# CLIMATE CLASSIFICATION OF TEXAS:

# A MULTIVARIATE STATISTICAL APPROACH

THESIS

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"We still do not know one-thousandth of one percent of what nature has revealed to us."

– Albert Einstein

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# CHAPTER I

# INTRODUCTION

Climate is often a factor in environmental problems because the synthesis of past weather observations reveals pertinent regional characteristics. The meteorological processes that determine climate are ubiquitous. Classifying climates leads to a better comprehension and understanding of the environment through the generalization of phenomena for explanation or clarification. In the words of Abler, Adams, and Gould (1971, 149), "the purpose of classification is to give order to the things we experience. We classify things so that we may learn more about them." Classification theory is important to environmental studies because the process depicts and explains "natural systems" or phenomena associated with nature in order to understand them better (Sokal 1974). Climate is one of these systems and, if specified into logical groups, can disclose essential information about a region.

In 1951, the National Weather Service (NWS) divided Texas into climatic regions based on geographic areas not directly related to climate or weather patterns. Eight years later, the same organization modified the map into the ten climatic regions most popular today and include: High Plains, Low Rolling Plains, North Central, East, Trans-Pecos, Edwards Plateau, South Central, Upper Coast, Southern, and Lower Valley. For uniformity and political purposes, the climate boundary lines were forced to follow the county borders; one county cannot be in more than one region (Griffiths and Bryan 1987). The 1959 climate classification of Texas shown in Figure 1 is the most recent iteration and is a well-known map.

The following question arises for the modernization of climatic regions in Texas: can a multivariate statistical analysis provide discrete classed regions of the macroclimate in Texas in order to interpret and compare with the 1959 NWS divisions map, the physiography, and the ecological patterns? It is hypothesized that cluster analysis and discriminant analysis of temperature and precipitation normals will naturally group the macroclimate of Texas for these types of meaningful comparisons. The map generated in this study and the 1959 NWS divisions map will be inspected and analyzed for differences and similarities. Also, the above interpretations will likely result in correlations with the physiography and vegetation patterns as evidenced in a hillshaded digital elevation model and satellite image both covering all of Texas. The purpose of this thesis is to define the research goals and processes for the stated problem and hypothesis. Incorporated is a literature review for background and significance, an explanation of the study area and data needs (including operational definitions), a step-by-step outline of the methodology, results presented with a discussion, and summary, conclusions, and future work sections.

The geographic research goals fit under the sub-disciplines of climatology and the techniques for spatial and non-spatial statistics. A new climate classification for Texas, in visual form, could help answer environmental and economic questions for state

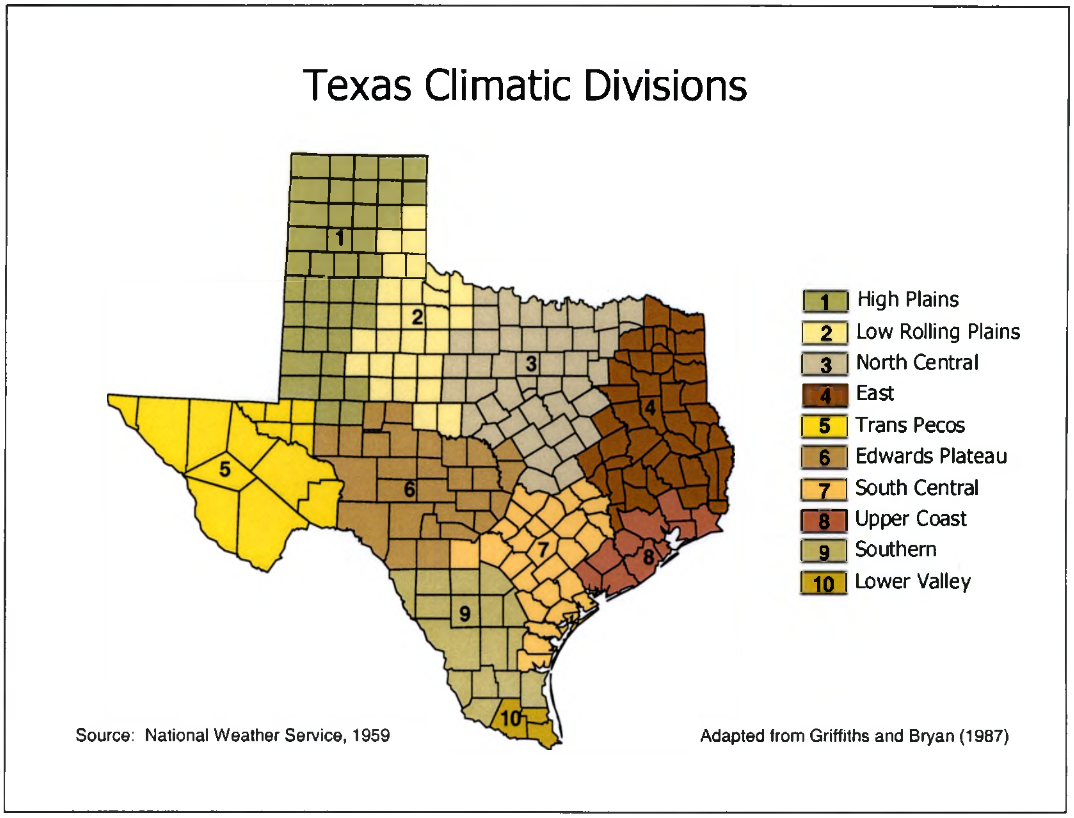



Fig. 1. The Texas climatic divisions produced by the National Weather Service.

agencies, research centers, and various other institutions. This study is also useful as a basis for understanding Texas as a region. The statistically derived climate zones could provide general meaning to modeling weather processes and understanding of the weather patterns in Texas. This study fills a void for this specific type of climate classification for Texas.

# CHAPTER II

# BACKGROUND

The intent of this review is to present a sufficient background from the literature related to the purpose and objectives of this research. In the following sections, genetic and empirical methods of climate classification are described using previous studies developed to identify and distinguish climatic zones for various parts of the world. Genetic classifications are based on the primary climate controls, such as radiation, and are explanatory in purpose. Empirical classifications are more applied and tend to develop from the mathematical and statistical manipulation of climatic data (Griffiths and Driscoll 1988). Griffiths and Driscoll (1988) list four characteristics of an effective climate classification: (1) reduces large amounts of data to a manageable form, (2) is easy to apply, (3) has a well defined usage, and (4) is based on climatological principles.

## Genetic Climate Classification

Traditional climate classifications are location specific and are not easily applied to other regions (McGregor 1993). Robinson and Henderson-Sellers (1999, 118) state, "The [climate classification] elements are usually chosen because they are perceived to be important in the context of the use to which the classification scheme is to be put." Early attempts used the natural surface characteristics of the Earth such as vegetation or physiographic properties involved with specific land uses such as agriculture or water resources (Hare 1973; McGregor 1993; Leber, Holawe, and Hausler 1995).

The most well-known climate classifications are based on vegetation-induced measures; the claim that plant growth is a direct result of the local climate (Hare 1973). The Köppen classification of 1918 is the most widely used and known visual representation of the global climates (Wilcock 1968). Wladimir Köppen recognized the reactions plants have to heat, and because phenomena in nature generally respond to climate, this theory could be used for producing climate thresholds for placing boundaries on a map (Wilcock 1968). His categorization is significant not only for its groundbreaking numerically based classification but also for his often times disputed methodology (Wilcock 1968; Hare 1973; Puvaneswaran 1990). Wilcock (1968) argues that if one is to use Köppen's classification in an analysis, awareness of the assumptions and limitations will help avoid misconceptions about the accuracy and validity of his development. Some American scholars feel his classification does not sufficiently represent the climates as related to the vegetation boundaries of the United States and so have altered them by changing Köppen's threshold values (Hare 1973). Thus, scale is an issue if a climate classification method is applied to regions unintended by the original author.

A second important genetic classification was developed by C. Warren Thornthwaite, published in 1931 and revised in 1948 (Hare 1973). Hare (1973) recognizes Thornthwaite's work as a highly developed and inclusive climate classification. The algorithms are based on variables that control plant growth and sustainability such as moisture content in plants and soil (evapotranspiration) as well as temperature and rainfall (Hare 1973).

## Empirical Climate Classification

Climate classification expresses complex statistical variables as simple spatial entities (Hare 1973). Multivariate statistics is a fairly new method for classifying climate regions using a more objective and non-biased approach. The automated processes eliminate subjective boundary assignment and do not rely on existing climatic thresholds or concepts (Puvaneswaran 1990; Goldreich and Raveh 1993). Steiner first utilized multivariate techniques in 1965 to systematize climates in the United States using only climatic variables (McBoyle 1973; Preston-Whyte 1974; Anyadike 1987; White and Perry 1989; Puvaneswaran 1990; Goldreich and Raveh 1993). Because climates are complex, Steiner also believed they should be classified with numerous variables to achieve accuracy and completeness (Puvaneswaran 1990; Garr and Fitzharris 1991). The most common techniques that have been used are cluster analysis followed closely by factor analysis and principal components analysis (Goldreich and Raveh 1993). In Table 1, published studies using multivariate statistical climate classification are listed by author(s), research site, and statistical technique(s). These studies used different combinations of multivariate statistical methods to produce classifications. The process and variable selection differ considerably by study site; there seems to be no one consistent approach to the statistical classification of climates.

Table 1. Multivariate Statistical Climate Classification Studies

| **Author(s)** | **Study Site and Year** | **Technique** |
|---|---|---|
| Steiner | United States, 1965 | FA, DA |
| McBoyle | Australia, 1973 | FA |
| Preston-Whyte | South Africa, 1974 | FA |
| Oliver, Siddiqi, and Goward | Pakistan, 1978 | CA, FA |
| Anyadike | West Africa, 1987 | CA, FA |
| White and Perry | England and Wales, 1989 | PCA, CA |
| Puvaneswaran | Queensland, Australia, 1990 | FA, CA |
| Garr and Fitzharris | New Zealand, 1991 | CA, DA |
| Goldreich and Raveh | Israel, 1993 | COPLOT, CA, FA |
| McGregor | China, 1993 | PCA, CA |
| Leber, Holawe, and Hausler | Tibet, 1995 | CA, FA, DA |

*CA = Cluster Analysis* *DA = Discriminant Analysis*
*FA = Factor Analysis* *PCA = Principal Components Analysis*
*COPLOT = Common Plots*

Often, the results of multivariate climate classifications were compared against an earlier method for the same region or sub region. For example, McGregor (1993) used a multivariate approach involving principal components analysis and cluster analysis of Chinese data, and Leber, Holawe, and Hausler (1995) used different variables combining factor analysis, cluster analysis, and discriminant analysis for the Tibet Autonomous Region. Similarly, McBoyle (1973) used factor analysis to classify climates of Australia, while Puvaneswaran (1990) applied a similar statistical methodology (factor analysis combined with cluster analysis) using more weather station data for the State of Queensland. Usually the newly predicted climate regions were analyzed and described in terms of their physical geographic features but were not labeled as specific climate types. This procedure would mean stepping backward to the earlier methods of experimentation and subjective interpretation as indicated by McGregor (1993).

