncdf(nc,type,"_FillValue")

  #Read in Lat and Lon
  lat <- get.var.ncdf(nc,"lat",verbose=F)
  nlat <- dim(lat)
  lon <- get.var.ncdf(nc,"lon")
  nlon <- dim(lon)

  # get index for lat lon subset

  wherenearest = function(val, matrix){

    dist = abs(matrix-val)
    index = which.min(dist)
    return(index)}

  lower_left_lon_lat = c(lon2,lat2)
  upper_right_lon_lat = c(lon1,lat1)

```

```

ix0 = wherenearest( lower_left_lon_lat[1], lon )
ix1 = wherenearest( upper_right_lon_lat[1], lon )
iy0 = wherenearest( lower_left_lon_lat[2], lat )
iy1 = wherenearest( upper_right_lon_lat[2], lat )

countx = ix1 - ix0 + 1
county = iy0 - iy1 + 1

#read in levels

#lev <- get.var.ncdf(nc,"level")
#nlev <- dim(lev)

library(chron)

# get time dimension
t <- get.var.ncdf(nc,"time")
tunits <- att.get.ncdf(nc,"time","units")

# print t and tunits
head(t)
tunits$value

# get "real" times
chron((t/24)-2,origin=c(month=1, day=1, year=0001))
time = chron((t/24)-2,origin=c(month=1, day=1, year=0001))

# get data subset

if (type == "hgt"){

  x = length(t)

  subset = get.var.ncdf(nc,type, start = c(ix0,iy1,level,1), count = c(countx,county,1,x))
  dim(subset)} else

  if (type == "slp"){x = length(t)

    subset = get.var.ncdf(nc,type, start = c(ix0,iy1,1), count = c(countx,county,x))
    dim(subset)}

# Put data in Loc Dataframe

lon = rep(seq(lon2, lon1, by = 2.5), each = county)

```



```

lat = rev(rep(seq(lat2,lat1,by = 2.5), countx))

names = time
colnames = c("hours", "month", "year", seq(1,length(lat)))

Loc2 = data.frame(row.names = names, hours(time), months(time), years(time))

for (j in 1:countx){
  for (k in 1:county){
    Loc2 = cbind(Loc2,subset[j,k,])}

names(Loc2) = colnames

Loc = rbind(Loc,Loc2)
}

#####

#Subset data to include only observation time and months of input

twelve = subset(Loc, hours == obstime)

month = c("Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec")

summertwelve = data.frame()

for (i in c(startmonth:endmonth)){
  monthname = month[i]
  monthtwelve = subset(twelve, month == monthname)
  summertwelve = rbind(summertwelve, monthtwelve)}

timedetails = summertwelve[, 1:3]

final = summertwelve[, 4:(length(lat)+3)]

final = as.matrix(final)

if (mode == "S"){

  list = list("subset" = final, "locations" = tMat, "timedetails" = timedetails)

} else

if (mode == "T"){

  list = list("subset" = t(final), "locations" = tMat, "timedetails" = timedetails) }

```

```

return(list)}

#####

# Perform Hybrid Classification

# Extract sea level pressure grids from nrrsubset list

subset = nrrsubset$subset

# Standardize sea level pressure grids

subset_standard = t(subset)
subset_standard = scale(subset_standard, center = TRUE, scale = TRUE)
subset_standard = t(subset_standard)

# Read in Muller Weather types from excel file and assign to sea level pressure grids
file2 = "J:/Thesis/Muller Types/1981-2001 Procedure/Muller_Types_81_01_Non_Transition.csv"
Muller = read.csv(file2,header = TRUE, sep = ",")
Muller = cbind(Muller, subset_standard)

# Aggregate by Muller Type to calculate mean grids for each
Muller_mean = aggregate(Muller, by = list(Muller$Baton.Rouge.6Z), FUN = mean)
Muller_mean = Muller_mean[,6:148]
Muller_mean = Muller_mean[2:9,]

# Calculate sum of squares between each grid and each mean grid

kirch = data.frame(row.names = rownames(subset1))

for (i in 1:8){
  grid = matrix(as.numeric(rep(Muller_mean[i,], 7670)), nrow = 7670, byrow = TRUE)
  grid = grid - subset_standard
  squares = grid^2
  sumofsquares = rowSums(squares)
  kirch = cbind(kirch, sumofsquares)}

