Digital Climatic Atlas of Texas

Final Project Report

prepared by

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Executive Summary

A digital climatic atlas of Texas has been created that defines the climate in terms of major climatic parameters, precipitation, maximum and minimum temperatures and lake evaporation. Datasets from wide-ranging sources of varying quality and resolutions were processed and assembled to create this comprehensive dataset of monthly and annual decadal means both in gridded (4 km) and point format for 11 decades from 1890 to 2000. The datasets used to develop these gridded and point decadal means went through a variety of QA/QC procedures, data homogenization and infilling techniques to create the best possible serially complete data for estimating long-term decadal means. The accuracy of gridded datasets of precipitation and temperature obtained from the PRISM database were assessed based on independent sets of observation from the Texas High Plains ET network. Due to low station density and lack of long-term pan evaporation data, the aerodynamic method was used to create high resolution lake evaporation estimates based on the gridded weather parameters obtained from PRISM and subsequently adjusted based on the point observations. ArcGIS geodatabases containing gridded data and a database containing point monthly and annual decadal means of climatic parameters were developed to facilitate efficient transfer and use of data. Further, using this high resolution spatial data, a schema has been proposed to classify Texas into climatic zones of varying size by using a statistical procedure. This high-resolution digital climatic dataset will be of immense use for large scale and local water resources planning and conservation projects in addition to analysis of extreme events such as droughts and floods.

1.0 Introduction

Water resource studies in Texas often require accurate, long-term spatial and temporal climatic data such as monthly and annual decadal means of temperature, precipitation and evaporation for a variety of purposes. Until recently *Climatic Atlas of Texas* (LP-192), prepared in 1983 (Larkin and Bomar, 1983), has been used across Texas for such studies. The data used in developing the 1983 atlas was based on a 30-year climatic record from 1951 to 1980. Thirty year monthly and annual average rainfall and temperature contour maps were generated from 389 rain gages and 156 temperature gages. However, the 1983 climatic atlas of Texas is old and needed to be updated using the most recent climatic data and the latest Geographical Information System (GIS) techniques.

To fill this need, major technological advances in GIS during the last 22 years were used to produce a digital climatic atlas that provides data in the form of summarized decadal monthly and annual climatic means for the period from 1890 to 2000. The digital atlas is organized in the form of a high-resolution (4 km) ArcGIS raster geodatabase consisting of more than 715 raster datasets of decadal monthly and annual climatic parameters. This rich long-term database will be a valuable resource for a wide variety of analyses including water resources management and conservation, analysis of the spatial and temporal variability of droughts, analysis of local and regional climate variability, identification and examination of the nature of extreme events, and hydrological modeling.

2.0 Objectives

The objectives of this study are to: 1) develop digital datasets of monthly and annual means of precipitation, maximum temperature, minimum temperature and evaporation for each decade from 1890 to 2000 and 2) produce a climatic atlas of Texas similar in content to LP-192. Seven tasks as outlined below were designed to accomplish the objectives of this study.

1) Collecting precipitation, temperature, and evaporation data for Texas from 1890 to 2000
2) QA/QC of the station data
3) Producing a serially complete set of station data
4) Generating gridded monthly precipitation, maximum and minimum temperatures and lake evaporation coverages
5) Verifying the gridded PRISM climatic data
6) Calculating monthly and annual decadal means of gridded and point climatic data
7) Creating an ArcGIS geodatabase containing gridded and a database containing point monthly and annual decadal means of climatic parameters

3.0 Data and Methods

3.1 Collecting precipitation, temperature, and evaporation data for Texas from 1890 to 2000

Historical records of weather data such as precipitation and temperature were collected across Texas with hundreds of weather stations operated by the National Weather Service (NWS) and archived at the National Climatic Data Center (NCDC).

Most of these weather stations belong to the Cooperative Observer Program (COOP) and have been monitored by volunteers and contractors belonging to various government and private agencies across Texas since the creation of the COOP program in 1890. There are a few stations (usually at airports) that are operated and maintained partly or wholly by NWS staff called First-Order stations. Some of the COOP and First-Order stations also belong to the U.S. Historical Climatology Network (USHCN), for which continuous historical climate records are available for a minimum of 80 years since the early 1900's. These USHCN data have been evaluated using a comprehensive QA/QC procedure.

In addition to the NWS network of weather stations, there are also small networks of weather stations operated by the U.S. Department of Forest Service (RAWS – Remote Automated Weather Stations), Natural Resources Conservation Service (SCAN – Soil and Climate Analysis Network), and other mesonets and agricultural experimental station sites. However, these networks contain only few stations and the weather record for most of the stations belonging to these networks only begin in the 1990's. However, for the objectives of this study long-term historical records are needed to develop the decadal means. Hence in this study, weather data only from the NWS's COOP and First-Order network were used to develop the long-term decadal means.

One of the important tasks in developing the decadal means is to have a serially complete time series for each climatic parameter. Hence, in addition to stations within Texas, stations that are within a 100 mile buffer zone around Texas for the neighboring states Louisiana, Arkansas, Oklahoma, and New Mexico were also selected. The numbers of stations selected from USHCN and COOP sources for each state are shown in

Table 1. Of these stations, 1730 measure precipitation (Figure 1), 886 measure maximum temperature (Figure 2) and 882 measure minimum temperature (Figure 3).

Table 1. Stations selected to develop the long-term decadal means.

State	USHCN	COOP
Texas	44	1318
Louisiana	14	127
Arkansas	13	40
Oklahoma	44	173
New Mexico	24	214

In contrast to the station density for the major climatic parameters aforementioned, pan evaporation is measured at very few stations. Even among the few stations that measure evaporation, the record does not extend back to the early 1900's as would be needed to develop the climatic atlas. Based on the available data from Texas Water Development Board (TWDB) and Cooperative weather station's Summary of the Month (Data Set 3220) from NCDC (http://www.ncdc.noaa.gov/), there were about 232 stations in Texas and surrounding states with monthly evaporation measurements (Figure 4). Although some stations have long records of monthly evaporation since the 1920's, most of the stations have a continuous record only since the 1960's. Hence, models were used to estimate lake evaporation from climatic parameters such as temperature. Details on the estimation procedure of monthly evaporation are provided in section 3.4 of this report.

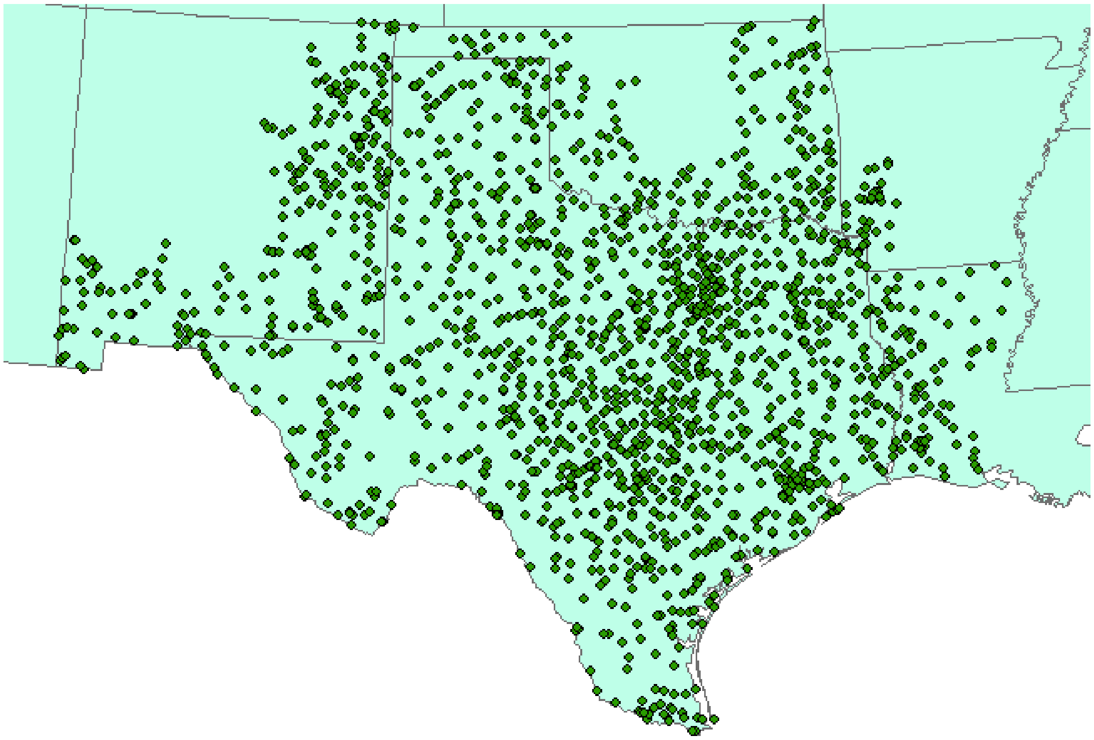

Figure 1. Stations that measure precipitation.

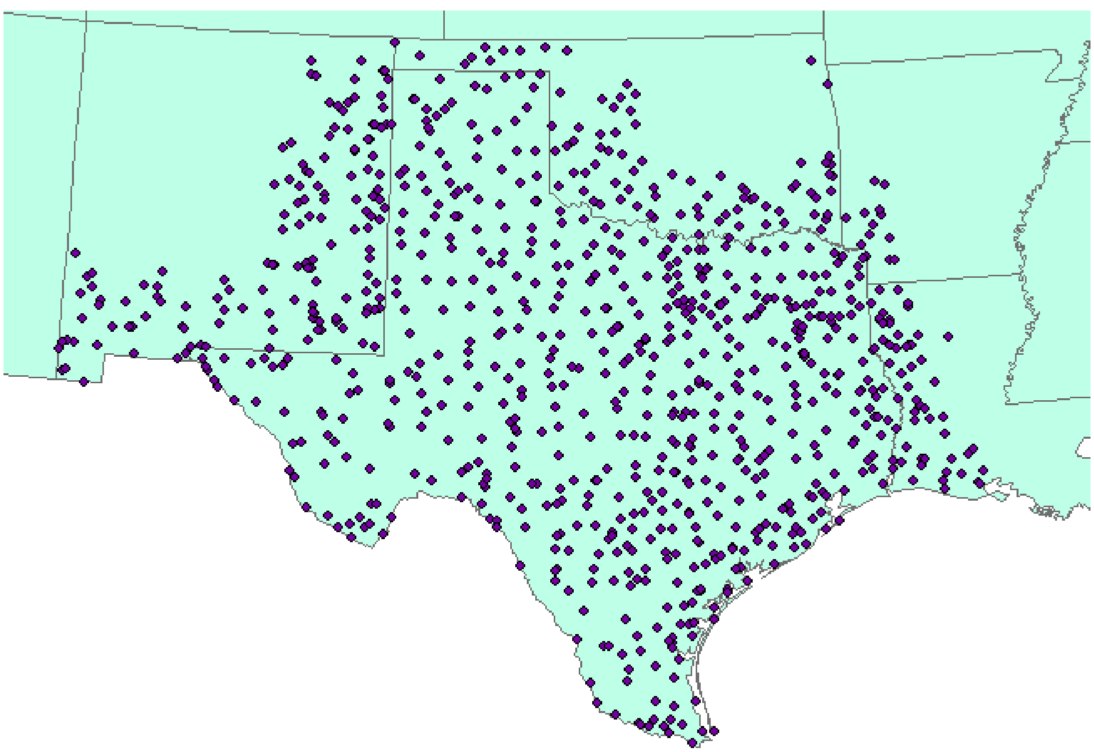

Figure 2. Stations that measure maximum temperature.

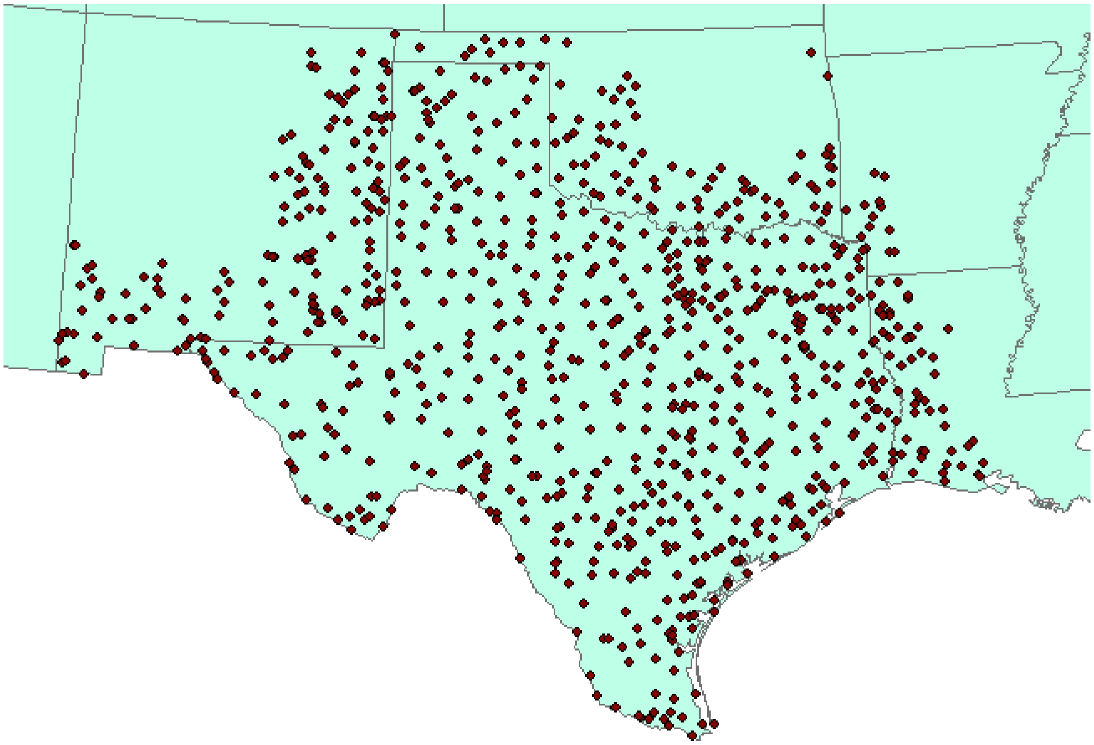

Figure 3. Stations that measure minimum temperature.