Classifications are mostly based on observed elements, so data limitations can include weather station records that are lacking in spatial and temporal extent (Wilcock 1968; Leber, Holawe, and Hausler 1995). Weather collection points may be denser in heavily populated areas, resulting in spatially irregular data (Leber, Holawe, and Hausler 1995). Different periods of record and changes in observation location and instrumentation could also lead to inhomogeneities in the data record (Linacre 1992). The number and distribution of weather stations and available data are unique to each study.

## Questions for Research

Given the incongruent approach to climate classification presented in the literature, what is the most accurate or acceptable method for classifying climates? Because the methods are specific to climate variables and sites, what method would be suitable for Texas? Early studies of climate classification had to rely on limited data from very few existent weather stations. Could a large number of weather stations of sufficient record length increase accuracy in the classification process? How many and which climate variables should be used for an appropriate classification in Texas? Typically, humans collect climate data on the ground, so there is limited coverage in sparsely populated areas. Could regularly spaced weather station data ease the communication and mapping process? Finally, after the macroclimate of Texas is produced, how can it be described and understood? The answers to these questions constitute my research.

# CHAPTER III

# STUDY AREA AND DATA

## Study Area

Texas demonstrates great geographic variability including an elevation range of almost 9,000 feet containing distinctly different ecological regions. The combination of a large area (over 267,000 square miles) and many changes in landform throughout the state permits disparate climate zones, usually characterized by temperature and precipitation statistics (Griffiths and Bryan 1987). Familiarity with a region drives a researcher's need to test or explain its natural processes in greater detail as opposed to studies conducted by a nonnative (Wilcock 1968). My personal experience and extensive geographic knowledge of the state of Texas yields greater insight and a stronger ability to analyze the macroclimate map.

## Variables

A temperature recording is the measurement of the molecular activity (average kinetic energy) in the air at a certain location and time, while precipitation is a cumulative measurement of rainfall, sleet, and snow at a certain location over time. Temperature and precipitation are considered the main climatic elements and both significantly fluctuate spatially and temporally (Bomar 1983; Robinson and Henderson-Sellers 1999). These data are physically measured at weather stations throughout Texas. Because temperature and precipitation data can vary from month to month and even year to year, "normals" are calculated to yield an average over a 30-year period for the climatic variables, mean temperature and total precipitation.

Climate in Texas is influenced by location in both latitude and longitude. Latitude lines, or parallels, run east or west across the Earth and measure north and south of the equator in degrees. Incoming solar radiation is more intense in south Texas than in the northern panhandle, so temperatures in the south are generally higher than in the north. Lines of longitude, or meridians, run north or south over the Earth and measure east and west of the prime meridian in degrees. Precipitation in Texas commonly follows a pattern along longitude lines due to physical relationships such as distance from the coast and continentality. Eastern Texas receives significantly more rainfall than the western edge of the state. Generally in Texas, temperature is latitudinally distributed and precipitation is longitudinally distributed, which in combination makes for distinct climate regions.

## Climate Data Set

For this study, data availability and format are important. Individuals record weather data daily with automatic recording devices at primary and cooperative weather stations across Texas. The National Climatic Data Center (NCDC) processes this information into various formats and makes the data accessible.

Data from the 1971-2000 normal period were used and included a large number of stations (n = 403 seen in Figure 2) obtained from the NCDC (2002). Monthly normals

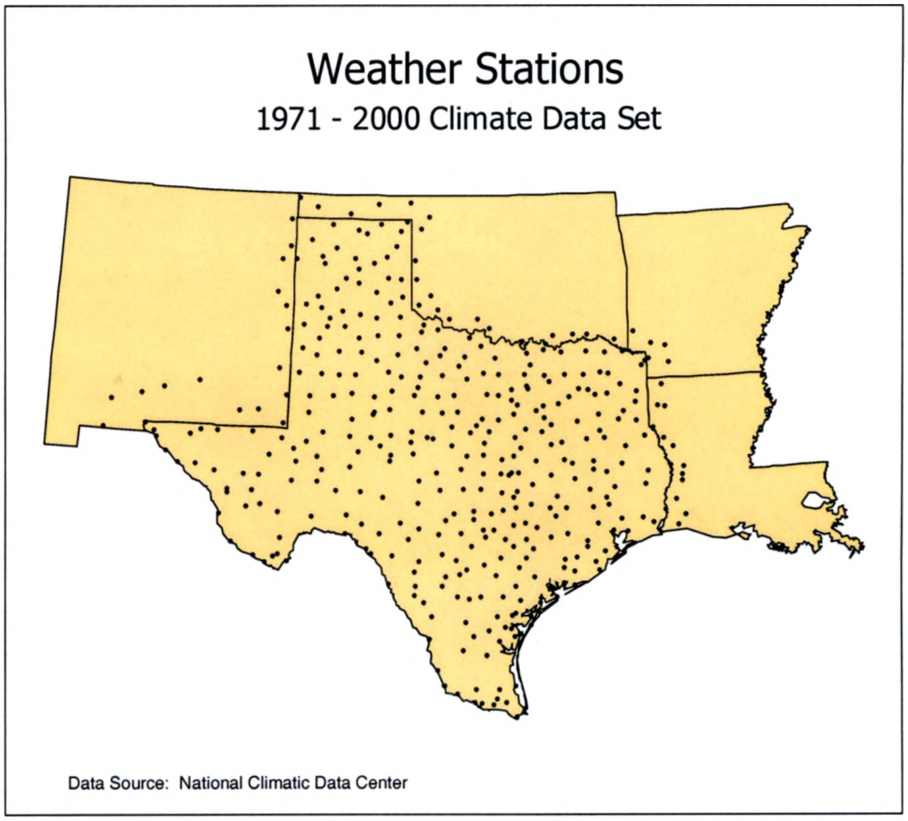



Fig. 2. Weather stations used in the thesis study.

were used from the climate data set. 1971-2000 temperature and precipitation normals were also collected for select New Mexico, Oklahoma, Arkansas, and Louisiana stations to control edge effects when surfacing the data. For the same purpose, an attempt was made to collect Mexico normals from the World Meteorological Organization, but appropriate data of this sort could not be obtained. However, weather stations along the Texas border are sufficient to address the edge effects at these locations.

Because temperature and precipitation are spatially continuous, class boundaries represent transition zones rather than discrete boundaries in the final map, even though the classes were defined from objective reasoning and calculation (Wilcock 1968; White and Perry 1989; Puvaneswaran 1990; McGregor 1993). In other words, change is not easily detected at the macro scale. Also, spacing of the weather stations was checked during data collection to avoid areas of sparse data; a uniform distribution was sought.

## Digital Elevation Model

A digital elevation model (DEM) for Texas was used in this study and served two purposes: (1) to act as the coordinate base (30 arc-second spacing in latitude and longitude) for surfacing the weather data into regular raster grids and (2) for comparison of the final classed map to the physiography or landforms of Texas. The 30 arc-second resolution DEM is available from the United States Geological Survey's Earth Resources Observation Systems Data Center and covers Texas completely. Because there are 3600 seconds in one degree of latitude or longitude, this raster data set has 120 regularly spaced elevation values per latitude or longitude degree. In other words, every grid cell accounts for one topographic height for a resolution of roughly 900 meters by 900 meters per grid cell footprint.

# CHAPTER IV

# METHODOLOGY

A macroclimate results from the combination of weather observations in a large region over a period of time (Robinson and Henderson-Sellers 1999). Applying multivariate statistics to classify the macroclimate in Texas using temperature and precipitation variables should produce a set of spatially consistent zones. The methodology is basically two-fold: (1) to create generalized temperature and precipitation grids for mapping purposes and (2) to use cluster analysis and discriminant analysis to classify the grids. The software package MVMAP (Eyton 2001) was used to perform the statistical operations. The procedures described in this section include data surfacing and classification.

## Data Surfacing

Because the weather stations are irregularly spaced across Texas, a surfacing technique was utilized to make them regularly distributed. Monthly temperature and precipitation values were surfaced into regular raster grids based on the latitude and longitude coordinates of the 30 arc-second DEM. Weather stations from the four states surrounding Texas were part of the data set to correct for edge effects. Sufficient numbers of data points along the Texas / Mexico border and along the Gulf coast eliminated this problem.

An attempt was made to find the proper surfacing technique that fit the data well but still produced a good level of generalization. Surfacing methodologies considered were: trend surfacing, multiple regression surfacing, multiquadric equation surfacing, inverse distance weighting function surfacing, and kriging. The analytical approach called trend surfacing was ultimately chosen to interpolate the monthly temperature and precipitation values into separate regular raster grids predicted from latitude and longitude. The trend surface model uses a multiple-curvilinear regression equation with two independent variables and powered polynomial functions of the general form $Z = f(X,Y)$ (Eyton and Roseman 1971). A group of terms is added each time the equation increases to a higher order as shown in the following example:

1st degree: $Z_1 = a_0 + a_1X + a_2Y$

2nd degree: $Z_2 = Z_1 + a_3X^2 + a_4XY + a_5Y^2$

3rd degree: $Z_3 = Z_2 + a_6X^3 + a_7X^2Y + a_8XY^2 + a_9Y^3$

4th degree: $Z_4 = Z_3 + a_{10}X^4 + a_{11}X^3Y + a_{12}X^2Y^2 + a_{13}XY^3 + a_{14}Y^4$

5th degree: $Z_5 = Z_4 + a_{15}X^5 + a_{16}X^4Y + a_{17}X^3Y^2 + a_{18}X^2Y^3 + a_{19}XY^4 + a_{20}Y^5$

6th degree: $Z_6 = Z_5 + a_{21}X^6 + a_{22}X^5Y + a_{23}X^4Y^2 + a_{24}X^3Y^3 + a_{25}X^2Y^4 + a_{26}XY^5 + a_{27}Y^6$

7th degree: $Z_7 = Z_6 + a_{28}X^7 + a_{29}X^6Y + a_{30}X^5Y^2 + a_{31}X^4Y^3 + a_{32}X^3Y^4 + a_{33}X^2Y^5 + a_{34}XY^6 + a_{35}Y^7$

(Eyton 1991)

The correlation, or strength of the relationship for each degree fit is given by the coefficient of determination or $r^2$ value, which is a ratio of the explained variation to the total variation. For this study, the seventh degree trend surfacing equation was used to create all the grids because in most cases, the $r^2$ value was highest (or closest to 1.0) as shown in Table 2. If, for example, the coefficient of determination was higher for the

Table 2. Trend Surfacing Statistics

| **Month** | **Temp. 7th Degree $r^2$** | **Precip. 7th Degree $r^2$** |
|---|---|---|
| JAN | 0 9601 | 0 9832 |
| FEB | 0 9446 | 0 9738 |
| MAR | 0 9327 | 0 9699 |
| APR | 0 9124 | 0 9499 (5th = 0 9533) |
| MAY | 0 8765 | 0 9229 (6th = 0 9268) |
| JUN | 0 7423 | 0 8445 (5th = 0 8493) |
| JUL | 0 6441 | 0 7804 |
| AUG | 0 7462 (6th = 0 7463) | 0 6164 (5th = 0 6294) |
| SEP | 0 8588 | 0 8635 |
| OCT | 0 9196 | 0 9296 |
| NOV | 0 9588 | 0 9707 |
| DEC | 0 9651 | 0 9756 |

fifth degree equation for a particular month, the seventh was still used for uniformity purposes; the differences were very slight. The trend surfacing was run in the MVMAP module TREND on each month's temperature and precipitation values once to obtain the statistics and again to surface the data with the specified seventh degree. One temperature grid and one precipitation grid for each month, January through December, resulted in a total of 24 raster data sets defined by row and column coordinates in latitude and longitude.