# Find minimum kirch score and assign a weather type to each grid

kirch = kirch * -1
kirch$types = max.col(kirch)
types2 = data.frame(row.names( kirch), kirch$types)
write.csv(hybridtypes, file = "Hybrid_Types.csv")

```

APPENDIX B. RESIDUAL ANALYSIS

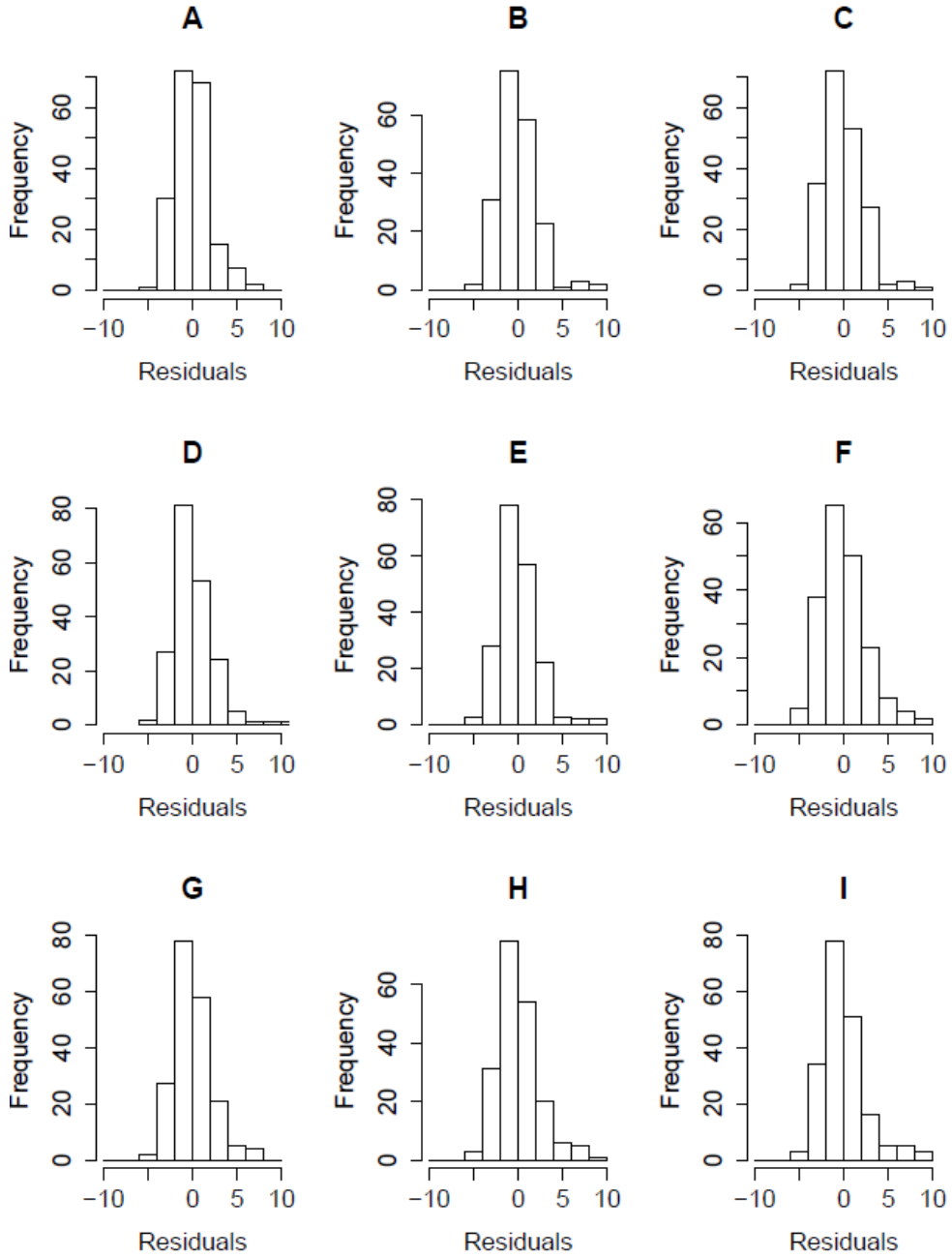


Figure A.1. Histogram of Winter Regression Model Residuals for the A) Northwest B) North Central