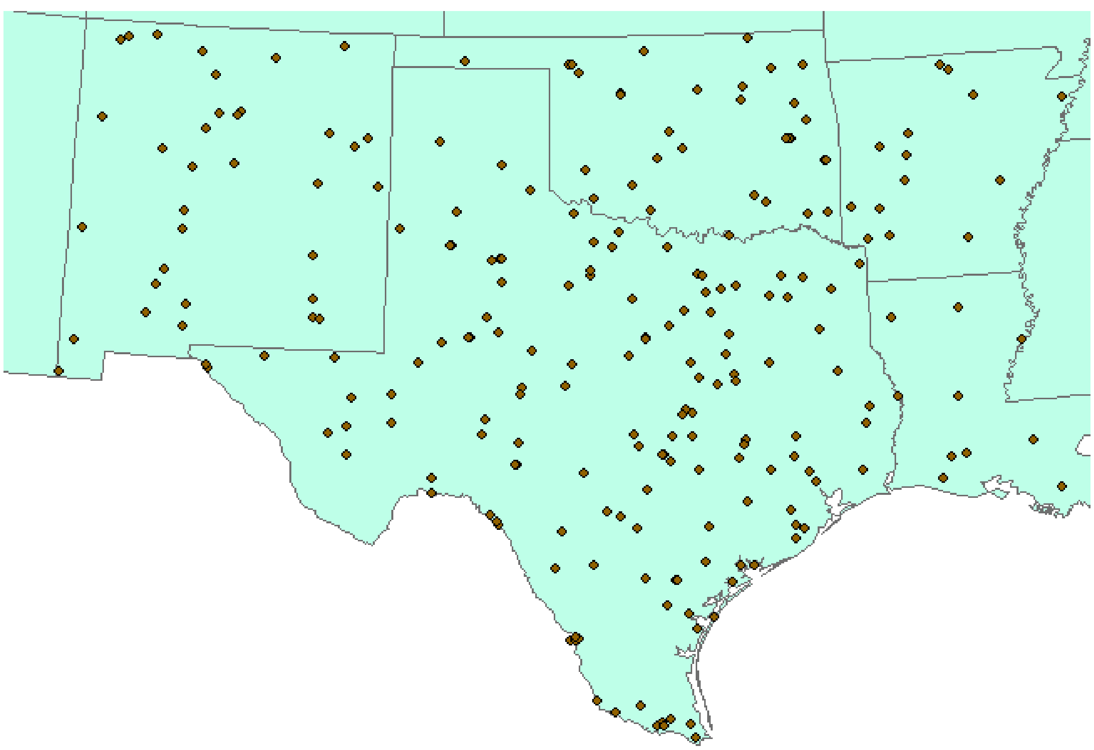

Figure 4. Stations that measure Pan Evaporation.

In addition to the climatic parameters from point locations, gridded estimates of monthly and annual climatic parameters such as precipitation, maximum temperature, minimum temperature and dew point temperature were obtained from USDA-NRCS National Water and Climate Center's (NWCC) PRISM climate layers. PRISM (Parameter-elevation Regressions on Independent Slopes Model) is an interpolation model developed by NRCS – NWCC and the Oregon State University (OSU) that uses spatial information such as elevation, proximity to coast and other information to interpolate the point measurements of climatic parameters. Monthly and annual data available from most of the COOP stations have been used by the PRISM model to create the gridded estimates. Decadal monthly and annual means of major climatic variables from the PRISM gridded data along with decadal means for point data from a serially complete dataset encompass the digital climatic atlas of Texas.

3.2 QA/QC of the station data

The point data obtained from NCDC had already undergone extensive QA/QC procedures at NCDC. No additional QA/QC was performed, except to correct some errors in the assignment of stations to particular climate divisions within Texas. Monthly values were created from the daily data obtained from NCDC only when data for each day of the month was available.

The monthly pan evaporation data obtain from TWDB and NCDC went through a manual QA/QC procedure to check for data and metadata errors as there were few stations with data and the time span of the data was shorter than with the other major climatic parameters. The evaporation data from TWDB included data from many COOP stations. However, the data were obtained by TWDB from those COOP stations in real time prior to undergoing the standard QA/QC procedures that are followed by NCDC. Hence, there were many inconsistencies in the TWDB dataset especially in the metadata such as station ID, name and location. Consequently, whenever there was overlapping data between the two sources, the NCDC data was preferred over the TWDB dataset. In addition to these COOP stations, there are many stations across Texas that measure and report pan evaporation to TWDB but that are not part of the COOP network and do not submit data to NCDC. These data from TWDB were appended to the dataset from NCDC. Further, the period of record for some of the COOP stations in TWDB is longer and extends back to the 1940's, whereas the data from NCDC is only available since the 1960's. Thus, combining the data from both TWDB and NCDC resulted in a larger and more comprehensive pan evaporation dataset.

3.3 Producing a serially complete set of station data

Historical weather data usually contain data gaps that are due to station down times during gauge maintenance and instrumentation problems. Data gaps may also occur during the QA/QC process when the data was flagged for inconsistency such as data being out of reasonable range. A consistent homogenous dataset with minimal data gaps is an essential component of the climatic atlas database. Although such a dataset has been produced by researchers previously during the development of gridded climatological datasets such as PRISM (Daly et al., 2002; Gibson et al., 2002; Mitchell and Jones, 2005; Peterson et al., 1998), the data for individual stations are not available to the public.

An essential first step in producing a serially complete set of climatic parameters is to select a set of reference/benchmark stations that are known to be homogeneous, against which target stations (COOP) can be compared (Mitchell and Jones, 2005). Long-term records from 139 USHCN stations in Texas and neighboring states that have undergone homogeneity corrections were selected as benchmark stations to fill the missing data as they have already gone through a rigorous QA/QC process. The method used for filling the missing monthly precipitation and temperature records is a modified form of Inverse Weighting of Squared Difference (IWSD) method developed by Sun and Peterson (2005). For each target station (COOP) - benchmark station (USHCN) combination, 12 weights were calculated using only the months when the data for both benchmark and target stations were available. The monthly weight is calculated as:

$$W_{month} = \frac{N}{\sum_{i=1}^{N} (P_{\mathrm{Benchmark}} - P_{Target})_i^{\,2}} \qquad (1)$$

Where:

W_{month} - Weight calculated per month for each target station - benchmark station combination

N - Number of months when both target data and benchmark data are available

$P_{Benchmark}$ - Monthly precipitation or temperature data for the benchmark station

P_{Target} - Monthly precipitation or temperature data for the target station

The larger the weight, the more similar the data are at target and benchmark stations. In addition to the 12 monthly weights, 12 monthly biases were also calculated for each target – benchmark station combination only for the months when the data for both benchmark and target stations were available. For precipitation, the monthly bias was calculated as:

$$Bias_{month} = \frac{\sum_{i=1}^{N}(P_{\text{Benchmark}})}{\sum_{i=1}^{N}(P_{\text{Target}})} \tag{2}$$

For the temperature data:

$$Bias_{month} = \frac{\sum_{i=1}^{N}(T_{\text{Benchmark}})}{N} - \frac{\sum_{i=1}^{N}(T_{\text{Target}})}{N} \tag{3}$$

The process of calculating the weights and bias was iterated 139 times per target station to combine each target station with every single benchmark station.

The benchmark stations with four highest weights for a particular month were used to create the interpolated value for the target station. For instance, the four stations that best correlate (highest weight) to the January data at a target station may be completely different stations than those that best correlate with the same target station in July. Before applying this methodology to all target (COOP) stations, test runs were made on the 44 Texas benchmark stations (USHCN) to determine the effects of several variables such as:

1. Effects of changing the length of the time period used to create the neighboring station monthly weights
2. Randomly eliminating target stations,
3. Limiting neighboring station based on geographical proximity, and
4. Using more than one month to weight neighboring stations for a particular month.

The test runs showed that for both precipitation and temperature, at least 10 years of matching data for both target and benchmark stations is needed to make reasonable interpolation of the missing value at the target station. Although this limits the number of target stations that can be used, it is necessary to maintain the integrity of the interpolation. While no interpolation can recover the data that does not exist, research shows that using less than ten years often produces erroneous interpolations (Figure 5). From Figure 5, for all climatic parameters using less than 10 years of training data increased the mean absolute error of interpolation, however increasing it beyond 10 years did not considerably reduce the error. Further, the test runs also showed that limiting the search for stations with four highest monthly weights from among the 20 closest benchmark station to the target station did not increase the interpolation error considerably (Figure 6).

Another important finding from this test run is that lower standard errors were obtained by using more than one month to create the monthly weights. For example, using both September and October data as opposed to using only the October data to calculate the October monthly weights produced a more accurate result (lower standard error). Table 2 shows the combinations of months that produced the lowest standard error, based on tests using one, two, and three months of data. Separate evaluations were made for East and West Texas to calculate the monthly weights for precipitation and temperature. Only for May and August in West Texas is a single month of data optimal for calculating the monthly weight.

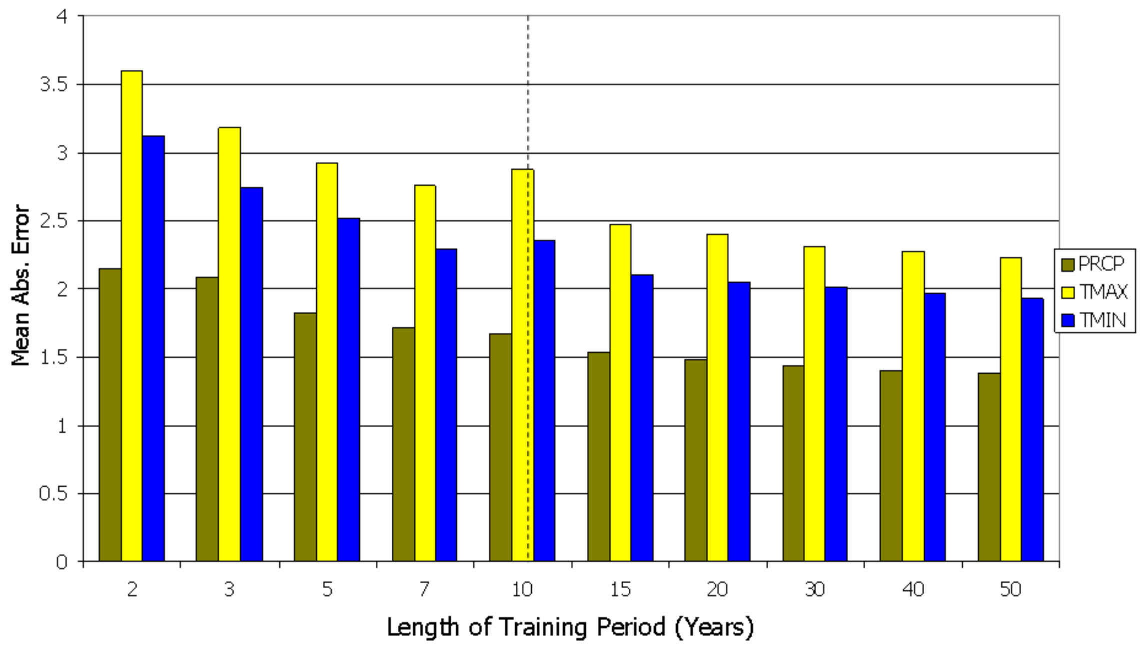

Figure 5. Effect of the length of training period on mean absolute error of interpolation. [PRCP: Precipitation (inch); TMAX: Maximum Temperature (ºF); TMIN: Minimum Temperature (ºF)].