## Classification

Multivariate statistical analyses were applied to the temperature and precipitation raw data observations for grouping macroclimates in Texas. Cluster analysis can be used to divide a region into smaller homogeneous spatial units based on observations that are grouped together (Aldenderfer and Blashfield 1984; Rogerson 2001). This procedure statistically groups the variables into mutually exclusive classes by maximizing the variance between groups and minimizing the variance within groups. An Iterative Partitioning Method (IPM) called k-Means Cluster Analysis was run on the raw (unsurfaced) weather station data consisting of the temperature and precipitation values from each month, January through December. All twelve months were used in order to obtain a complete annual time series with an acceptable amount of variability.

The k-Means algorithm randomly "seeds" or finds cluster centroids in multidimensional feature space based on a user-defined number of groups. Each temperature and precipitation data observation is assigned to the closest cluster centroid (defined by the means of the variables). The cluster means are calculated again and data observations are reassigned to the new closest cluster. These iterations repeat until there is no significant change in the assignment of data observations to the clusters (Aldenderfer and Blashfield 1984; Lillesand and Kiefer 1994).

Determining the optimal number of groups or clusters in a k-Means Cluster Analysis is a problem (Aldenderfer and Blashfield 1984). To find the optimum number of clusters, the MVMAP module CLUSTER was run with 5 as the initial number of groups and 25 as the last number of groups, producing 21 runs or analyses. By examining the F-Ratio (between group variance / within group variance) for all groups, local maximums were determined (Figure 3). This instance occurred on clusters 7, 9, 15, 18, and 24, but 7 (although not a strong local maximum) was chosen to produce a parsimonious or manageable and interpretable solution (Table 3). CLUSTER was run again setting the number of clusters at seven and assigning group membership (1 – 7) to the original observations. Because temperature and precipitation are measured with different units, the data were standardized during the cluster analysis so that the data are all measured on the same relative scale (Aldenderfer and Blashfield 1984).

Discriminant analysis determines decision rules called classification functions to allocate raw observations to groups of similar properties (Klecka 1980; Mertler and Vannatta 2002). A discriminant analysis was first run in the MVMAP module DISCRIM to test the performance of the linear classification functions using monthly temperature and monthly precipitation as the analysis variables and the seven k-Means Clusters as the group variable. This statistical technique builds a set of linear functions called classification functions from the 24 analysis variables. A constant and a coefficient for

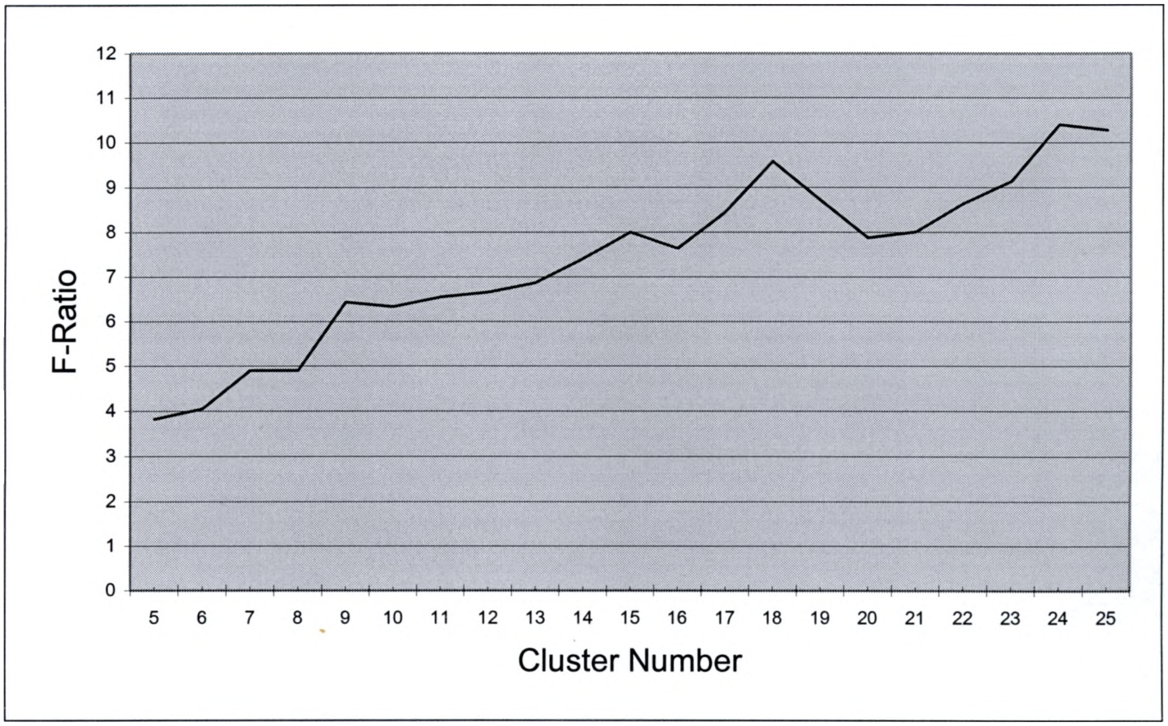



Fig. 3. The local maximums from 21 cluster runs or analyses.

Table 3. Local Maximum of Cluster Number 7

| | |
|---|---|
| CLUSTER NUMBER 6 | |
| WITHIN GROUP VARIANCE = | 5 8014 |
| BETWEEN GROUP VARIANCE = | 23 5005 |
| F-RATIO = | 4 0508 ← **< 4.9015** |
| | |
| CLUSTER NUMBER 7 | |
| WITHIN GROUP VARIANCE = | 4 8967 |
| BETWEEN GROUP VARIANCE = | 24 0013 |
| F-RATIO = | **4.9015** ←LOCAL MAXIMUM |
| | |
| CLUSTER NUMBER 8 | |
| WITHIN GROUP VARIANCE = | 4 6555 |
| BETWEEN GROUP VARIANCE = | 22 8146 |
| F-RATIO = | 4 9005 ← **< 4.9015** |

each variable were obtained for each of the seven functions that were determined from the analysis of the structure of a covariance matrix (Klecka 1980). Each monthly temperature and precipitation value from every weather station were then run through the discrete classification functions and classified into one of the seven groups according to which function equaled the highest score (Klecka 1980). After each observation had been classified, a percent correct classification table or confusion table was generated to assess the accuracy of the classification functions and is discussed in the results section.

Once the classifier was put into place, each temperature and precipitation value from each monthly trend surfaced grid were classed and assigned a color for mapping in the MVMAP module COLORMAP. The 30 arc-second DEM was used to produce a relative radiance grid, which was utilized by the COLORMAP program to produce hillshading. An image raster file called a mask was applied to the classed color grid to control for the study area being mapped. The mask was created with the state of Texas labeled as the cartographic area of interest; classes within the state kept their originally assigned colors. All areas in the grid outside of the Texas border were assigned the mask background color of black. Descriptive statistics were run on the original clustered climate groups using the MVMAP module DESCRIBE to produce mean values per variable per group.

# CHAPTER V

# RESULTS AND DISCUSSION

## Pilot Study

The purpose of the pilot study was to test the methodology and to develop expertise in interpreting the statistics associated with the modeling and mapping. This process gave the researcher experience working with the climate data before beginning the actual thesis work. The pilot study data set included the 1961-1990 normals for the annual temperature and precipitation recorded at 164 weather stations in Texas. For this preliminary study, the data were not surfaced. Because 1961-1990 normals were not readily available from NCDC at the time of data collection, the set included normals that were manually calculated from the departures from normals using 1996 data from the National Oceanic and Atmospheric Administration (1996). Julie Henry, a former graduate student of the Southwest Texas State University Geography Department, collected the data and calculated the normals.

After I chose 11 groups by examining local maximums from F-Ratios of 21 cluster runs (5 – 25), cluster analysis was used to group the data. A discriminant analysis was run with an overall correct classification of 100.00%. The Texas climate centroids were mapped from the mean latitude and longitude values calculated for each group. The results in Figure 4 illustrate the Texas climate centroids, which correspond well with the 1959 NWS climatic divisions.

The pilot study proved successful and provided a good preliminary view of how a statistical set of climate classes can be spatially derived for Texas. Most importantly, however, is that the procedure revealed natural discrete climate groups in Texas. These early findings validated the parallel methodology proposed for the thesis research, which utilized 1971-2000 monthly normals and surfaced grids of climate data to obtain a more accurate and higher definition classification.

### Texas Climate Classification Map and Statistics

The Texas climate map classed from multivariate statistical analyses is shown in Figure 5. Larkin and Bomar (1983, 3) list five physical reasons the state of Texas contains disparate climate zones: "the State being located (1) downwind from mountain ranges to the west, (2) proximate to the Gulf of Mexico and the southern Great Plains, (3) west of the center of the Bermuda high pressure cell, (4) at relatively a low latitude, and by (5) the changes in land elevation from the high plains and mountains to the coastal plains." Corroboration of the climate regions is discussed with regard to the basic inferences of climatological controls such as solar radiation and the Texas land/ocean configuration. Knowledge about the physical processes and natural systems in Texas from my regional physical perspective as a native greatly aided the analysis section of the research. The numerical results from the multivariate statistical approach to climate classification are also discussed.