C) Northeast D) West Central E) Central F) East Central G) Southwest H) South Central I) Southeast Climate Divisions.

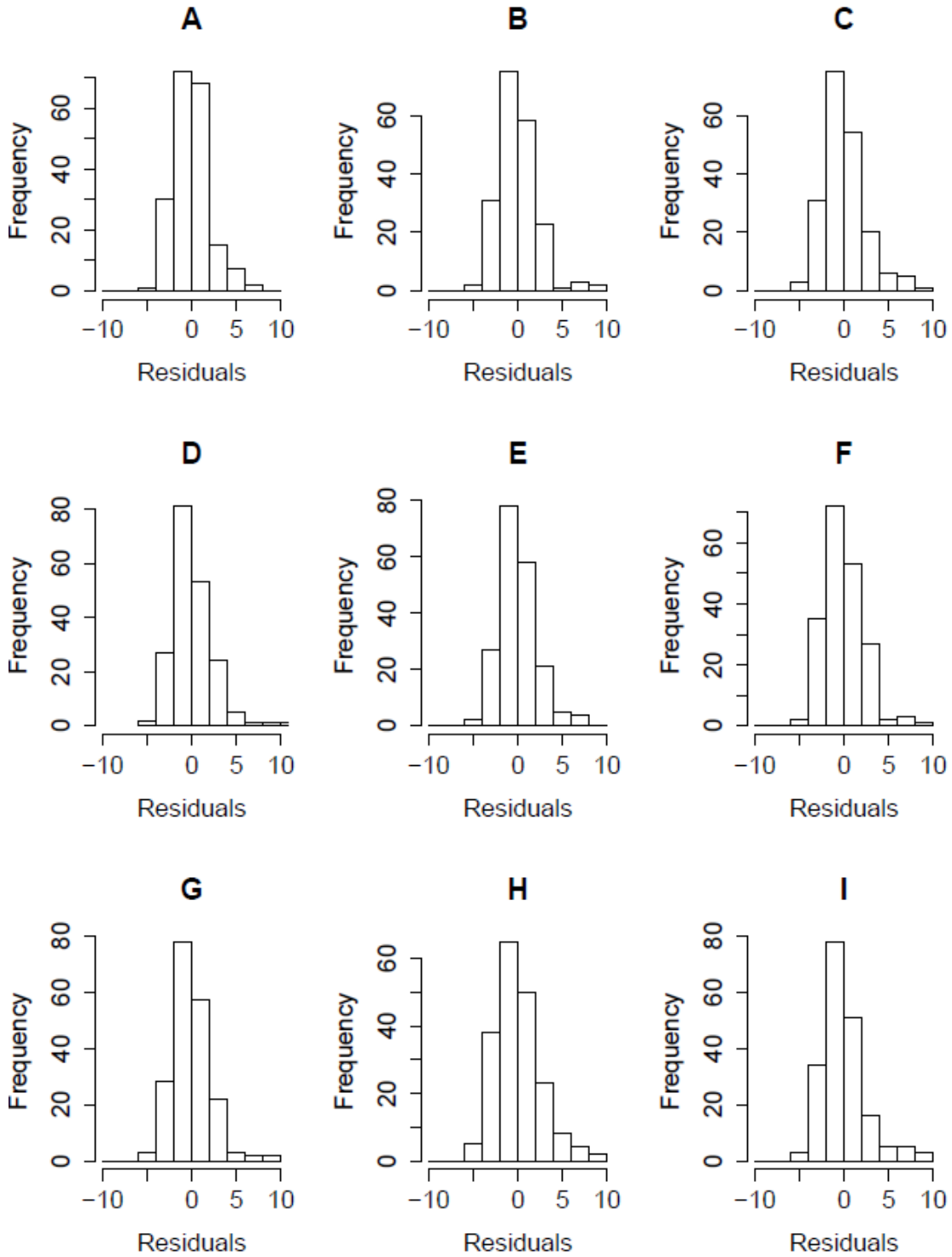


Figure A.2. Histogram of Spring Regression Model Residuals for the A) Northwest B) North Central C) Northeast D) West Central E) Central F) East Central G) Southwest H) South Central I) Southeast Climate Divisions.