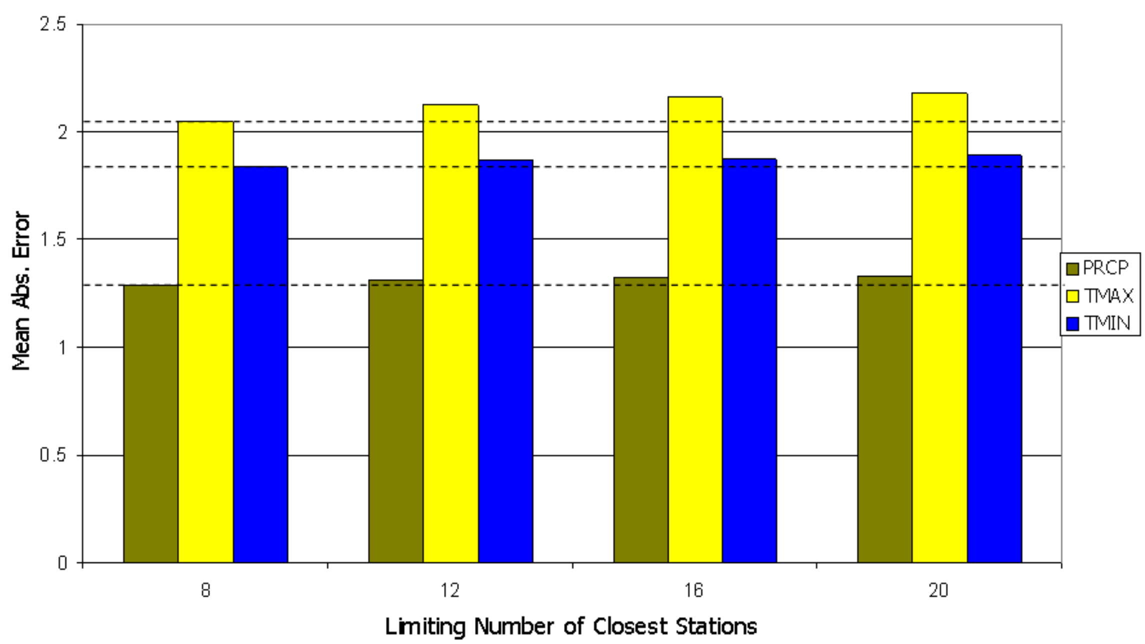

Figure 6. Effect of limiting the number of closest benchmark station used for interpolation on mean absolute error. [PRCP: Precipitation (inch); TMAX: Maximum Temperature (ºF); TMIN: Minimum Temperature (ºF)].

Table 2. Combination of months used to calculate monthly weights

Month	Precipitation		Temperature	
	East Texas	West Texas	East Texas	West Texas
1	12,1	12,1	1,2	1,2
2	1,2	1,2	1,2	1,2
3	2,3	2,3	3,4	3,4
4	4,5	4,5	3,4	4,5
5	4,5	4,5	5,6	5
6	5,6,7	5,6,7	6,7	6,7
7	6,7	6,7	6,7	6,7
8	7,8	7,8	8,9	8
9	8,9	8,9,10	8,9	8,9
10	9,10	9,10	9,10	9,10
11	10,11	10,11	10,11	10,11
12	11,12	11,12	11,12	11,12

Note: Climatic divisions 1, 2, 5 and 6 belong to West Texas and rest of the six climatic divisions belongs to East Texas (See Figure 12).

Based on the procedure outlined previously and the results of the test run, missing monthly precipitation data at target stations were filled starting from January 1890 to December 2001. The data were filled only for those target stations with at least 10 years of matching record with benchmark stations. Data from four benchmark stations with the highest weights for the month from among the 20 closest stations were used to fill the missing value at the target station. The missing values at target stations were interpolated from the four benchmark stations as:

$$Interpolated\ value\ (month, year) = \frac{\sum_{i=1}^{4}\left[W_{i,month} \times \frac{Value_{(i,month,year)}}{Bias_{i,month}}\right]}{\sum_{i=1}^{4} W_{i,month}} \qquad (4)$$

However, when fewer than four stations were available for a particular month of the year from among the twenty closest benchmark stations to the target station, the process was repeated by adding the next closest station until four stations with data for a particular month and year were found and used for interpolation. This process keeps distance as an important variable but assures that four stations will be used in the interpolation regardless of the station density near the target station. It is important to note that the weights for individual months are calculated based on the combination of months as listed in Table 2.

Interpolation of maximum and minimum temperature data at COOP stations was performed as described previously for precipitation except that the bias calculated by equation 3 is actually temperature anomaly because it is the difference in temperatures between the benchmark and target station rather than the ratio. Hence, the equation used to calculate missing temperature data is:

$$Interpolated\ value\ (month,\ year) = \frac{\sum_{i=1}^{4}\left(W_{i,month} \times (Value_{(i,month,year)} - Bias_{i,month})\right)}{\sum_{i=1}^{4} W_{i,month}} \quad (5)$$

It is important to note that no attempt was made to fill the missing pan evaporation data available from individual stations due to low station density and lack of long-term measurements.

3.4 Generating gridded monthly precipitation, maximum and minimum temperatures and lake evaporation coverages

3.4.1 Precipitation, maximum and minimum temperatures

High spatial resolution (4 km) monthly and annual gridded precipitation and temperature data from 1895 to 2000 were obtained from the PRISM climatic database. As the station density prior to 1895 was poor, monthly and gridded estimates of climatic parameters were not calculated by PRISM during 1890 to 1894. The gridded PRISM climatic dataset is the product of a multi-year multi-agency effort involving scientists from NRCS National Water and Climate Center (NWCC) and the Oregon State University (OSU). PRISM (Parameter-elevation Regressions on Independent Slopes Model) is an interpolation model developed by NWCC and OSU that uses spatial information such as elevation, proximity to coast and other information to interpolate the point measurements of climatic parameters (Daly et al., 2002). Most of the COOP stations were used in producing these gridded climatic layers and the base data went through a rigorous QA/QC and data infilling procedures so that the gridded layers are of highest quality with the best possible estimate (Johns et al., 2003).

The gridded datasets were in the Arc/Info ASCII GRID format and in the Geographic Coordinate System encompassing the conterminous United States. Hence, the data were clipped to the spatial extent of Texas and projected to Texas Centric Mapping System - Albers Equal Area Conic Projection with the projection parameters given in Table 3 as required by the Texas Administrative Code – Geographic Information Standards. The unit of the precipitation was millimeters and the temperature was in degrees Celsius; these were converted to inches and degrees Fahrenheit.

Table 3. Texas Centric Mapping System Parameters

Mapping System Name	Texas Centric Mapping System/Albers Equal Area
Abbreviation	TCMS/AEA
Projection	Albers Equal Area Conic
Longitude of Origin	100 degrees West (-100)
Latitude of Origin	18 degrees North (18)
Lower Standard Parallel	27 degrees, 30 minutes (27.5)
Upper Standard Parallel	35 degrees (35.0)
False Easting	1,500,000 meters
False Northing	6,000,000 meters
Datum	North American Datum of 1983 (NAD83)
Unit of Measure	meter

3.4.2 Estimation of lake evaporation

Evaporation is an important climatic and hydrologic parameter that quantifies the amount of water lost from open water bodies due to atmospheric conditions. Due to its nature, often evaporation is not measured directly but estimated from measurements made using a network of Class A evaporation pans and multiplied using pan coefficients to estimate lake evaporation. Such an estimate of evaporation is also used to infer plant and soil evaporation for irrigation water allocation, estimating reservoir water balance, and forecasting long-term water supply conditions, among other applications. Although evaporation is a major component of the water budget, there is a paucity of stations that measure evaporation. Gridded estimates of lake evaporation cannot be generated directly from the available point measurements due to the low density of stations that measure pan evaporation. Further, the period of record of such measurements is too short to generate decadal monthly and annual means of lake evaporation for the entire state. Hence, evaporation models were used along with gridded climatic layers available from PRISM database to produce a gridded lake evaporation estimate.

Many evaporation models have been developed over the years to estimate evaporation from water surfaces based on climatic parameters such as maximum and minimum temperature, dew point temperature, solar radiation, wind speed and relative humidity. The simple models such as the Thornthwaite method use only temperature and the more complex models such as Penman-Monteith require inputs of almost all of the climatic parameters mentioned previously to estimate evaporation (ASCE 1996). However, all of these datasets are not readily available for 1890 to 2000. Hence, an optimal balance had to found by selecting a model that computes evaporation with reasonable accuracy using limited climatic data.

The aerodynamic method is one of the widely used procedures for estimating evaporation from lakes and large reservoirs. The model was originally developed by U.S. Geological Survey in the 1950's (ASCE 1996):

$$E = M(e_s - e_z)u_z \qquad (6)$$

where E is the evaporation in mm per day, M is the mass transfer coefficient, e_s is the saturation vapor pressure at the surface water temperature Ts (kPa), e_z is the vapor pressure of the air at height z (kPa) and u_z is the wind velocity at level z in m/s. Although direct measurements of saturated vapor pressure (e_s) and actual vapor pressure (e_z) were not available, they can be calculated from maximum, minimum, and dew point temperatures. The saturation vapor pressure and actual vapor pressure were calculated as follows (Allen et al., 1998):

$$e(T) = 0.6108 \exp\left[\frac{17.27T}{T + 237.3}\right] \qquad (7)$$

$$e_s = \frac{e^0(T_{\max}) + e^0(T_{\min})}{2} \tag{8}$$

$$e_z = 0.6108 \exp\left[\frac{17.27 T_{dew}}{T_{dew} + 237.3}\right] \tag{9}$$

Where: e(T) is saturation vapor pressure at the air temperature T (kPa), T air temperature (°C).

All the temperature data were readily available in the gridded format from the PRISM dataset. Monthly and annual dew point temperature from 1895 to 2000 were obtained from the PRISM database and processed using the same procedures described in section 3.4.1.

However, long term wind speed data were not available since wind speed is measured at a limited number of stations. Based on the longest available records of wind speed between 1961 and 1990, contour maps of monthly and annual average wind speed were available from the NCDC CLIMAPS dataset. However, the contours are widely spaced and each represents an average wind speed increment of one mile per hour and range in value between 6 miles per hour to 12 miles per hour. Hence, these contour lines were interpolated between lines to get a fine breakdown of intermediate values so that the output evaporation grid will be smooth.

The mass transfer coefficient M is calculated as (ASCE 1996):

$$M = 53740 \frac{\rho_a}{P} C_E \tag{10}$$

Where ρ_a is the density of air (kg m^{-3})), P is the atmospheric pressure (kPa) and C_E is the bulk evaporation coefficient (0.0015). Atmospheric pressure was calculated based on elevation from the digital elevation model using the simplified form of the gas law for a standard atmosphere (Allen et al., 1998):

$$P = 101.3\left(\frac{293 - 0.0065z}{293}\right)^{5.26} \tag{11}$$

Where, z is the elevation above mean sea level (m). The air density was calculated from pressure and temperature as (ASCE 1996):

$$\rho_a = \frac{1000P}{T_v R} \tag{12}$$

$$T_v = \frac{T}{1 - 0.378\frac{e_z}{P}} \tag{13}$$

Where, R is the specific gas constant for dry air, 287 J/kg/K, Tv is the virtual temperature (K), e_z is the actual vapor pressure (kPa) and P is atmospheric pressure (kPa).

3.4.3 Correction of lake evaporation

The evaporation estimated using the aerodynamic method described above should be adjusted based on measured pan evaporation and multiplied by a pan coefficient for estimating lake evaporation. Best estimates of monthly evaporation with at least five years of data during a 30 year period from 1971 to 2000 were available for about 94 stations out of the 232 stations that measure evaporation (Figure 7).

The evaporation estimated using the aerodynamic method was compared with the monthly measurements at these 94 evaporation stations from 1971 to 2000 and an evaporation ratio (ER) was estimated for each month the measurement was available as:

ER = measured evaporation / model evaporation (14)

Based on the ER calculated for at least 5 years for each month during the 30 year period, monthly average evaporation ratio was estimated for each of the 94 stations. These estimates of ER where then used to estimate lake evaporation as:

Lake evaporation = model evaporation X ER X pan coefficient

Monthly pan coefficients were available for each one degree quadrangle across Texas and were based on the Evaporation Atlas of the United States (Farnsworth et al., 1982).