The results from the discriminant analysis in Table 4 indicate a 95.53% overall

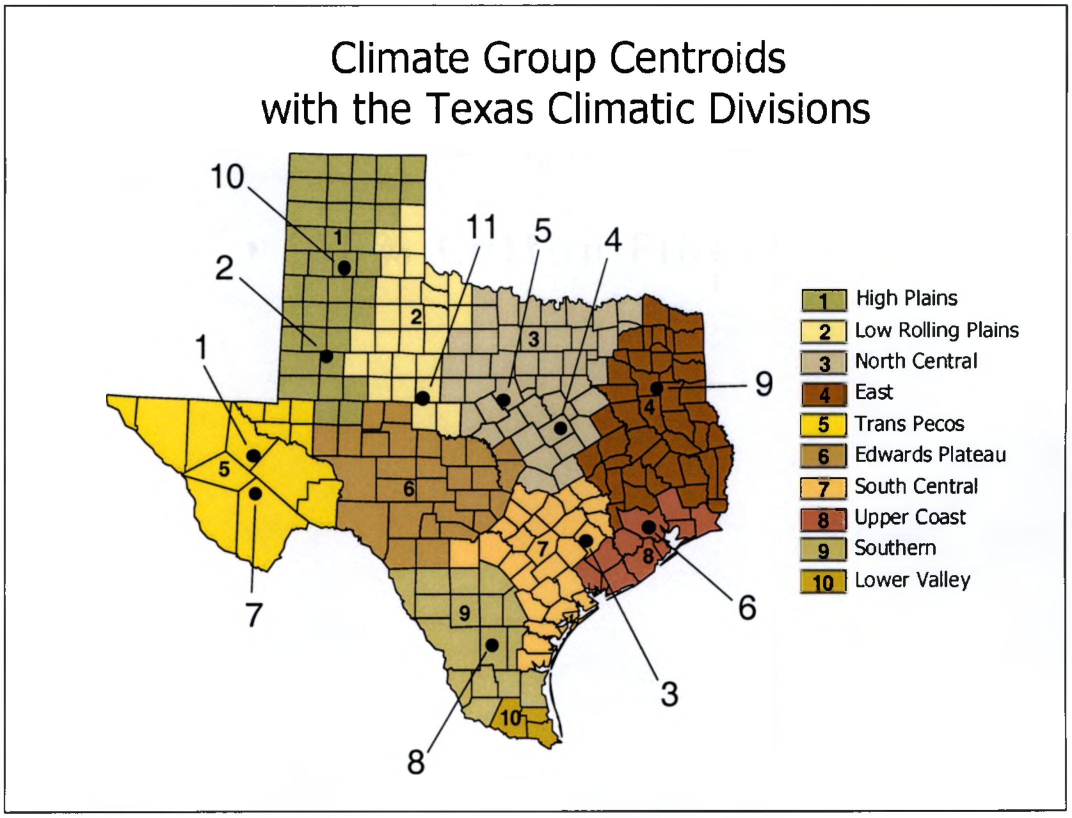



Fig. 4. Climate group centroids from the pilot study overlaid on the NWS Texas climatic divisions.

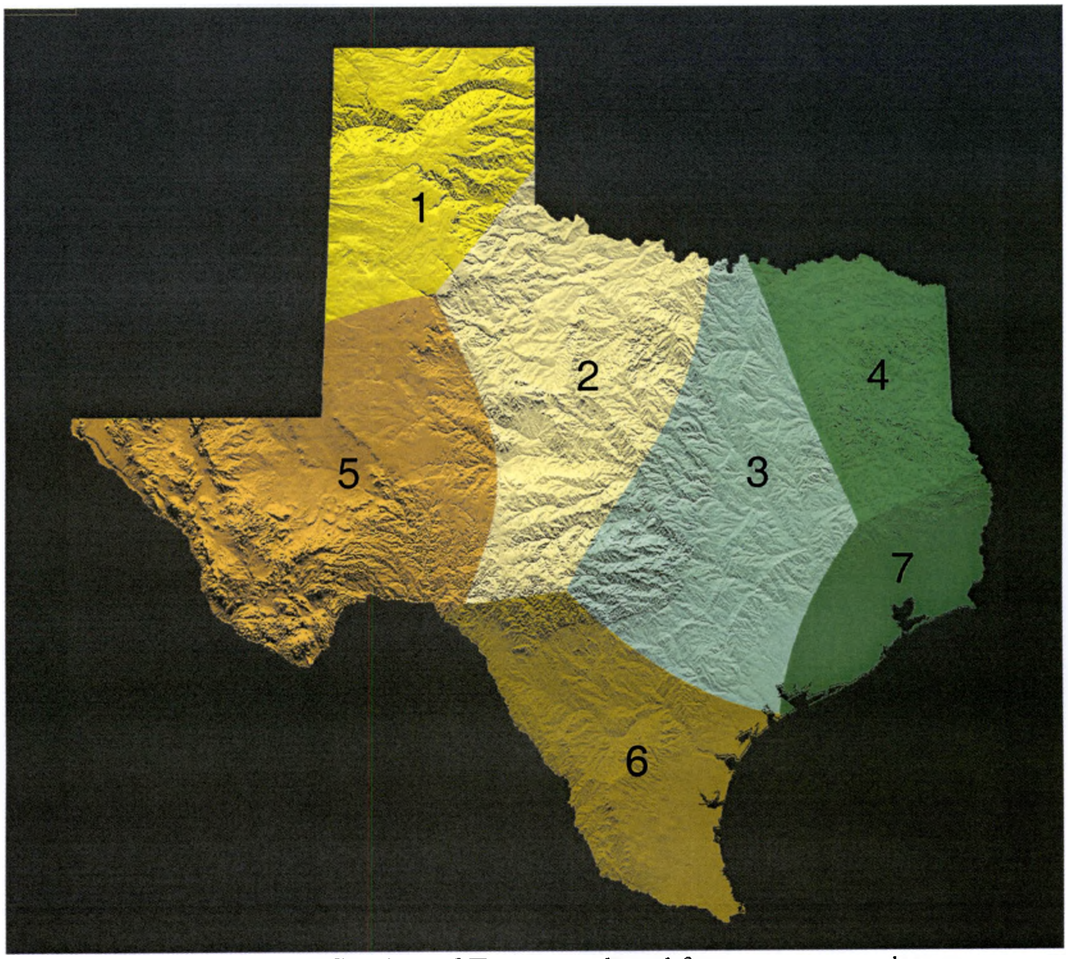



Fig. 5. The climate classification of Texas produced from my research.

Table 4. Confusion Table

**% CORRECT CLASSIFICATION**
(FROM ROW CLUSTER NUMBER TO
COLUMN CLUSTER NUMBER)

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | **TOTAL** |
|---|---|---|---|---|---|---|---|---|
| 1 | **95.52** (**64**) | 0.00 (0) | 0 00 (0) | 0 00 (0) | 4 48 (3) | 0.00 (0) | 0 00 (0) | **100.00** (**67**) |
| 2 | 1 33 (1) | **93.33** (**70**) | 5.33 (4) | 0 00 (0) | 0 00 (0) | 0 00 (0) | 0 00 (0) | **100.00** (**75**) |
| 3 | 0 00 (0) | 1 47 (1) | **97.06** (**66**) | 1 47 (1) | 0.00 (0) | 0.00 (0) | 0 00 (0) | **100.00** (**68**) |
| 4 | 0 00 (0) | 0 00 (0) | 5 66 (3) | **90.57** (**48**) | 0 00 (0) | 0 00 (0) | 3 77 (2) | **100.00** (**53**) |
| 5 | 0 00 (0) | 4 17 (2) | 0 00 (0) | 0.00 (0) | **95.83** (**46**) | 0.00 (0) | 0.00 (0) | **100.00** (**48**) |
| 6 | 0 00 (0) | 0 00 (0) | 0 00 (0) | 0.00 (0) | 1.75 (1) | **98.25** (**56**) | 0.00 (0) | **100.00** (**57**) |
| 7 | 0 00 (0) | 0.00 (0) | 0 00 (0) | 0 00 (0) | 0 00 (0) | 0 00 (0) | **100.00** (**35**) | **100.00** (**35**) |
| **TOTAL** | | | | | | | | **(385)/(403)** |

OVERALL CORRECT CLASSIFICATION
= **95.53%**

(# of weather stations in each group)

correct classification. Because the classification functions were generated from the same data observations as were run through them, the percent correct classification is overestimated. An independent set of sample observations (not used in the initial run) would need to be used to determine true classification accuracy (Klecka 1980).

The confusion table reveals not only the misclassification among the groups but also the differences between classes (Klecka 1980). Each group lists a percentage of the "known" observations that were correctly classed such as 90.57% for group 4. The rest of the misclassified stations (9.43% total) fall in groups 3 (5.66%) and 7 (3.77%), or group 4 was "confused" with groups 3 and 7. Observing the Texas climate classification map in Figure 5 shows that groups 3 and 7 border group 4, and the "confused" weather stations are located near the group transition zone boundaries. Because of the close proximity to group 4, these groups would have similar climate characteristics to this climate zone than group 4 would have with, for example, group 1.

## Graphical Comparison

The graphs in Figure 6 display the mean temperature and precipitation values from each month per group along with the number of observations (weather stations) from the descriptive statistical procedure. Refer to the Appendix for the entire numerical descriptive statistical outputs, including standard deviation values, per group per variable. The graphs helped reveal meaningful characteristics of each group. Because the new climate classes resemble the NWS climatic divisions, the Climatic Division Descriptions in Griffith and Bryan's *The Climates of Texas Counties* (1987) were used to assess the