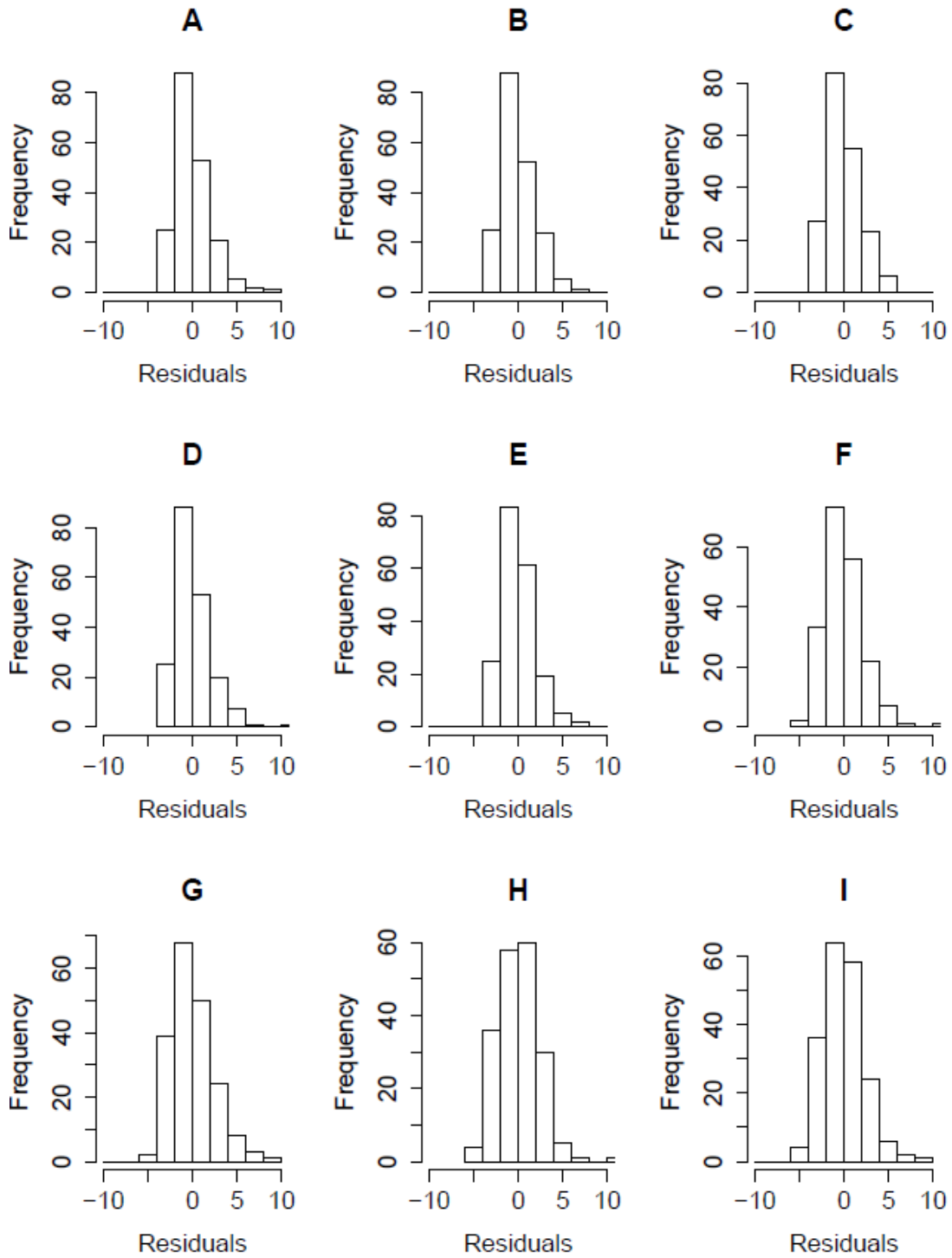


Figure A.3. Histogram of Summer Regression Model Residuals for the A) Northwest B) North Central C) Northeast D) West Central E) Central F) East Central G) Southwest H) South Central I) Southeast Climate Divisions.

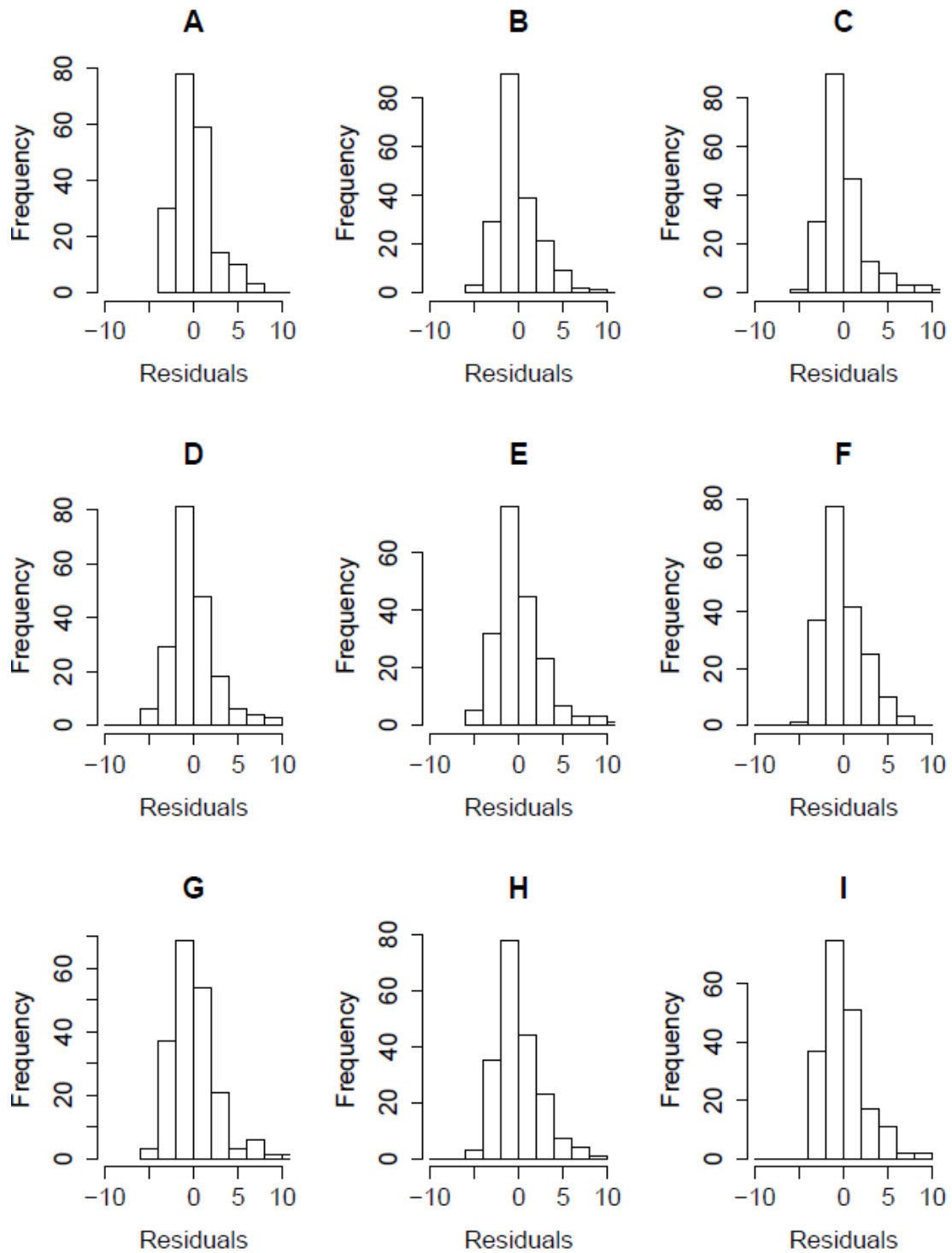


Figure A.4. Histogram of Fall Regression Model Residuals for the A) Northwest B) North Central C) Northeast