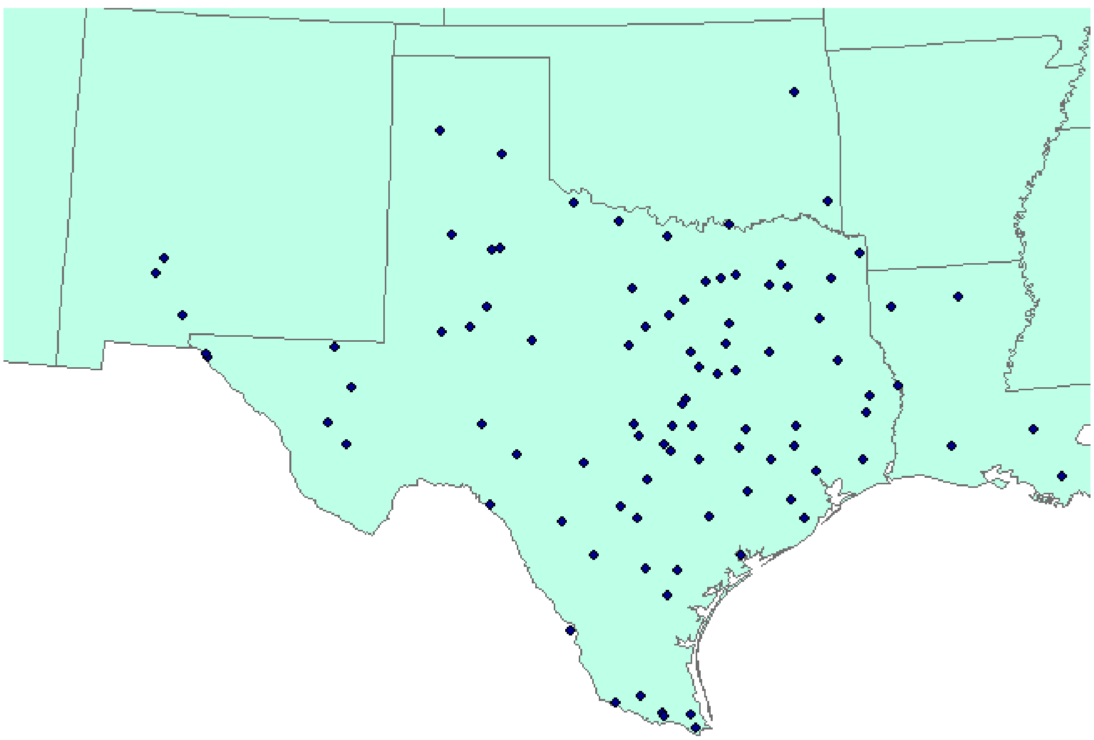

Figure 7. Evaporation stations with at least five years of data from 1971-2000.

Monthly pan coefficients were assigned to each of the 94 evaporation stations based on the quadrangles in which they lie. These pan coefficients were then multiplied with the 30-year average evaporation ratio described earlier. The product of pan coefficients and ER for individual stations was then spatially interpolated using regularized spline technique across the entire state for each month. The average of these twelve monthly grids was calculated to obtain the average annual correction grid. These interpolated correction grids were then multiplied with the model evaporation grid calculated for each month from 1895 to 2000 to produce gridded lake evaporation grids.

3.5 Verifying the gridded PRISM climatic data

The PRISM climatic data layers were calculated using sophisticated interpolation techniques that incorporates a conceptual framework which addresses the spatial scale and pattern of orographic precipitation and temperature using information such as elevation, proximity to coast, and other information to interpolate the point measurements of climatic parameters (Daly et al., 2002). As most of the COOP stations were already used in the creation of this gridded data set, it is difficult to assess the accuracy of PRISM grids. Independent weather stations that are not part of the COOP network and that do not report to NCDC were available only at very few locations such as in the North Texas High Plains Evapotranspiration Network of the Texas Agricultural Experiment Station (http://amarillo2.tamu.edu/nppet/petnet1.htm) (Figure 8).

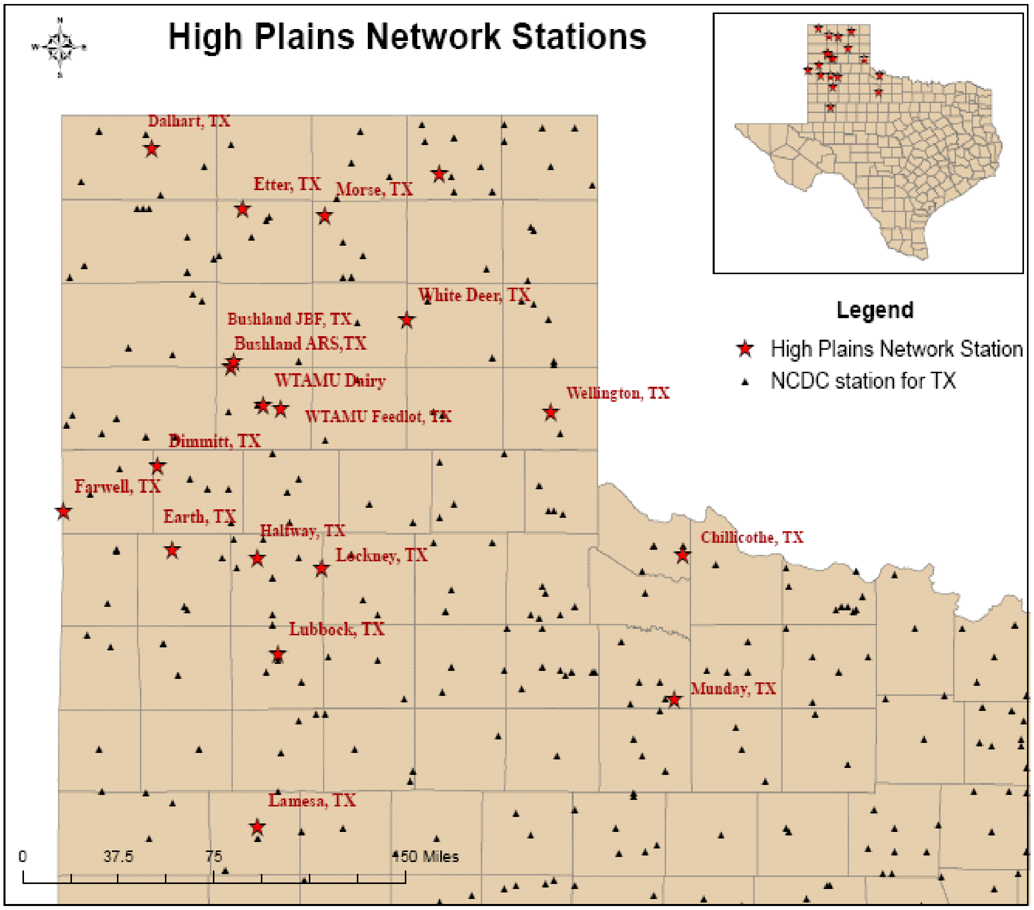

Figure 8. North Texas High Plains ET network stations along with the COOP stations.

There are 16 weather stations that are part of the High Plains ET network that measure precipitation, maximum and minimum temperature on a daily basis. The daily values for these climatic parameters were available for a 5 year period from 1996 to 2000 for most of the 16 stations. Monthly means of these climatic parameters where calculated for these 16 stations for the 5 year period and compared with the PRISM grids to verify their accuracy. The average difference in monthly precipitation for the 5 year period for the 16 stations was about 0.25 inches for an average monthly rainfall of 2.26 inches (Figure 9) and average difference in temperature was within 0.4 and 0.7 degree Fahrenheit for minimum and maximum temperatures respectively (Figure 10).

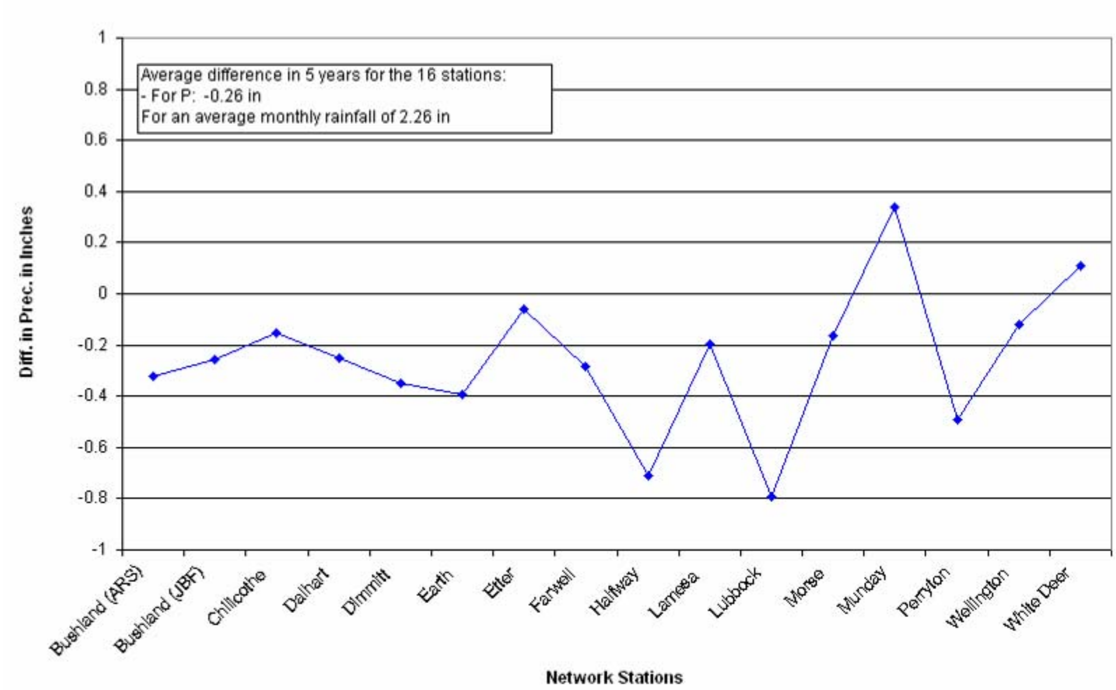

Figure 9. Difference in monthly precipitation between PRISM grids and the High Plains ET network stations.

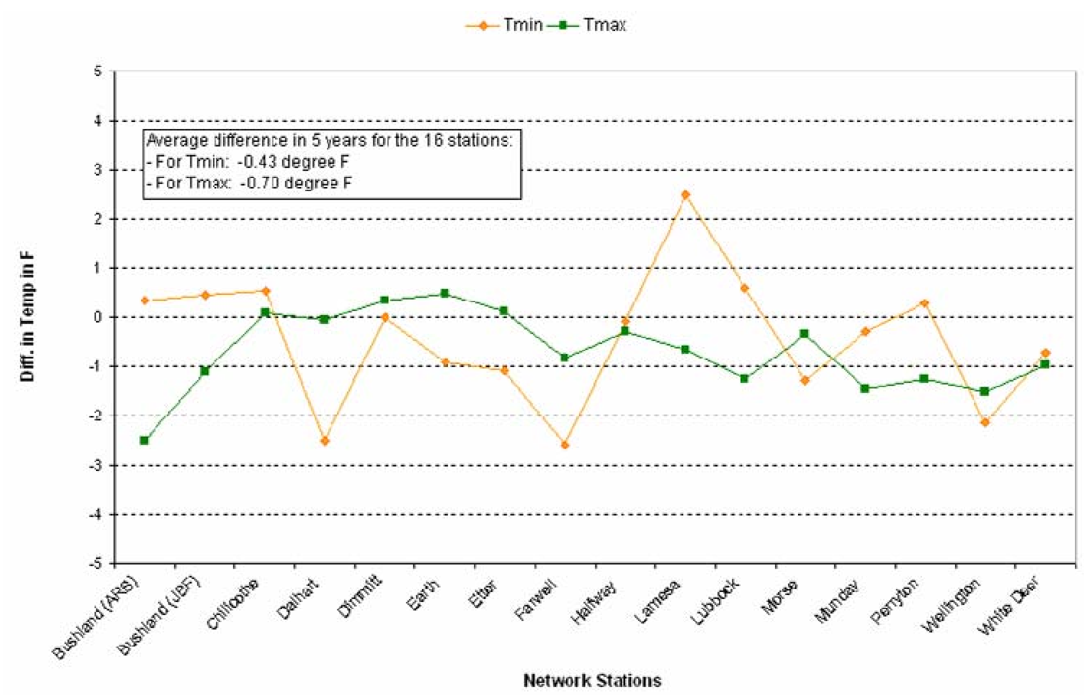

Figure 10. Difference in monthly temperature between PRISM grids and the High Plains ET network stations.

It was interesting to note that at most of the High Plain stations the temperatures were below the PRISM gridded estimates. This is probably because most of the COOP stations are located close to urban occupation where the temperature could be slightly higher than the surrounding area due to radiation from asphalt and concrete in urban structures.

Based on the COOP station density in the Texas High Plains (Figure 8) and comparing it with the density of COOP network for the rest of Texas (Figure 1, 2, 3) we can infer that the error in PRISM grids might be high in the west Texas Trans Pecos region due to comparatively low station density and high differences in topography. In the Rolling Plains, Edward Plateau and south Texas the errors in PRISM grids should be similar to that of High Plains due to similar station densities. In Central and East Texas regions the error in PRISM grids could be lower than that of High Plains due to the higher station density. While it is imperative to understand that no interpolation technique can duplicate the exact measurements, these errors are well within the acceptable range for the purpose of creating long-term decadal means of gridded climatic parameters.

3.6 Calculating monthly and annual decadal means of gridded and point climatic data

The gridded and point climate data consisting of monthly and annual precipitation, maximum and minimum temperature and evaporation were generated based on the data available from various sources ranging from 1890 to 2000. Then decadal monthly and annual means for each climatic parameter were calculated for the 11 decades. With the exception of measured pan evaporation, the decadal statistics for most of the stations were available for all the 11 decades. However, gridded evaporation produced using the methodology described in Section 3.4.2 were used to calculate grids of decadal monthly and annual means of lake evaporation. It is important to note that for the decade of 1891 to 1900, only six years of gridded data from 1895 to 1900 were available from the PRISM database for calculating the decadal statistics. In addition to the decadal statistics, 30 year (1971-2000) monthly and annual means were also calculated for each climatic parameter and included in the database.