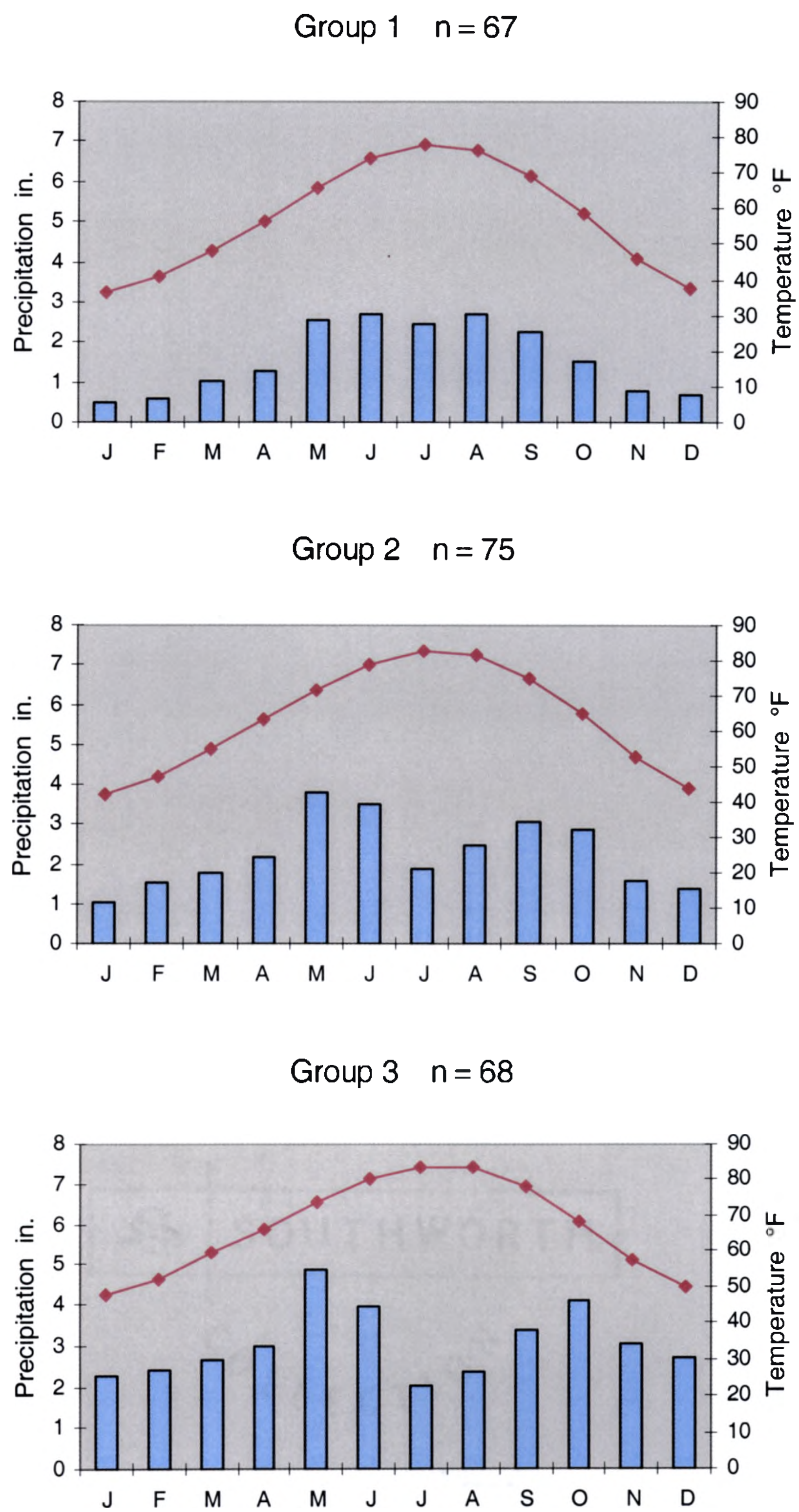
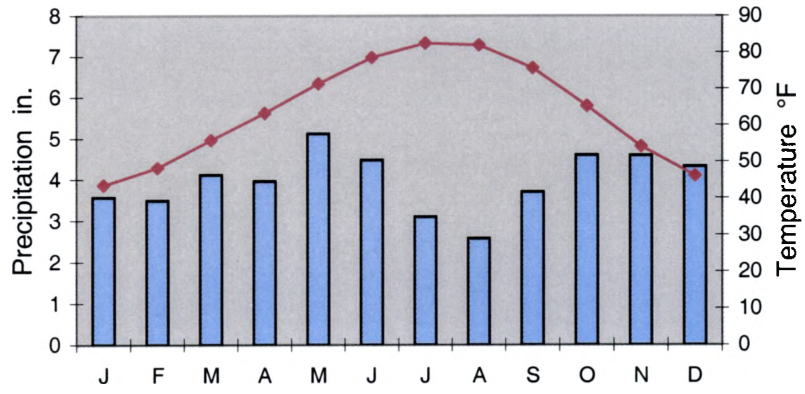
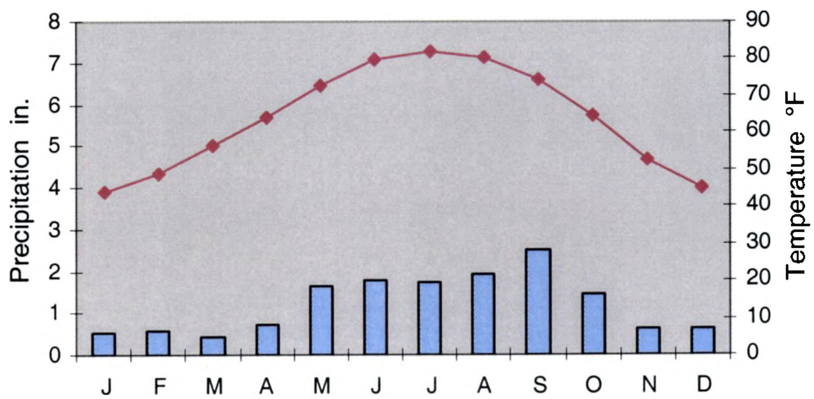



Fig. 6. The monthly mean temperature and precipitation charts per climate group. The lines show temperature in degrees Fahrenheit, and the bars show precipitation in inches.

Group 4 n = 53




Group 5 n = 48




Group 6 n = 57

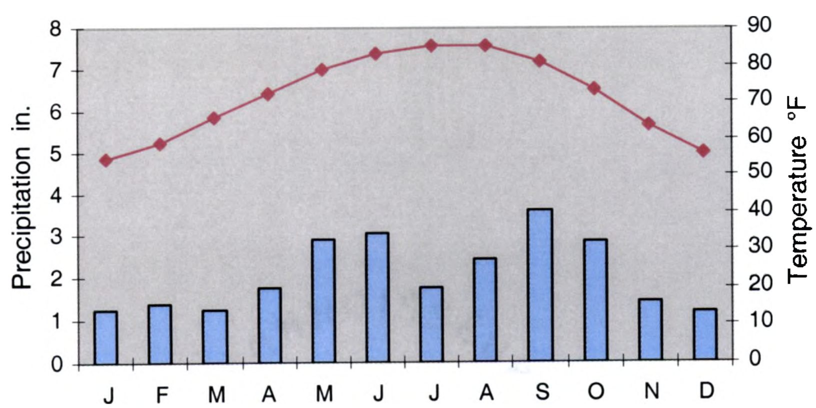



Fig. 6. - *Continued.* The lines show temperature in degrees Fahrenheit, and the bars show precipitation in inches.

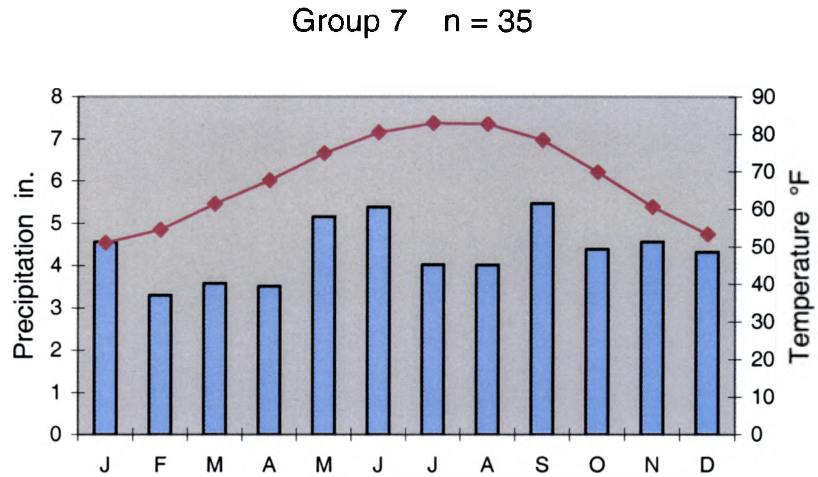



Fig. 6 - *Continued.* The lines show temperature in degrees Fahrenheit, and the bars show precipitation in inches.

accuracy of the descriptive statistics and the spatial arrangement of the Texas macroclimate zones produced from this study.

The groups follow a very similar pattern throughout the year with peak mean temperatures in July and August, and the coolest mean temperatures in January and December. The main difference is the higher temperatures in group 6 compared to all the other groups except group 7 which is only slightly cooler than group 6 throughout the year. Maritime air masses slightly cool temperatures for group 7 more so than group 6. Groups 6 and 7 are the southernmost Texas groups and so receive greater amounts of incoming solar radiation resulting in the higher temperatures.

Groups 2, 3, 4, 6, and 7 show a bimodal distribution for precipitation. These groups are situated in the central and eastern parts of the state and are effected mainly by rainfall in late spring and secondly by tropical disturbances from the Gulf of Mexico in early fall (Bomar 1983; Swanson 1995). Groups 1 and 5 in west Texas have generally unimodal distributions with the bulk of rainfall occurring from late spring through the summer and into early fall due to convective thunderstorms in the summer months (Bomar 1983). The group 5 region, considered a Subtropical Arid climate (Larkin and Bomar 1983), receives the majority of precipitation from orographic lifting due to mountainous topography (Bomar 1983).

Precipitation varies across the groups more than temperature. This is apparent not only when comparing the graphs but also by observing the separability plot (Figure 7). The seven groups were plotted with mean annual temperature on the x-axis and total annual precipitation on the y-axis to graphically display the separability between the

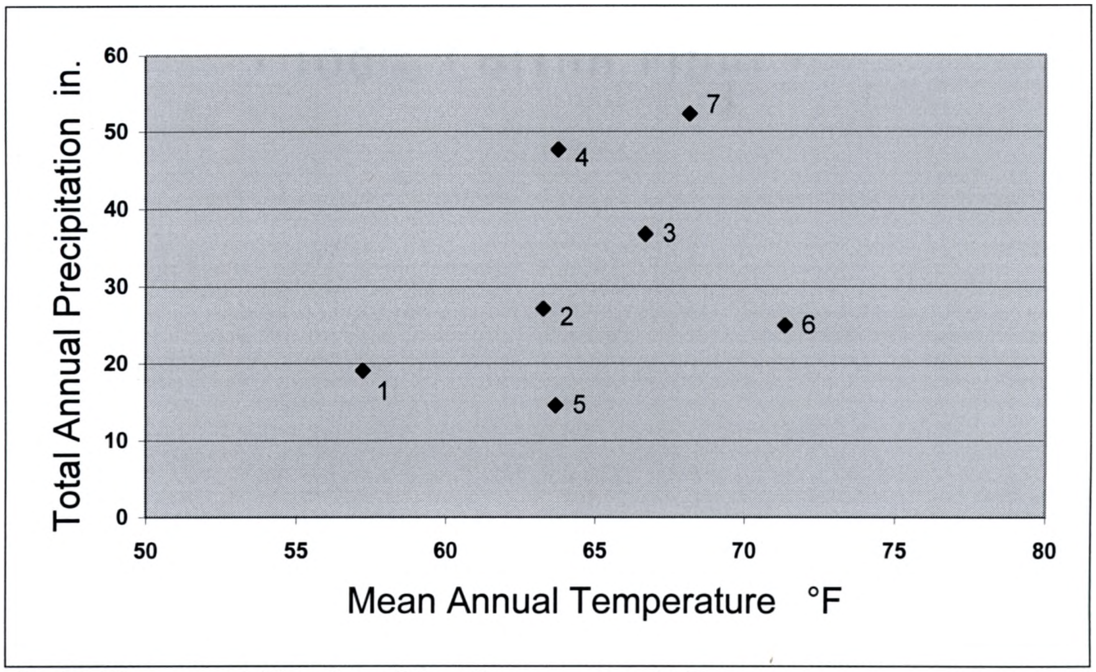
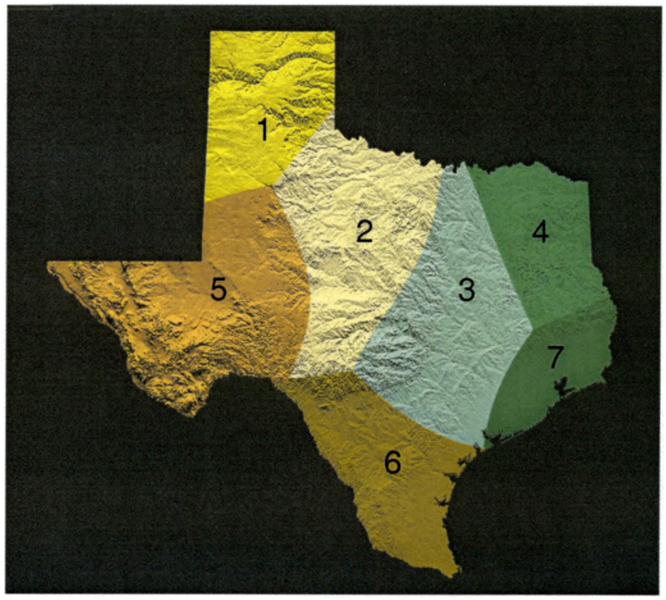