D) West Central E) Central F) East Central G) Southwest H) South Central I) Southeast Climate Divisions.

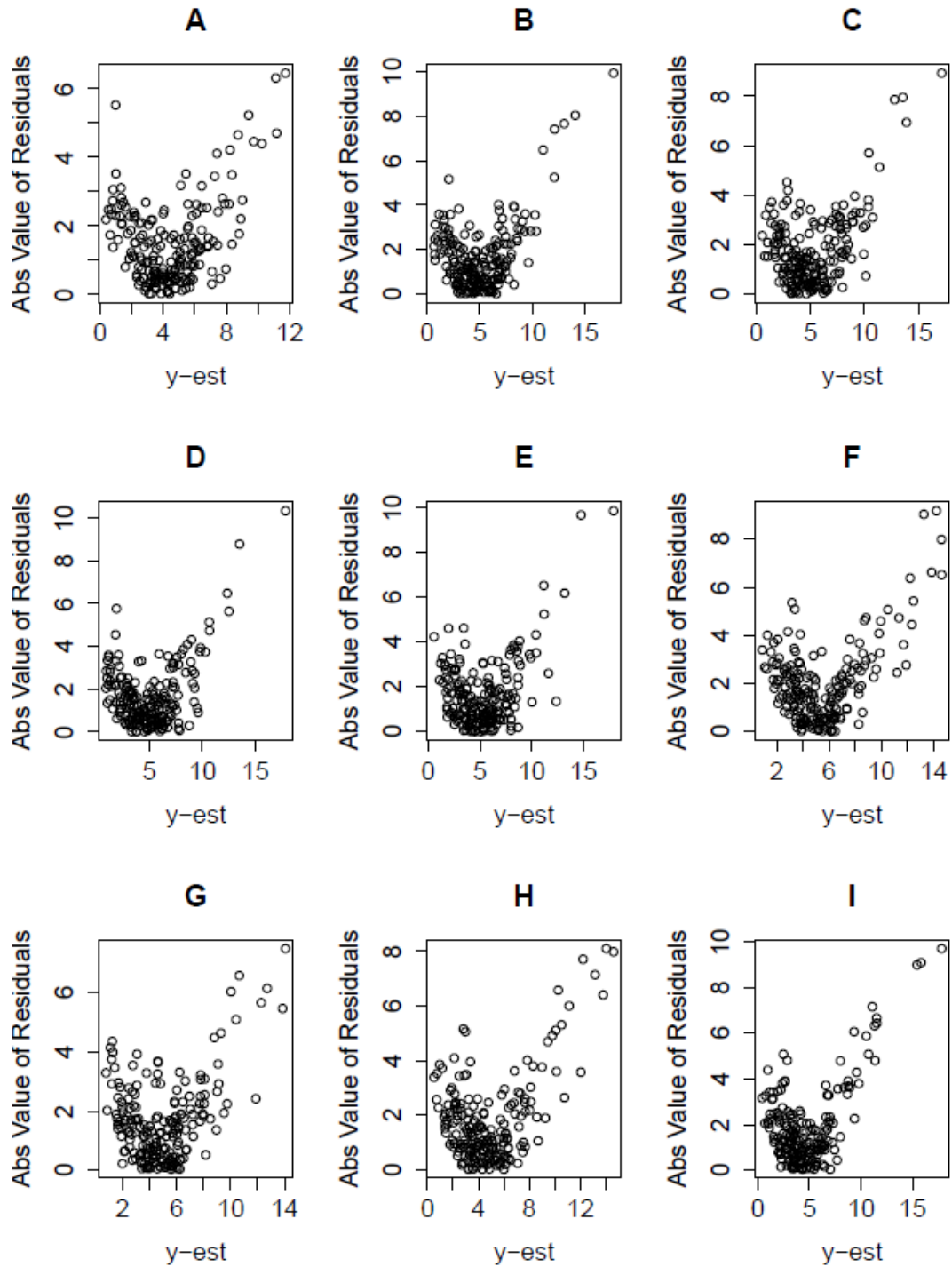


Figure A.5. Winter Regression Model Residuals vs. Winter Precipitation Estimates for the A) Northwest B) North Central C) Northeast D) West Central E) Central F) East Central G) Southwest H) South Central I) Southeast Climate Divisions.