3.7 Creating an ArcGIS geodatabase containing gridded and a database containing point monthly and annual decadal means of climatic parameters.

The gridded monthly and annual decadal means of climatic parameters were imported into an ArcGIS geodatabase. The advantage of using a geodatabase is that the data can be easily queried, displayed, analyzed and the integrity of the dataset can be maintained while allowing efficient storage and distribution of this large dataset. In addition to this gridded geodatabase of climatic parameters, the decadal statistics of climatic parameters for the individual stations were included in a complementary database. This database can be used to query hundreds of weather stations for data on any particular decade, month, or station. The 30-year monthly and annual climatic statistics were also mapped into layouts along with contour lines following a similar pattern as that of the earlier climatic atlas (Appendix A).

4.0 Dividing Texas into smaller climatic divisions

The 1983 climatic atlas (LP192) described Texas as having three major climatic types which are classified as Continental, Mountain, and Modified Marine. The Modified Marine was further sub-classified into four “Subtropical” zones (Figure 11).

Subsequently NCDC divided Texas into ten climatic zones of homogenous climatic patterns based on statistical analysis. The regions were made to coincide with political

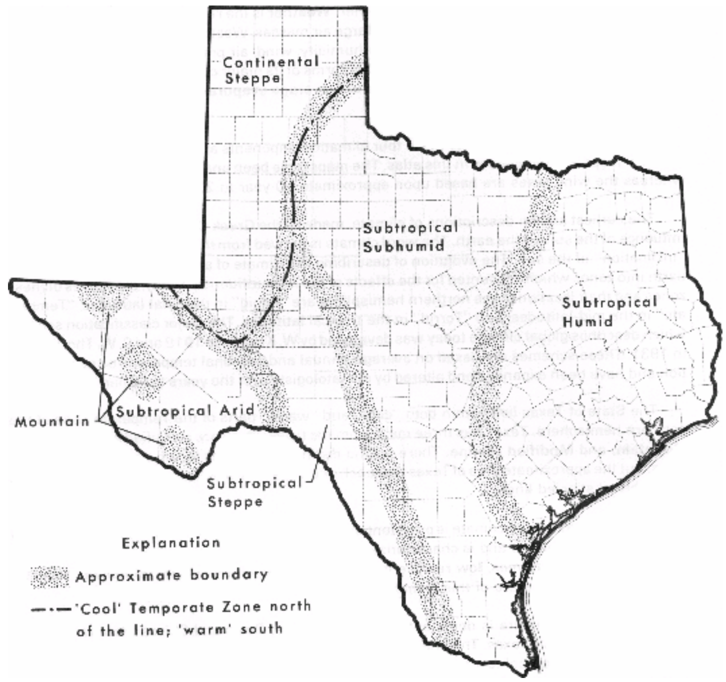

Figure 11. Texas climatic types (LP192- 1983 climatic atlas).

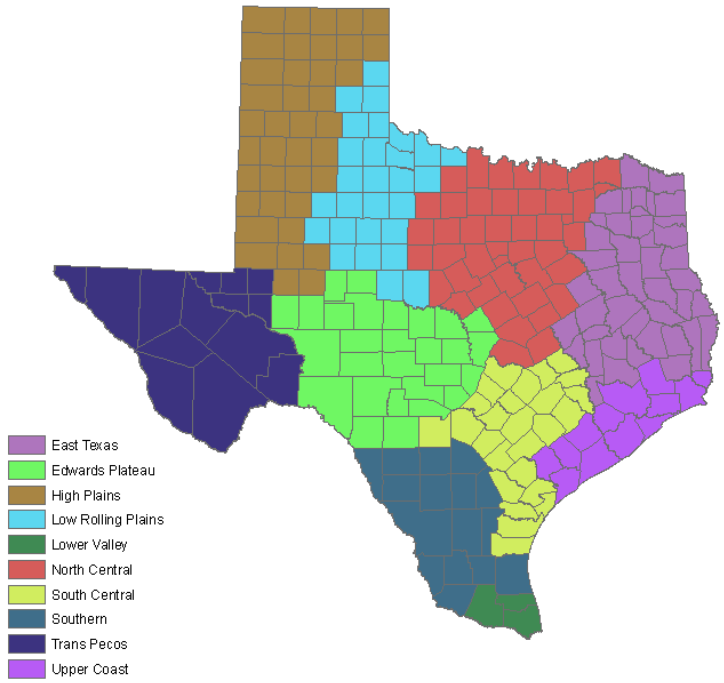

Figure 12. NCDC climatic divisions

boundaries (Figure 12) for issuing warnings and forecasts of climatic events such as drought. However, there is a growing concern among the action agencies responsible for drought monitoring and response that these climatic divisions are rather too large to be of use for providing information on local impacts. The gridded climatic layers produced in this study are of immense use for identifying climatic divisions of varying sizes based on an agencies' requirements.

Thirty year monthly means (1971-2000) of precipitation, maximum and minimum temperature, dew point temperature and mean monthly wind speed (60 data layers) were used to identify unique climatic zones of varying size across Texas. In order to identify the unique climatic zones, each climatic parameter was normalized using the maximum and minimum values of the climatic parameters to make sure that the resultant data layer was unit less. Using these 60 layers of information the Iterative Self-Organizing Data Analysis Technique (ISODATA) (Tou and Gonzalez, 1974) was used to find clusters with unique climatic properties. This clustering algorithm identifies unique patterns of temporal variations in the five climatic parameters and then assigns each pixel to a unique class iteratively until about 95% of the pixel does not change classes within subsequent iterations. The procedure was used to classify Texas into 5, 10, 25 and 50 different climatic classes. Appendix B contain illustrations of these climatic divisions along with an overlay of the NCDC's 10 climatic division (image on the left) along with the new climatic division boundaries corrected to align with county political boundaries (image on the right) based on the dominant climatic zone of the county. It is interesting to note that the 10 climatic zones produced by ISODATA are different from the current NCDC climatic divisions, except for the High-Plains climatic division. The area of the smallest and largest climatic divisions created from this procedure are given in Table 4.

Table 4. Area of climatic divisions produced by varying the number of unique climatic classes.

No. of classes	Smallest Area Sq.mi	Largest Area Sq.mi	Average Area Sq.mi
5	41,347	68,912	54,777
10	19,367	35,330	27,389
25	5,622	16,074	10,955
50	500	11,577	5,478
NCDC*	3,044	38,761	26,410

* NCDC 10 climatic divisions

5.0 Conclusions

The current work developed and assembled the best possible data to produce gridded and point decadal monthly and annual statistics for 11 decades since 1890. This rich data source will be of immense benefit to the wider community of Texas in better understanding the spatial and temporal climatic variability across the state. It is our hope that the digital database will significantly improve the decision making process during the analysis, and planning phases of major water resources projects across Texas.

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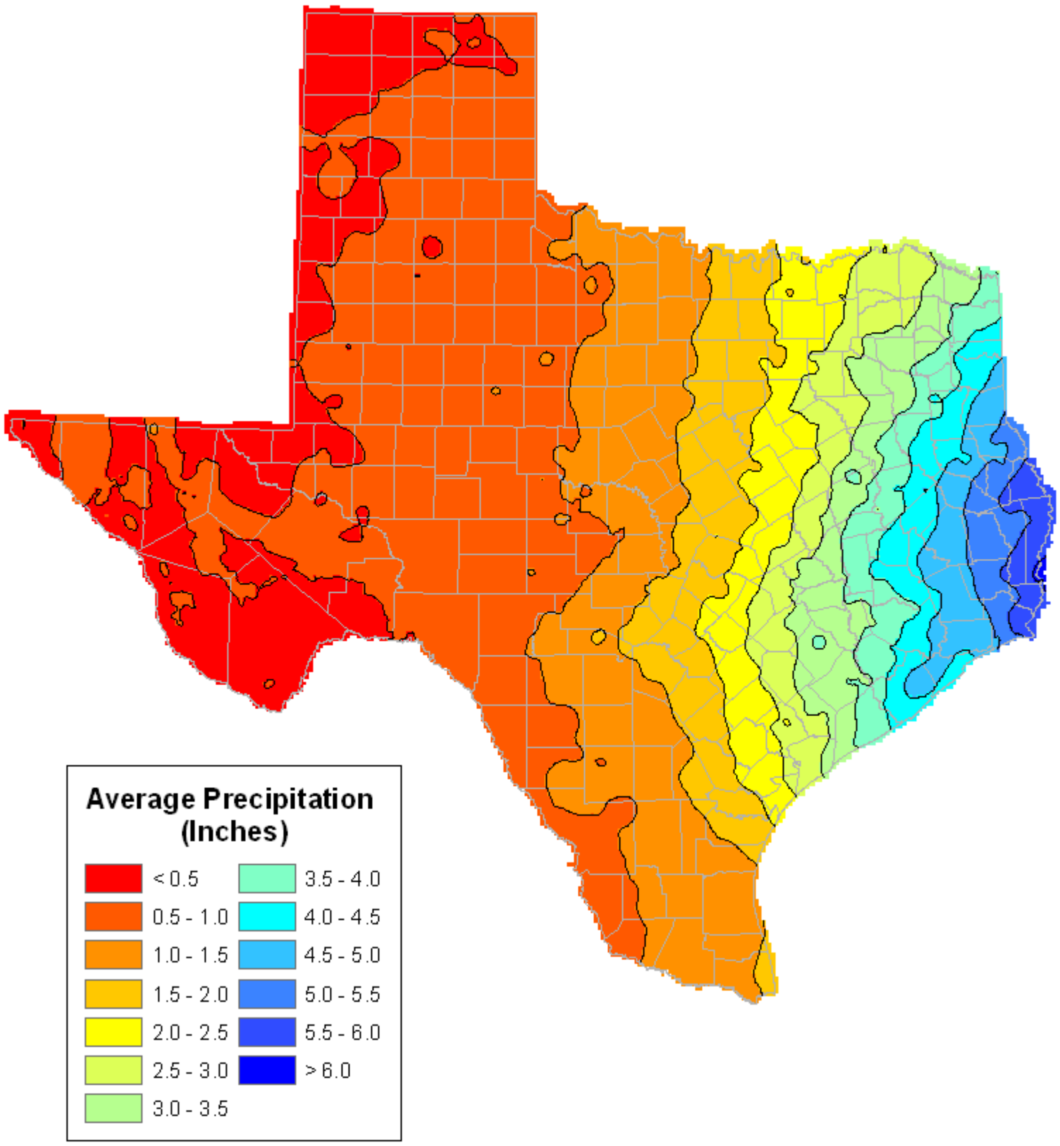
Appendix A

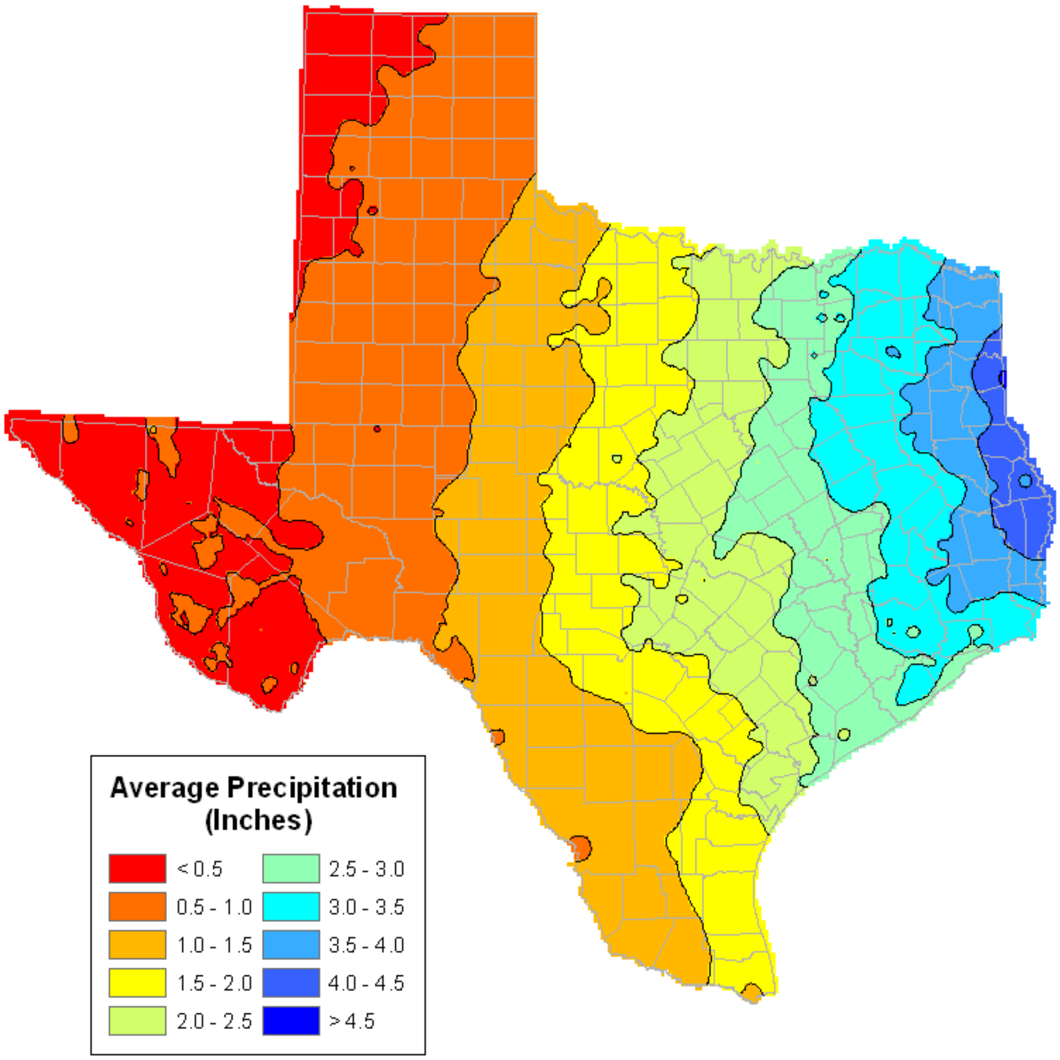
In the following section, 30 year (1971-2000) monthly and annual means of precipitation, maximum temperature, minimum temperature and lake evaporation are mapped into layouts along with contour lines following a similar pattern as that of the earlier climatic atlas LP 192. Decadal monthly and annual means of precipitation, maximum temperature, minimum temperature and lake evaporation for each decade from 1890 to 2000 are available in the ESRI Geodatabase format in the attached DVD.