Fig. 7. The separability plot of the climate groups in Texas.

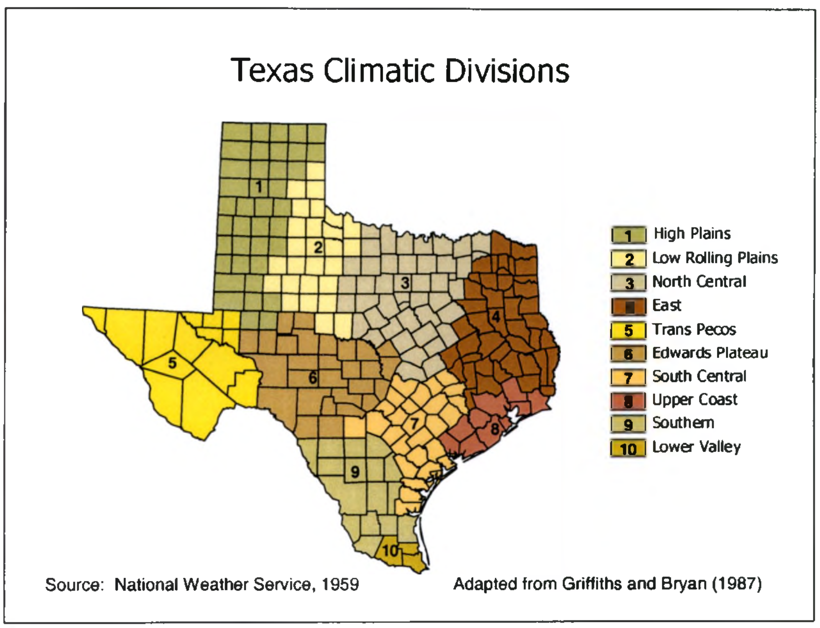
groups. The data points' structure reveals greater variability for the total annual precipitation than the mean annual temperature. For example, groups 4 – 2 – 5 have almost the same mean annual temperature but significantly different total annual precipitation values. Groups 4 and 5 have approximately a 30-inch range in precipitation but only a tenth of a F° difference in temperature; these groups are located at similar latitudes but at extreme longitudinal positions in Texas.

## Comparison to the NWS Climatic Divisions Map

A comparison is made with the statistically derived climate map completed in this research and the 1959 NWS divisions map shown together in Figure 8. A very similar pattern exists between the two maps. Group 1 corresponds with the High Plains, group 2 with the Low Rolling Plains, group 3 with the North Central and South Central, group 4 with the East, group 5 with the Trans Pecos, group 6 with the Southern, and group 7 with the Upper Coast. The major differences are the absences of the Edwards Plateau and Lower Valley climate zones that are shown on the NWS map but not the map derived from my research. More than likely, the Edwards Plateau region was not defined on my map as a distinct climate class because the area is a convergence or transition zone between several different macroclimate types commonly called a Subtropical Subhumid climate (Larkin and Bomar 1983). This region fluctuates between abnormally wet and dry years, and the 30-year averaged data used in this study reduced the impact of these extremes. This climate type was not distinct enough (did not manifest itself in the raw station data) to appear as a separate zone in my statistically derived climate classification map. The Lower Valley region is likely very similar to the climate of group 6 and so was




a.




b.

Fig. 8. The comparison of: *a,* the climate classification of Texas produced from my research and *b,* the NWS Texas climatic divisions.

not classed separately. These two differences were probably included on the 1959 NWS map due to common perceptions of these areas as distinct physiographic and cultural regions, which were the main controls behind the spatial arrangement of the NWS climatic divisions.

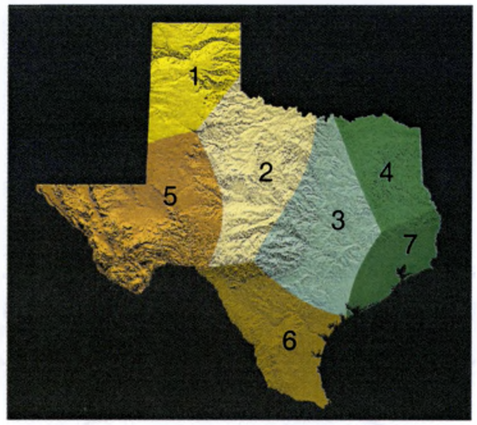
Because physiographic connections to climate were important for the NWS climate map, my new climate classes were overlaid on the DEM as a hillshade (refer to Figure 5). My map revealed only a few associations between major landforms and the climate in Texas. My climate classification transition zones are fairly close to physiographic boundaries, most apparent between groups 4 and 7 and between groups 2 and 6. However, there seems to be no major physiographic breaks between groups 2 and 3, groups 1 and 5, and groups 3 and 4 because the classification process utilized the statistical properties of the station data, not the physics operating at a particular point. Although documentation supports the relationship between Texas landforms and climate (Swanson 1995), such as orographic precipitation on the Edwards Plateau by the abrupt elevation change of the Balcones Escarpment, these trends are apparently not significant in the 30-year averaged temperature and precipitation data.

## Comparison to a MODIS Satellite Image

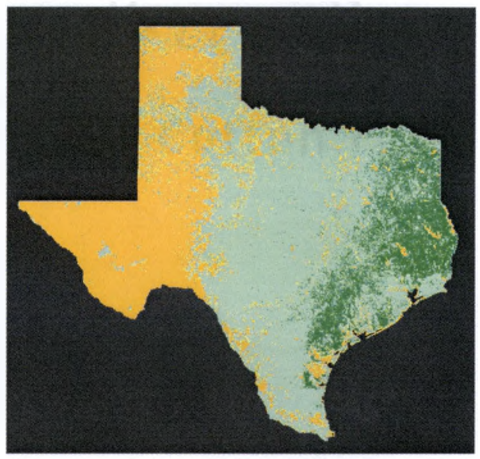
A MODIS (Moderate Resolution Imaging Spectroradiometer) satellite NDVI (Normalized Difference Vegetation Index) image of Texas was also compared to my statistically derived Texas climate map. The cloudless MODIS image was acquired on October 14, 2001. The near infrared (NIR) and red (R) bands were used to calculate the NDVI ratio (credited to Rouse et al. 1973) utilizing the following equation:

(NIR – R) / (NIR + R). The NDVI is a good indicator of vegetation because the NIR band detects a high infrared reflectance from plants and trees due to leaf skin properties, and the R band detects high absorption levels of visible light from leaf pigments caused by chlorophyll (Ray 1994). In other words, this ratio is high for healthy plants and trees and is indicated on the NDVI image in Figure 9b as dark green pixels. The brown areas indicate low NDVI values; light green pixels are in between these two extremes. The spatial pattern of vegetation health is similar to the general longitudinal distribution of precipitation because of the direct relationship between vegetation and rainfall. Groups 4 and 7 from the statistical climate classification of Texas map (Figure 9a) correspond to the dark green areas on the NDVI image because these zones receive high precipitation totals, while groups 1 and 5 are matched with the brown NDVI areas because these climate classes do not accumulate as much precipitation as the other zones. Groups 2, 3, and 6 fall in the light green interim NDVI category.

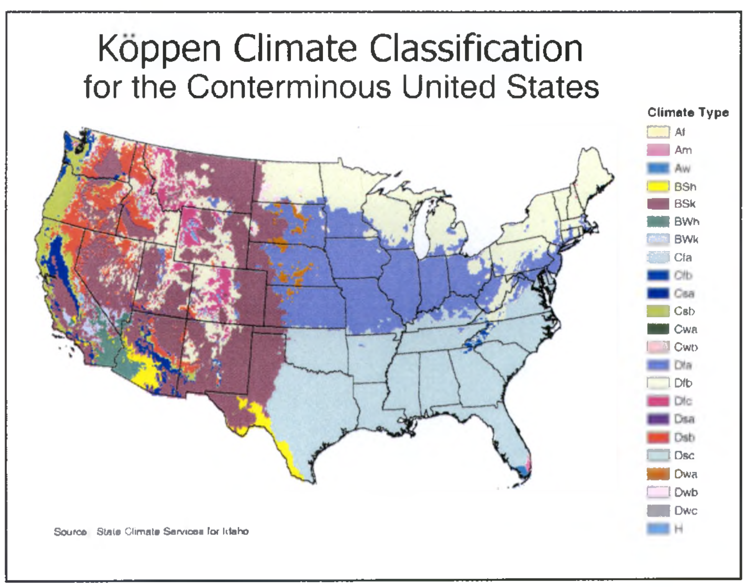
Because climate classifications were traditionally based on the vegetation / precipitation dependence, a climate map of the conterminous United States classed from Köppen's thresholds (generated from vegetation characteristics) by the State Climate Services for Idaho is included for comparison in Figure 9c. Three main types of climate can be distinguished in Texas on Köppen's map: Cfa, Humid Subtropical; BSh, Tropical and Subtropical Steppe; and BSk, Middle Latitude Desert. Some Köppen climate maps show BWh, Tropical and Subtropical Desert, as a climate region in western portions of Texas too (Espenshade, Hudson, and Morrison 1995). These general longitudinally distributed climate regions in Texas correspond well with the NDVI because




a.



b.




c.