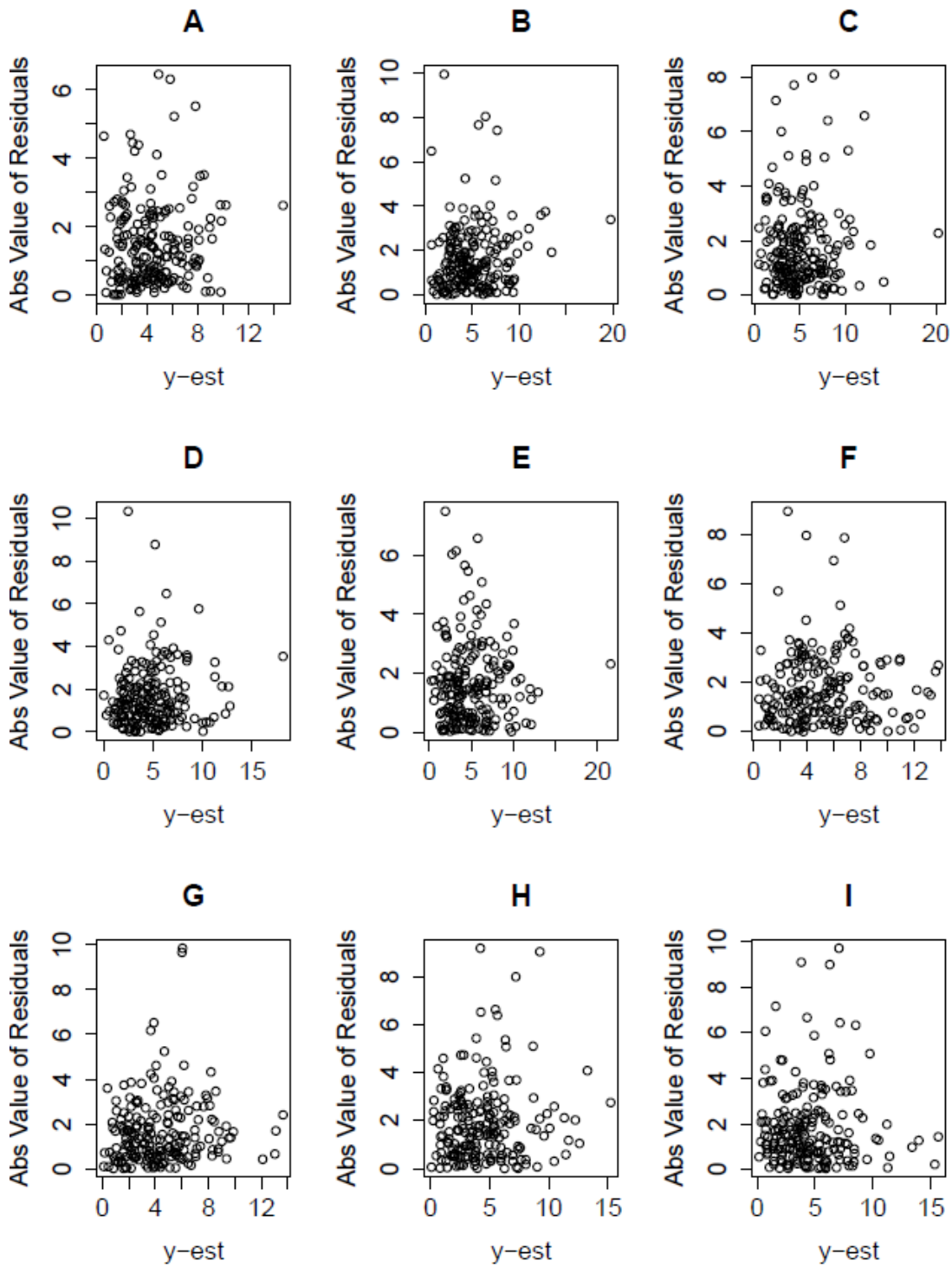


Figure A.6. Spring Regression Model Residuals vs. Spring Precipitation Estimates for the A) Northwest B) North Central C) Northeast D) West Central E) Central F) East Central G) Southwest H) South Central I) Southeast Climate Divisions.

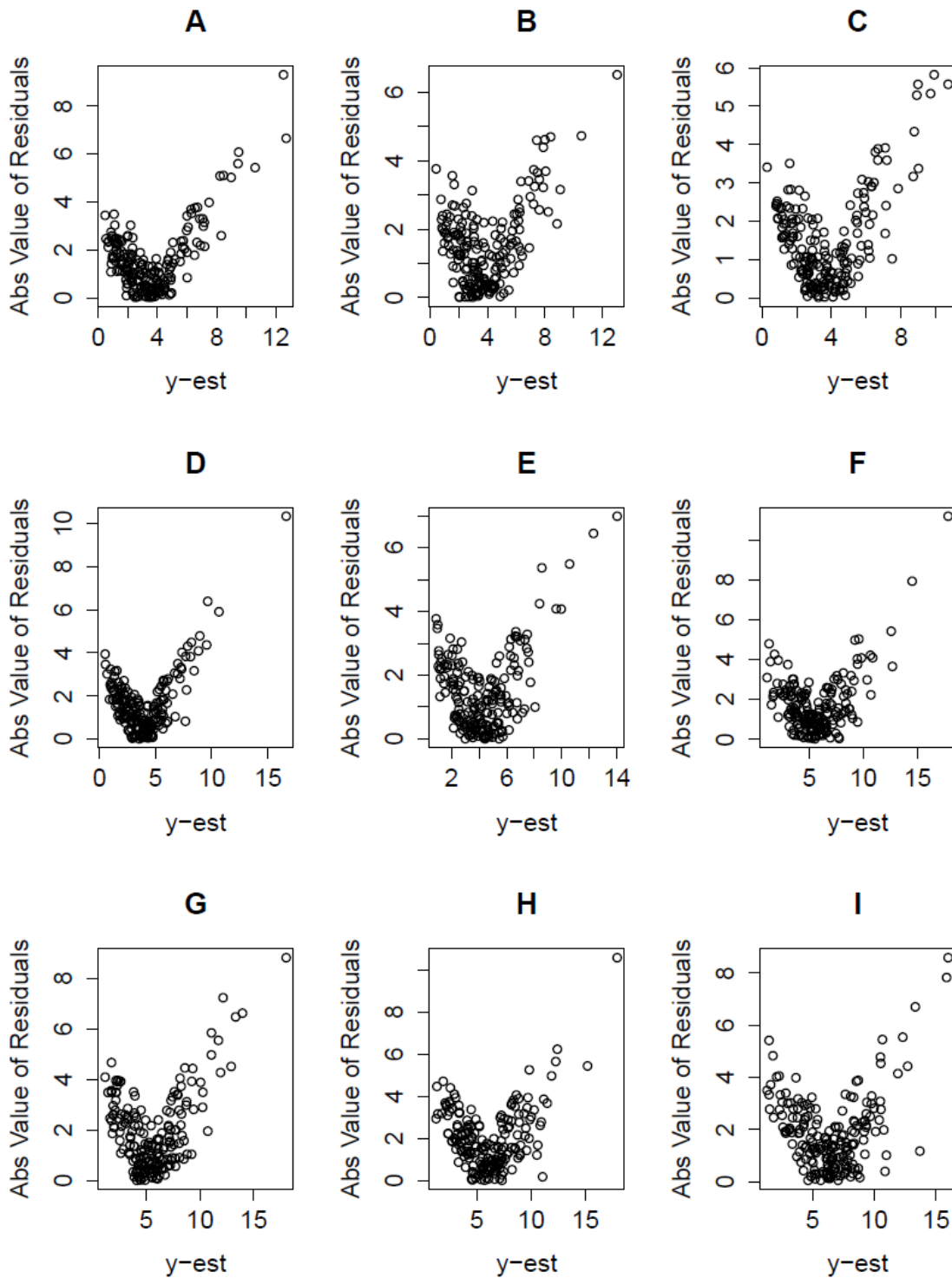


Figure A.7. Summer Regression Model Residuals vs. Summer Precipitation