Average Monthly Precipitation Maps

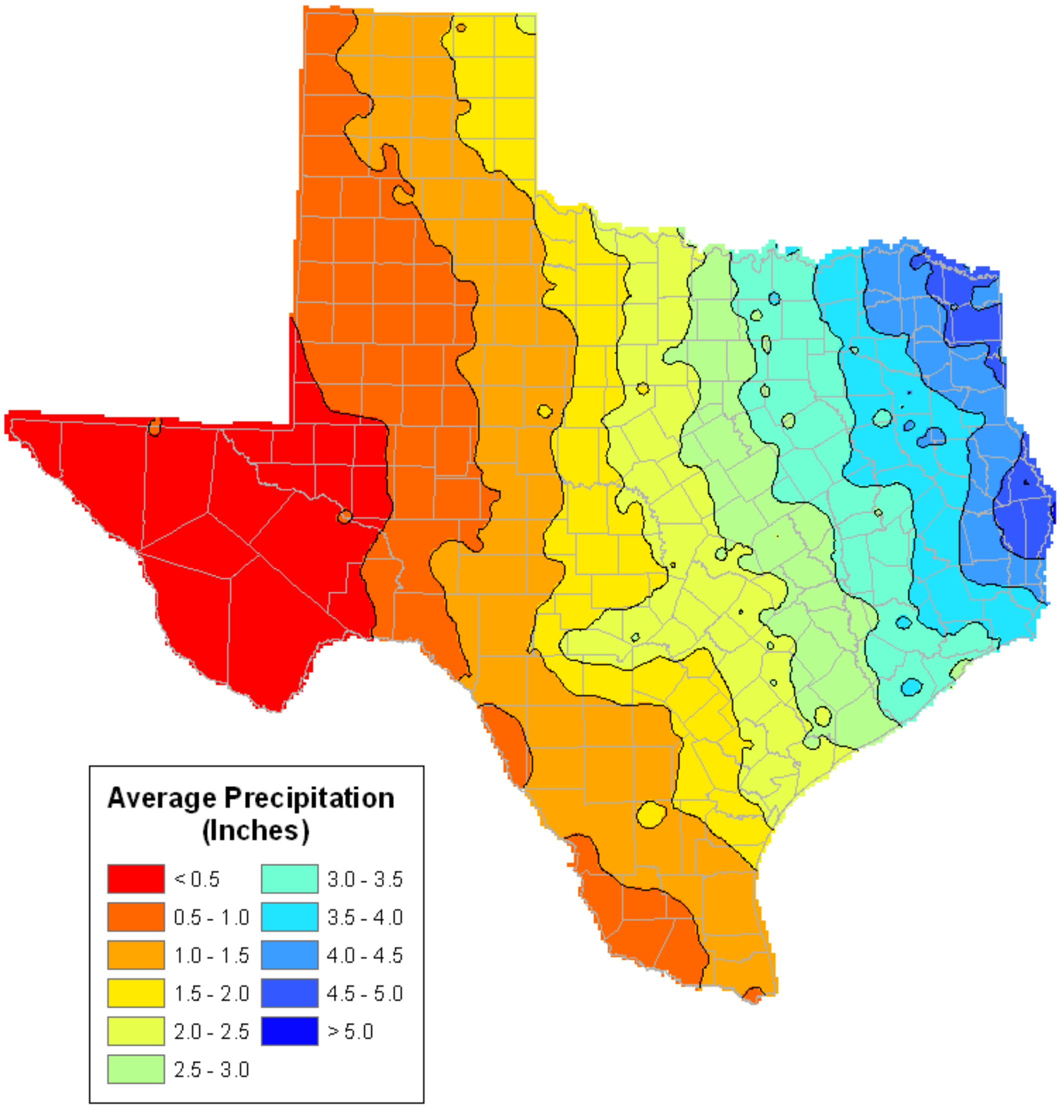
JANUARY
Average Monthly Precipitation
1971 - 2000



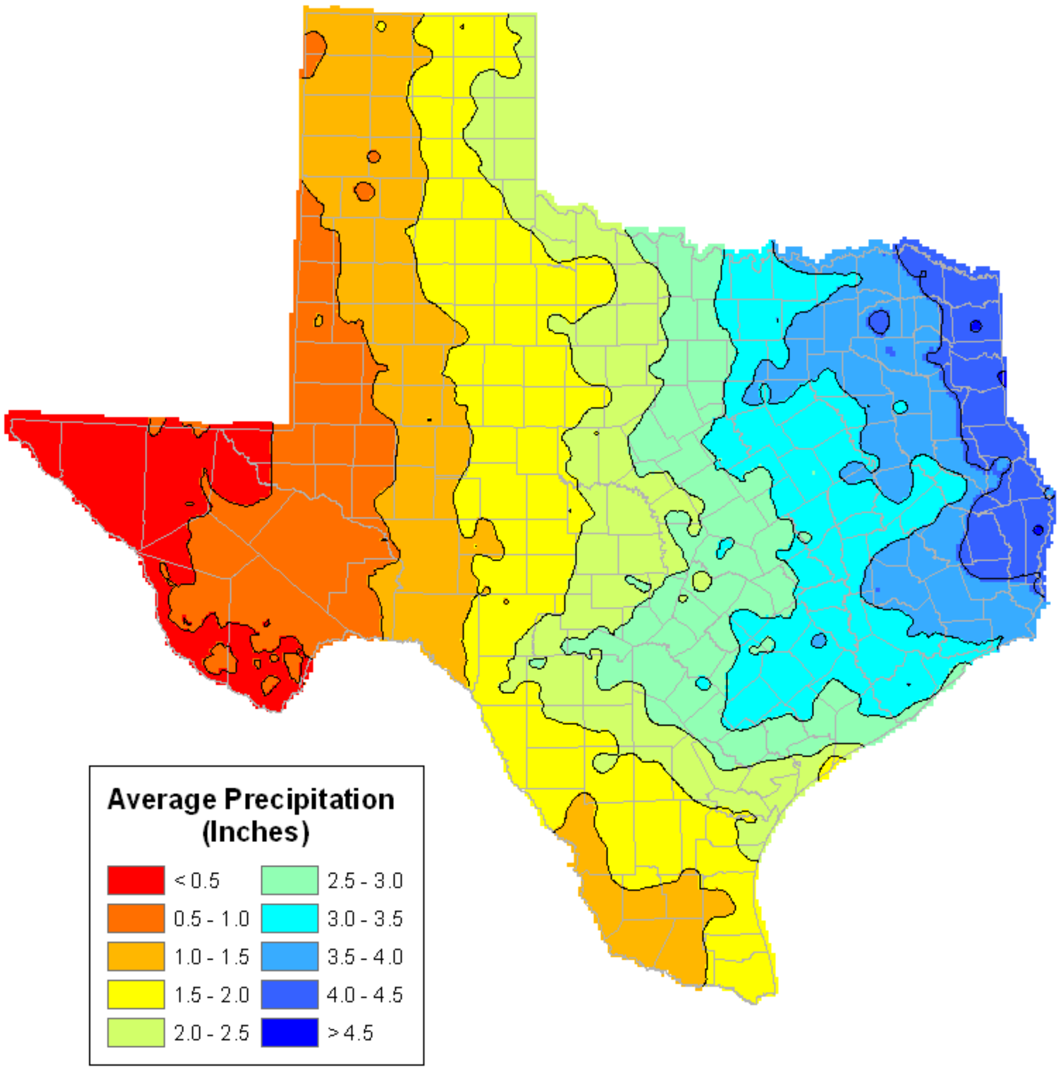
FEBRUARY
Average Monthly Precipitation
1971 - 2000



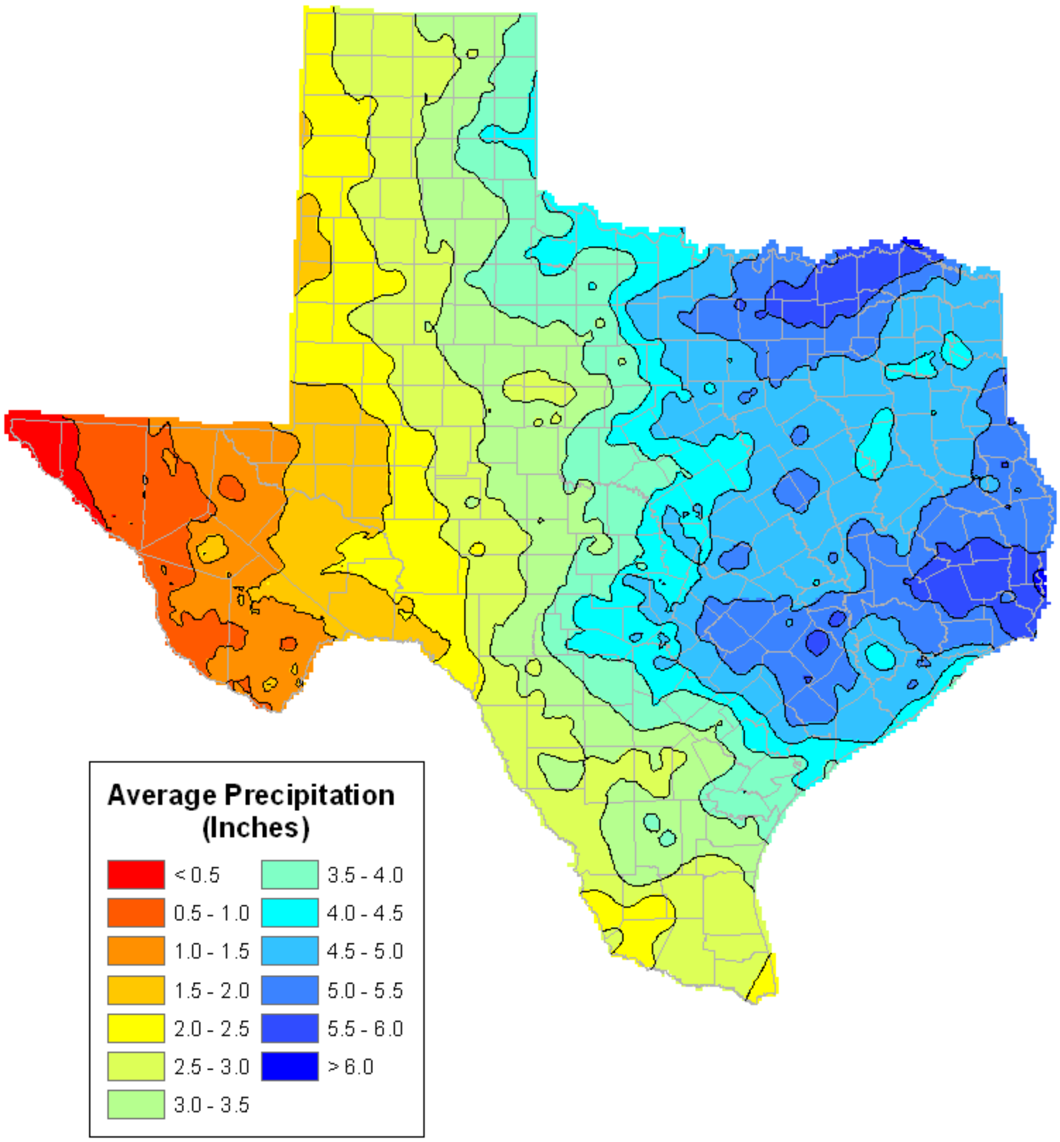
MARCH
Average Monthly Precipitation
1971 - 2000