Fig. 9. The climate and vegetation representations for comparisons: *a,* the climate classification of Texas produced from my research; *b,* the NDVI of a MODIS satellite scene; and *c,* a Köppen climate classification of the conterminous United States.

vegetation is traditionally the major control for Köppen maps.

## Strengths and Limitations

The Texas macroclimate map, classed from multivariate statistics with the 1971-2000 data set, was analyzed to identify the classification's strengths and limitations. The following are important strengths of my Texas climate classification map:

1. Climate variables (monthly temperature and precipitation normals) were used instead of forming transition zones based on physiographic or political boundaries.
2. The classification produced discrete homogeneous climate zones in Texas. The weather station locations were interpolated into grids to simplify the cartographic and therefore communication process.
3. Most climate maps display data as isolines of a single climate element as in Larkin and Bomar's *Climatic Atlas of Texas* (1983). The new Texas climate classification used a combination of two climate elements (temperature and precipitation) to create a more inclusive climate map.

Conversely, limitations of my Texas climate classification map exist and are listed here:

1. Temperature and precipitation normals were the only climatic elements used, but many other factors contribute to the climate of a region such as wind and evaporation variables (Larkin and Bomar 1983).
2. The new groups or classes were not subjectively labeled with common names. Identifying and making connections with the Texas macroclimate zones and

familiar geographic features (physical and cultural) may present problems for the user.

# CHAPTER VI

## SUMMARY, CONCLUSIONS, AND FUTURE WORK

After a critical evaluation of climate classification literature, an attempt was made to naturally group the macroclimates of Texas. Trend surfacing interpolated 403 weather stations into regular raster grids from NCDC 1971-2000 monthly temperature and precipitation normals. The multivariate statistical procedures cluster analysis and discriminant analysis classed the original data from the 403 weather stations into discrete groups and established decision rules for mapping the temperature and precipitation grids.

A multivariate statistical analysis provided discrete classed regions of the macroclimate in Texas in order to interpret and compare with the 1959 NWS divisions map, the physiography, and the ecological patterns. The hypothesis is accepted that cluster analysis and discriminant analysis of temperature and precipitation normals will naturally group the macroclimate of Texas for these types of meaningful comparisons. This study was successful for disclosing the following research matters and considerations for statistically classifying the climate of Texas:

1. The proposed methodology for classifying climates for Texas was deemed appropriate based on the statistical and visual analysis of the results.

2. The fairly large number of weather stations used in this study improved the accuracy in the statistically based classification process; this is a considerable improvement over previous statistical approaches to climate classifications that used small numbers of stations.
3. Two climate variables (monthly mean temperature normals and monthly mean precipitation normals) for January through December did a good job classifying the study area. Temperature and precipitation are the main climate controls, and the data set was inclusive for all twelve months over a 30-year period.
4. Temperature and precipitation surfaces facilitated the cartographic process and unlike previous studies, graphically displayed a raster grid of the climate classes that were overlaid on a hillshaded DEM.
5. Describing and understanding the new Texas climate classification was less complicated from the point of view of the map display, statistics indicated by the confusion table, information imparted from the mean graphs, and the overall perspective obtained from the separability plot.

Possible objectives for future work with this study are plentiful. Within the results, more descriptive statistics could be presented and evaluated. Instead of just the means for each variable per group, minimums, maximums, ranges, and standard deviations could be analyzed to draw more conclusions about the spatial differences between the climate classes. For example, the coefficient of variation could be calculated for the precipitation variables to demonstrate the structure of each class through the amount of dispersion expressed as a percentage (Spiegel 1961). Elevation could be added to the trend surfacing equation because of the variable's effect on climate. More climate variables such as evaporation and wind could be added to the classification process as well as different data time periods. Depending on the nature of the study, the methodology developed in this research for producing a multivariate statistical climate classification could easily be applied to other states or regions.

# APPENDIX

## DESCRIPTIVE STATISTICS PER CLIMATE GROUP PER CLIMATE VARIABLE

**GROUP 1 n = 67**

| Climate Variable | Minimum | Maximum | Range | Mean | Standard Deviation |
|---|---|---|---|---|---|
| *Temperature °F* | | | | | |
| January | 30.700000 | 46.900000 | 16.200000 | 36.364180 | 3.315602 |
| February | 36.200000 | 50.300000 | 14.100000 | 40.970140 | 3.025366 |
| March | 43.000000 | 56.200000 | 13.200000 | 48.110440 | 2.621145 |
| April | 51.700000 | 62.600000 | 10.900000 | 56.429840 | 2.356819 |
| May | 59.500000 | 70.300000 | 10.800000 | 65.459720 | 2.216034 |
| June | 67.100000 | 77.100000 | 10.000000 | 74.216420 | 1.747963 |
| July | 69.000000 | 81.600000 | 12.600000 | 77.774640 | 2.249525 |
| August | 67.600000 | 80.000000 | 12.400000 | 76.019410 | 2.262693 |
| September | 62.000000 | 72.000000 | 10.000000 | 69.047750 | 1.802844 |
| October | 53.300000 | 62.300000 | 9.000000 | 58.573120 | 1.935152 |
| November | 41.300000 | 54.100000 | 12.800000 | 46.020900 | 2.491908 |
| December | 32.700000 | 48.300000 | 15.600000 | 37.782090 | 3.074638 |
| *Precipitation inches* | | | | | |
| January | .280000 | .710000 | .430000 | .511940 | .102206 |
| February | .270000 | .970000 | .700000 | .592090 | .193466 |
| March | .220000 | 2.220000 | 2.000000 | 1.022388 | .554379 |
| April | .100000 | 2.470000 | 2.370000 | 1.282090 | .582927 |
| May | .310000 | 4.560000 | 4.250000 | 2.569104 | .957261 |
| June | .680000 | 3.960000 | 3.280000 | 2.700000 | .734431 |
| July | 1.340000 | 3.820000 | 2.480000 | 2.469254 | .394440 |
| August | 2.060000 | 4.020000 | 1.960000 | 2.716268 | .402509 |
| September | .930000 | 3.460000 | 2.530000 | 2.236866 | .514092 |
| October | .710000 | 2.390000 | 1.680000 | 1.497164 | .305786 |
| November | .300000 | 1.360000 | 1.060000 | .806716 | .238845 |
| December | .320000 | .930000 | .610000 | .673731 | .152632 |

**GROUP 2 n = 75**

| Climate Variable | Minimum | Maximum | Range | Mean | Standard Deviation |
|---|---|---|---|---|---|
| *Temperature °F* | | | | | |
| January | 36.500000 | 47.400000 | 10.900000 | 42.124000 | 2.643163 |
| February | 42.200000 | 51.800000 | 9.599998 | 47.071990 | 2.383289 |
| March | 50.300000 | 59.400000 | 9.100002 | 54.953330 | 2.171674 |
| April | 59.600000 | 67.200000 | 7.599998 | 63.249320 | 1.684336 |
| May | 68.700000 | 75.100000 | 6.400002 | 71.589340 | 1.312345 |
| June | 77.000000 | 80.900000 | 3.900002 | 78.919990 | .914232 |
| July | 79.600000 | 85.100000 | 5.500000 | 82.861330 | 1.212046 |
| August | 79.000000 | 84.100000 | 5.099998 | 81.840020 | 1.123875 |
| September | 72.200000 | 77.200000 | 5.000000 | 74.932010 | 1.069471 |
| October | 61.600000 | 67.600000 | 6.000000 | 64.802660 | 1.433818 |
| November | 48.400000 | 56.700000 | 8.299999 | 52.726660 | 1.998517 |
| December | 38.600000 | 49.100000 | 10.500000 | 44.144000 | 2.457615 |
| *Precipitation inches* | | | | | |
| January | .570000 | 1.730000 | 1.160000 | 1.052533 | .277577 |
| February | .730000 | 2.390000 | 1.660000 | 1.526267 | .392498 |
| March | .760000 | 3.370000 | 2.610000 | 1.764800 | .520127 |
| April | 1.430000 | 3.330000 | 1.900000 | 2.160666 | .432732 |
| May | 2.570000 | 5.170000 | 2.600000 | 3.810933 | .647893 |
| June | 2.480000 | 4.410000 | 1.930000 | 3.496000 | .441892 |
| July | 1.100000 | 2.680000 | 1.580000 | 1.889733 | .278275 |
| August | 1.570000 | 3.180000 | 1.610000 | 2.473866 | .326722 |
| September | 2.140000 | 4.080000 | 1.940000 | 3.083600 | .411261 |
| October | 1.600000 | 4.390000 | 2.790000 | 2.887467 | .556616 |
| November | .890000 | 2.730000 | 1.840000 | 1.577867 | .449252 |
| December | .620000 | 2.380000 | 1.760000 | 1.388267 | .432076 |

**GROUP 3 n = 68**

| Climate Variable | Minimum | Maximum | Range | Mean | Standard Deviation |
|---|---|---|---|---|---|
| *Temperature °F* | | | | | |
| January | 42.400000 | 53.500000 | 11.100000 | 47.548530 | 2.802654 |
| February | 47.600000 | 57.300000 | 9.700001 | 51.948520 | 2.391718 |
| March | 55.100000 | 63.700000 | 8 600002 | 59.448530 | 2.168243 |
| April | 63.000000 | 69.700000 | 6.699997 | 66.364720 | 1.678798 |
| May | 71.300000 | 76.600000 | 5.299995 | 73.842640 | 1.319414 |
| June | 77.900000 | 82.000000 | 4 099998 | 80.241150 | 863790 |
| July | 80.600000 | 85.400000 | 4.800003 | 83.649990 | .857491 |
| August | 80.600000 | 85.200000 | 4.599998 | 83.467660 | 856054 |
| September | 75 600000 | 80.100000 | 4.500000 | 77 891170 | 1.091812 |
| October | 65.300000 | 72.300000 | 7.000000 | 68.517640 | 1.643179 |
| November | 53.600000 | 62.700000 | 9.100002 | 57.677940 | 2 190475 |
| December | 45.400000 | 55.200000 | 9.799999 | 46.683820 | 2.576684 |
| *Precipitation inches* | | | | | |
| January | 1.270000 | 3.810000 | 2.540000 | 2.245294 | .583381 |
| February | 1.450000 | 3.370000 | 1.920000 | 2.421324 | .380279 |
| March | 1.550000 | 3.700000 | 2 150000 | 2 665294 | .432307 |
| April | 2.210000 | 3.890000 | 1.680000 | 3.003088 | .344966 |
| May | 3.780000 | 5.750000 | 1.970000 | 4 862206 | .378008 |
| June | 2.950000 | 5.030000 | 2 080000 | 3.941765 | .499781 |
| July | 1.180000 | 2.900000 | 1.720000 | 2.027353 | .319070 |
| August | 1.390000 | 3.340000 | 1.950000 | 2.381470 | .412136 |
| September | 2.420000 | 5.000000 | 2.580000 | 3.377353 | .552932 |
| October | 2.870000 | 4.810000 | 1.940000 | 4.088530 | .404167 |
| November | 1.830000 | 4 170000 | 2.340000 | 3.016029 | .519829 |
| December | 1.400000 | 3.880000 | 2.480000 | 2.722059 | .509295 |