Estimates for the A) Northwest B) North Central C) Northeast D) West Central E) Central F) East Central G) Southwest H) South Central I) Southeast Climate Divisions.

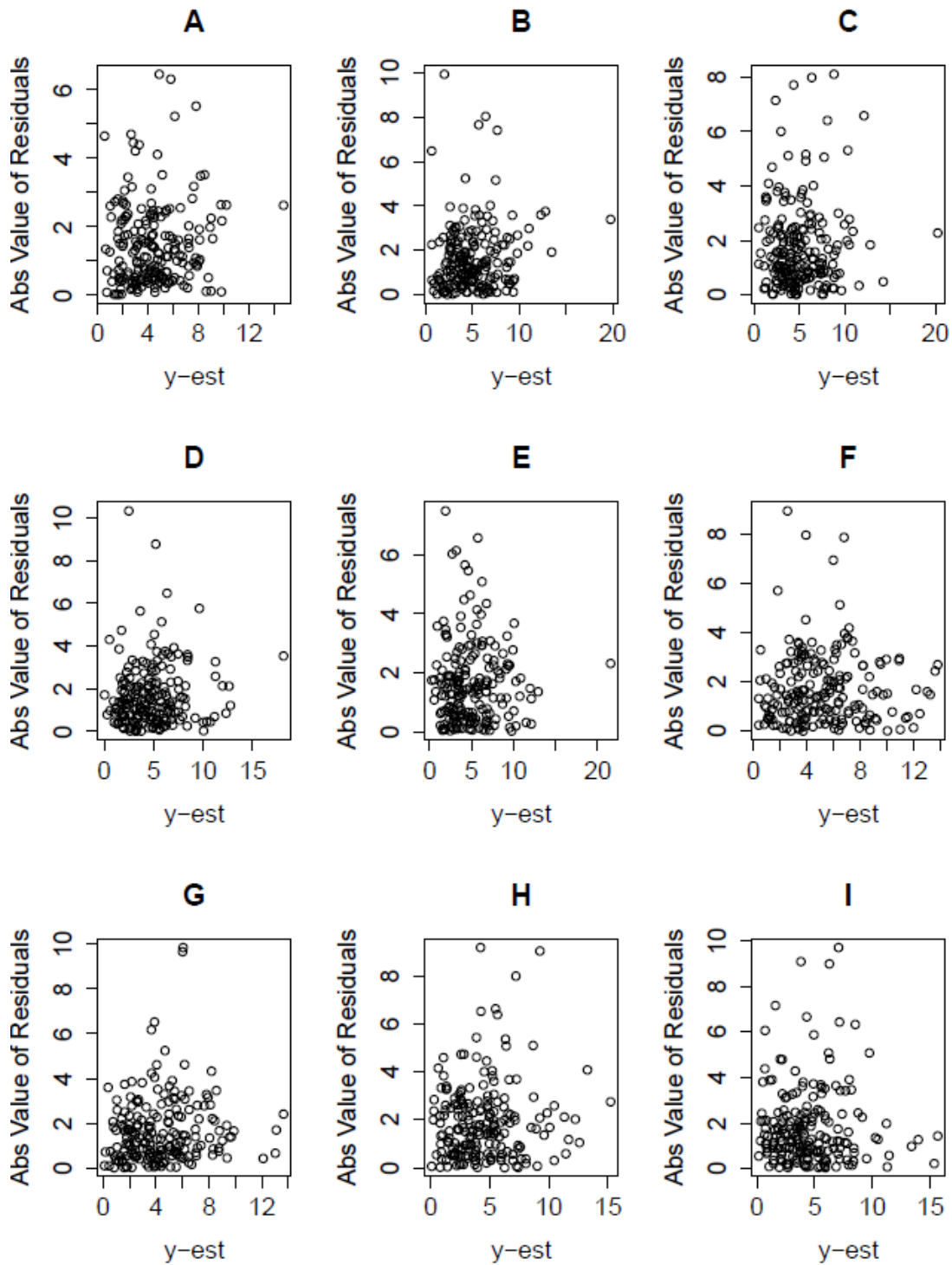


Figure A.8. Fall Regression Model Residuals vs. Fall Precipitation Estimates for the A) Northwest B) North Central C) Northeast D) West Central E) Central F) East Central G) Southwest H) South Central I) Southeast Climate Divisions.

THE VITA

Amanda Billiot, a native of Southeast Louisiana, received her bachelor's degree in Meteorology at the University of South Alabama in 2011. She entered graduate school in the Department of Anthropology and Geography at Louisiana State University shortly thereafter. Amanda plans to begin work on her doctorate upon graduation.