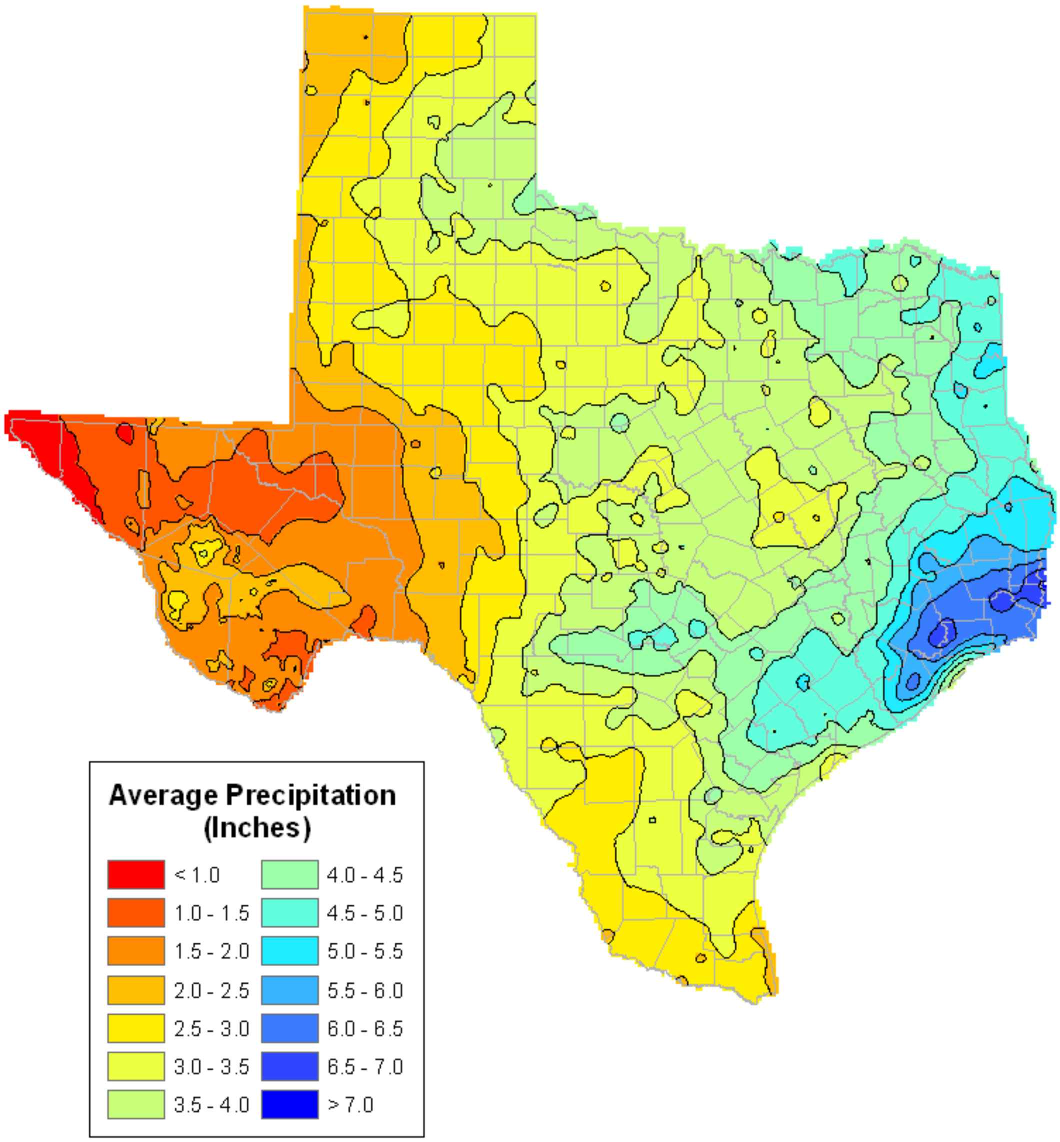
APRIL
Average Monthly Precipitation
1971 - 2000



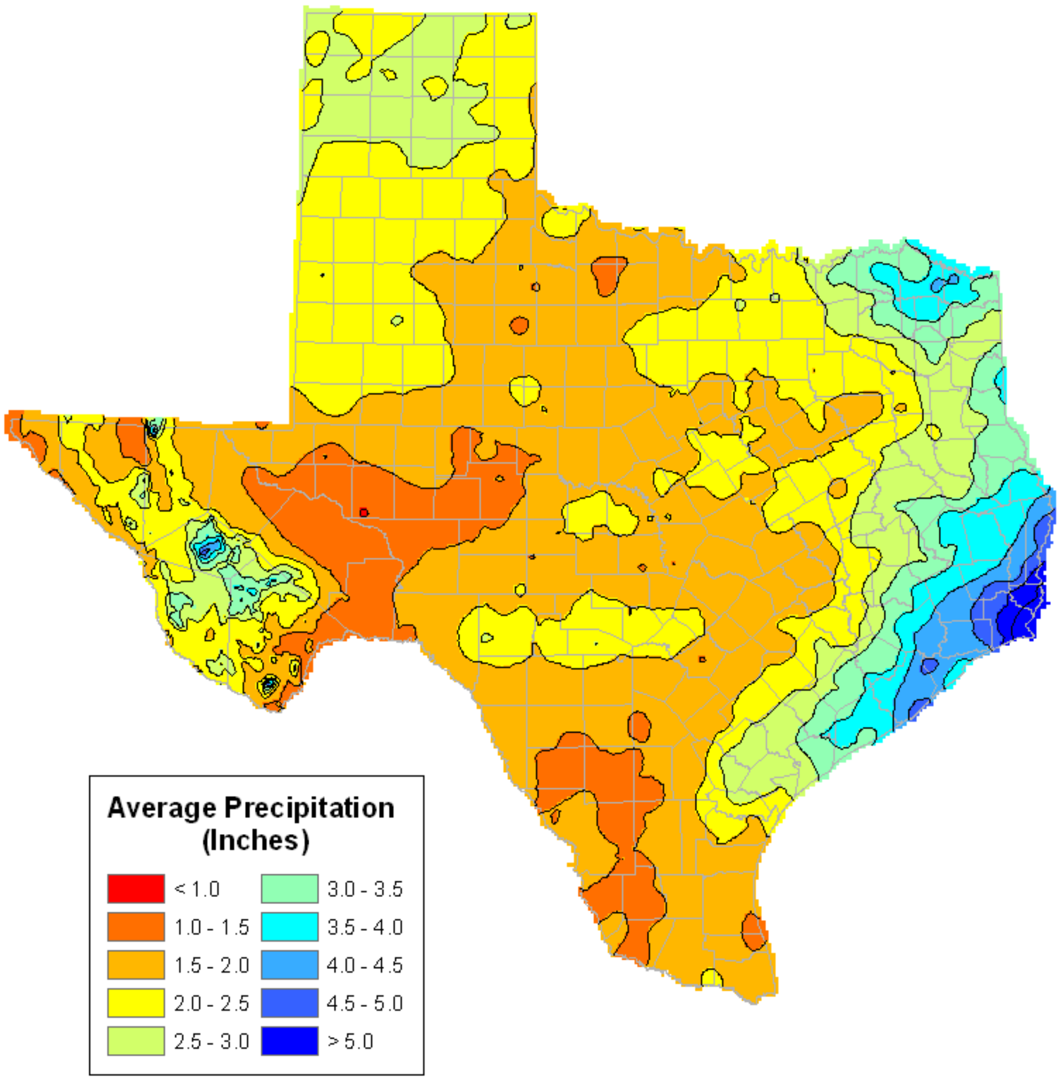
MAY
Average Monthly Precipitation
1971 - 2000



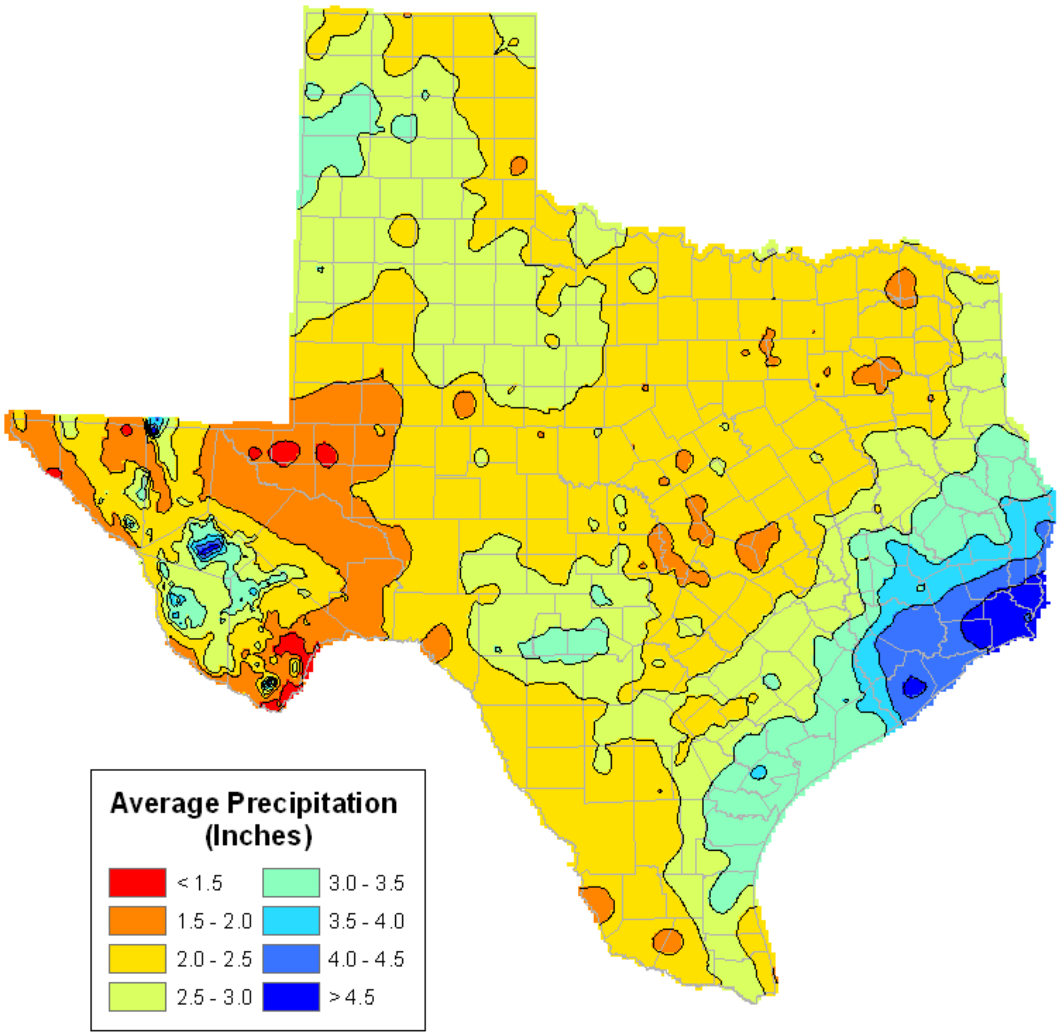
JUNE
Average Monthly Precipitation
1971 - 2000



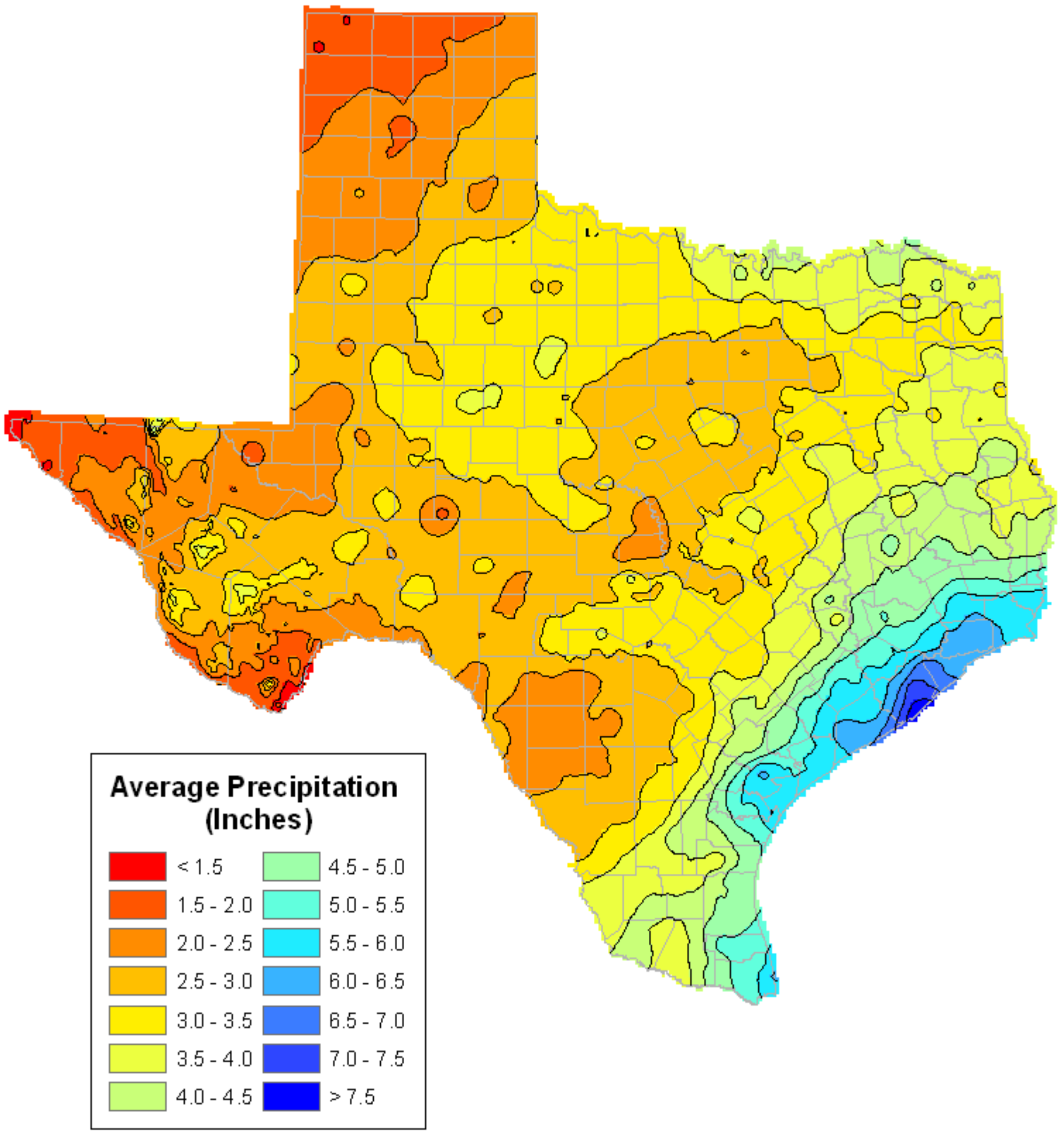
JULY
Average Monthly Precipitation
1971 - 2000