**GROUP 4 n = 53**

| Climate Variable | Minimum | Maximum | Range | Mean | Standard Deviation |
|---|---|---|---|---|---|
| *Temperature °F* | | | | | |
| January | 39.400000 | 48.600000 | 9.199997 | 43 420760 | 2.534826 |
| February | 44.700000 | 52.900000 | 8.200001 | 48 147170 | 2.244564 |
| March | 52 300000 | 60.300000 | 8.000000 | 55.811330 | 2 051776 |
| April | 60.300000 | 66.600000 | 6 299999 | 63.164150 | 1.571366 |
| May | 69.000000 | 73.800000 | 4.800003 | 71.269810 | 1.299187 |
| June | 76.600000 | 80.300000 | 3.700005 | 78.466040 | .896449 |
| July | 80.600000 | 85.000000 | 4.400002 | 82.432080 | .781458 |
| August | 80.000000 | 84.300000 | 4.300003 | 81.901890 | .853224 |
| September | 73.300000 | 77.700000 | 4.399994 | 75.558490 | 1.136408 |
| October | 62.600000 | 67.700000 | 5.099998 | 65.122640 | 1 437870 |
| November | 51 000000 | 57.700000 | 6.700001 | 54.047170 | 1.878110 |
| December | 42.300000 | 50.300000 | 8.000000 | 45.947160 | 2.254447 |
| *Precipitation inches* | | | | | |
| January | 1.880000 | 5.730000 | 3 850000 | 3.573773 | .974570 |
| February | 2.230000 | 4.560000 | 2.330000 | 3.488680 | .522507 |
| March | 3.070000 | 5.170000 | 2 100000 | 4.117925 | .513966 |
| April | 3 130000 | 4 890000 | 1.760000 | 3.959622 | 382729 |
| May | 4.290000 | 6.250000 | 1.960000 | 5.121132 | .505393 |
| June | 2.780000 | 5 490000 | 2 710000 | 4.483396 | .448694 |
| July | 1 810000 | 4 420000 | 2.610000 | 3 104906 | .589973 |
| August | 1.680000 | 3 870000 | 2.190000 | 2 581132 | .466399 |
| September | 2.980000 | 4.740000 | 1.760000 | 3.705848 | .409302 |
| October | 3.750000 | 5.400000 | 1.650000 | 4.601320 | .382443 |
| November | 3.030000 | 6.200000 | 3.170000 | 4.590566 | .689714 |
| December | 2.600000 | 6 080000 | 3 480000 | 4.326982 | 754936 |

**GROUP 5 n = 48**

| Climate Variable | Minimum | Maximum | Range | Mean | Standard Deviation |
|---|---|---|---|---|---|
| *Temperature °F* | | | | | |
| January | 39.600000 | 49.100000 | 9.500000 | 44.054170 | 2.131774 |
| February | 44.200000 | 54.200000 | 10.000000 | 48.985420 | 2.083275 |
| March | 51.700000 | 61.100000 | 9.399998 | 56.225000 | 2.265115 |
| April | 59.600000 | 69.200000 | 9.599998 | 64 041670 | 2.281595 |
| May | 68.600000 | 77.600000 | 9.000000 | 72.668750 | 2.115426 |
| June | 75.500000 | 83.200000 | 7.699997 | 79 706250 | 1.853257 |
| July | 76.200000 | 84.300000 | 8.100006 | 81.679160 | 1 969599 |
| August | 74.500000 | 83.500000 | 9.000000 | 80.152090 | 2.072063 |
| September | 70.200000 | 78.100000 | 7 900002 | 74.143750 | 1.869969 |
| October | 61.100000 | 68.700000 | 7.599998 | 64.550000 | 1.811673 |
| November | 49.300000 | 57.500000 | 8.200001 | 52.847910 | 1.999311 |
| December | 41.200000 | 50.000000 | 8.799999 | 45.097920 | 2.059361 |
| *Precipitation inches* | | | | | |
| January | .320000 | .850000 | .530000 | .508958 | .125584 |
| February | 290000 | .920000 | .630000 | .557708 | 192986 |
| March | .160000 | 1.070000 | .910000 | 452917 | .258160 |
| April | .080000 | 1.530000 | 1.450000 | .736667 | .397735 |
| May | .260000 | 3.180000 | 2.920000 | 1.643333 | 794814 |
| June | .600000 | 2.840000 | 2.240000 | 1.760417 | .589182 |
| July | .940000 | 3.040000 | 2.100000 | 1.739167 | .431218 |
| August | 1.060000 | 2.920000 | 1.860000 | 1.947708 | .405741 |
| September | 1.200000 | 3.630000 | 2.430000 | 2.506875 | .619409 |
| October | .810000 | 2.270000 | 1.460000 | 1.443541 | .419952 |
| November | .350000 | 1 150000 | .800000 | .641458 | .194586 |
| December | .380000 | .980000 | .600000 | .643958 | .123232 |

**GROUP 6 n = 57**

| Climate Variable | Minimum | Maximum | Range | Mean | Standard Deviation |
|---|---|---|---|---|---|
| *Temperature °F* | | | | | |
| January | 47.400000 | 60.100000 | 12.700000 | 54.412280 | 2.912330 |
| February | 52.700000 | 63.800000 | 11.100000 | 58.533320 | 2.478020 |
| March | 61.700000 | 70.800000 | 9.100002 | 65.838580 | 2.249140 |
| April | 68.900000 | 76.000000 | 7.099998 | 72.061400 | 1.884157 |
| May | 75.800000 | 82.600000 | 6.799995 | 78.512280 | 1.714593 |
| June | 80.800000 | 87.600000 | 6.799995 | 83.226310 | 1.626598 |
| July | 83.000000 | 88.500000 | 5.500000 | 85.080690 | 1.303164 |
| August | 82.800000 | 87.900000 | 5.099998 | 84.899990 | 1.082442 |
| September | 78.800000 | 83.200000 | 4.399994 | 80.887720 | .998584 |
| October | 69.500000 | 76.400000 | 6.900002 | 73.084200 | 1.714696 |
| November | 57.500000 | 69.500000 | 12.000000 | 63.663150 | 2.792989 |
| December | 48.600000 | 61.600000 | 13.000000 | 56.080710 | 3.034496 |
| *Precipitation inches* | | | | | |
| January | .300000 | 3.070000 | 2.770000 | 1.244386 | .544796 |
| February | .280000 | 2.840000 | 2.560000 | 1.387369 | .524498 |
| March | .130000 | 2.830000 | 2.700000 | 1.253158 | .573454 |
| April | .290000 | 3.190000 | 2.900000 | 1.763158 | .590337 |
| May | .660000 | 4.490000 | 3.830000 | 2.926492 | .775329 |
| June | 1.340000 | 4.960000 | 3.620000 | 3.053158 | .737543 |
| July | 1.020000 | 3.050000 | 2.030000 | 1.764035 | .467335 |
| August | 1.260000 | 3.560000 | 2.300000 | 2.448772 | .570955 |
| September | 1.180000 | 6.120000 | 4.940000 | 3.587719 | 1.291322 |
| October | .990000 | 4.610000 | 3.620000 | 2.896842 | .897015 |
| November | .290000 | 2.560000 | 2.270000 | 1.451404 | .554863 |
| December | .230000 | 2.270000 | 2.040000 | 1.189123 | .425971 |

**GROUP 7 n = 35**

| Climate Variable | Minimum | Maximum | Range | Mean | Standard Deviation |
|---|---|---|---|---|---|
| *Temperature °F* | | | | | |
| January | 46.400000 | 55.800000 | 9.399998 | 51.111430 | 2.417994 |
| February | 50.500000 | 59.000000 | 8.500000 | 54.562860 | 2.087482 |
| March | 58.300000 | 65.400000 | 7.100002 | 61.408570 | 1.798590 |
| April | 64.800000 | 70.400000 | 5.599998 | 67.637150 | 1.627488 |
| May | 72.700000 | 77.100000 | 4.400002 | 74.914280 | 1.277773 |
| June | 78.400000 | 82.400000 | 4.000000 | 80.545710 | 1.032401 |
| July | 81.000000 | 84.700000 | 3.699997 | 82.951430 | 846574 |
| August | 80.700000 | 84.400000 | 3.700005 | 82.711430 | .899365 |
| September | 76.100000 | 81.100000 | 5.000000 | 78.448580 | 1.235617 |
| October | 66.000000 | 74.100000 | 8.099998 | 69.822850 | 2.060101 |
| November | 56.600000 | 65.400000 | 8.800003 | 60.562860 | 2.340002 |
| December | 49.000000 | 58.100000 | 9.099998 | 53.285720 | 2.429189 |
| *Precipitation inches* | | | | | |
| January | 2.860000 | 6.300000 | 3.440000 | 4.563143 | .974561 |
| February | 2.450000 | 4.630000 | 2.180000 | 3.302857 | .620888 |
| March | 2.420000 | 5.370000 | 2.950000 | 3.579142 | .816675 |
| April | 2.170000 | 4.590000 | 2.420000 | 3.510857 | .604997 |
| May | 3.700000 | 6.060000 | 2.360000 | 5.157429 | .569537 |
| June | 3.960000 | 6.950000 | 2.990000 | 5.385429 | .858082 |
| July | 2.670000 | 6.620000 | 3.950000 | 4.024571 | .902902 |
| August | 3.160000 | 5.870000 | 2.710000 | 4.017429 | .648554 |
| September | 3.970000 | 7.800000 | 3.830000 | 5.467144 | .957889 |
| October | 3.460000 | 5.770000 | 2.310000 | 4.391143 | .550564 |
| November | 3.390000 | 5.880000 | 2.490000 | 4.560286 | .622200 |
| December | 2.390000 | 6.670000 | 4.280000 | 4.316857 | 1.128232 |

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# VITA

Gayla Jewell Malson was born in Chanute, Kansas, on December 7, 1978. After completing her diploma requirements at Martin High School, Arlington, Texas, in 1997, she entered Southwest Texas State University in San Marcos, Texas. Gayla searched for the appropriate personal career path for a few semesters and soon declared Geography as her major. She received the degree of Bachelor of Science in Geography concentrating in Cartography / Geographic Information Systems from Southwest Texas State University in May 2001. In June 2001, Gayla entered the Graduate School for a Master of Applied Geography at Southwest Texas State University, San Marcos, Texas. Throughout her graduate work, she was employed as a Graduate Assistant (teaching and research) at the SWT Geography Department. In the summer and fall of 2002, Gayla held an internship at the Texas Natural Resources Information System, Austin, Texas.

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