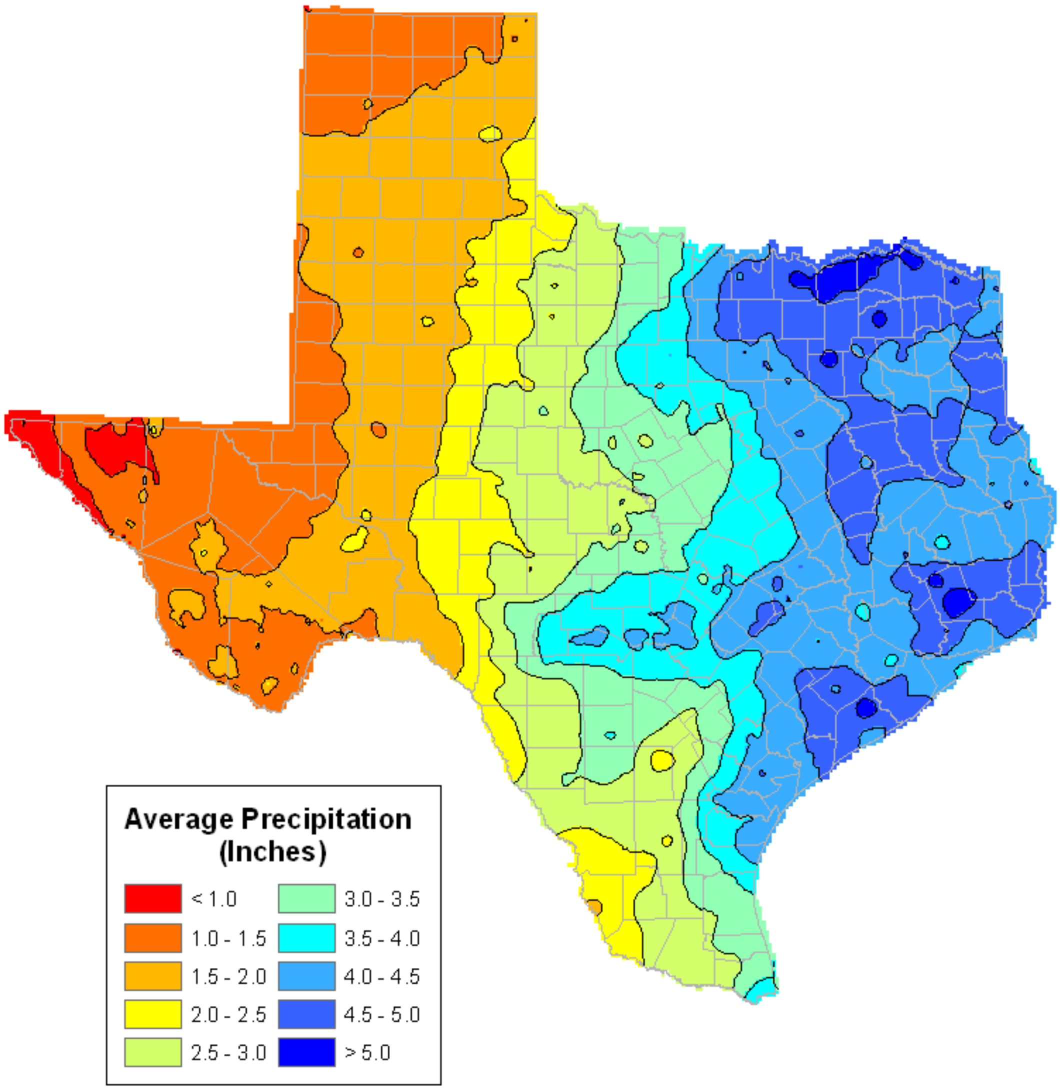
AUGUST
Average Monthly Precipitation
1971 - 2000



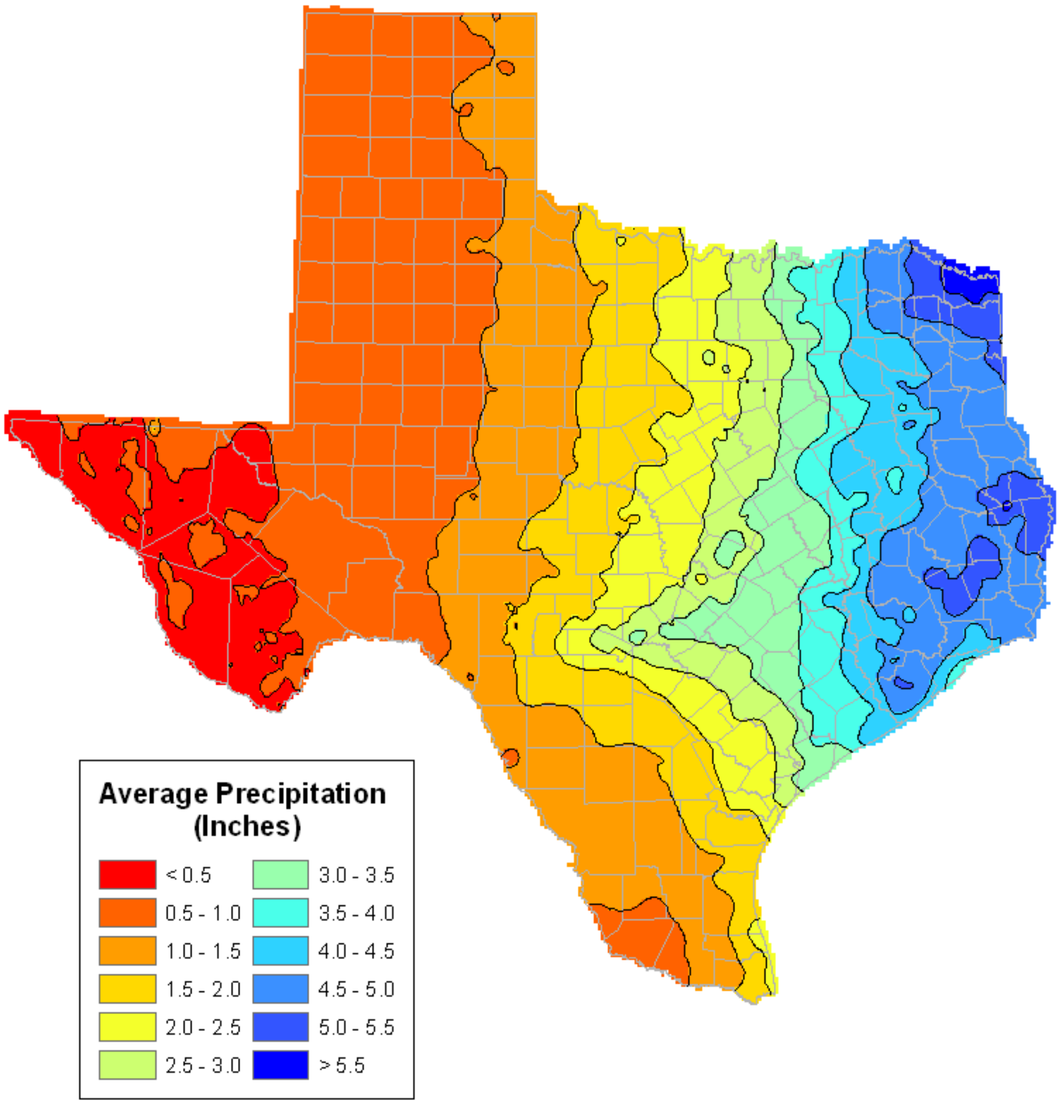
SEPTEMBER
Average Monthly Precipitation
1971 - 2000



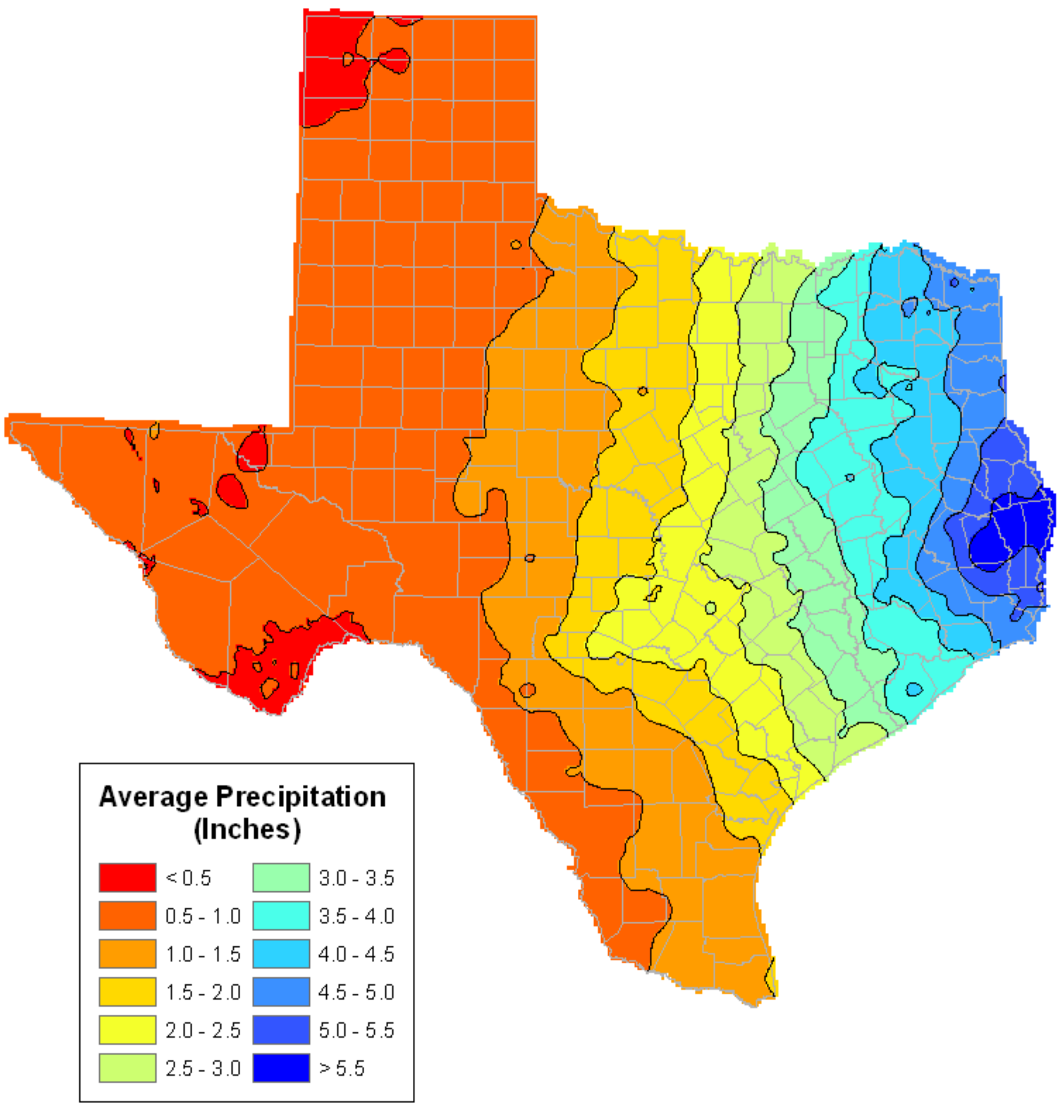
OCTOBER
Average Monthly Precipitation
1971 - 2000



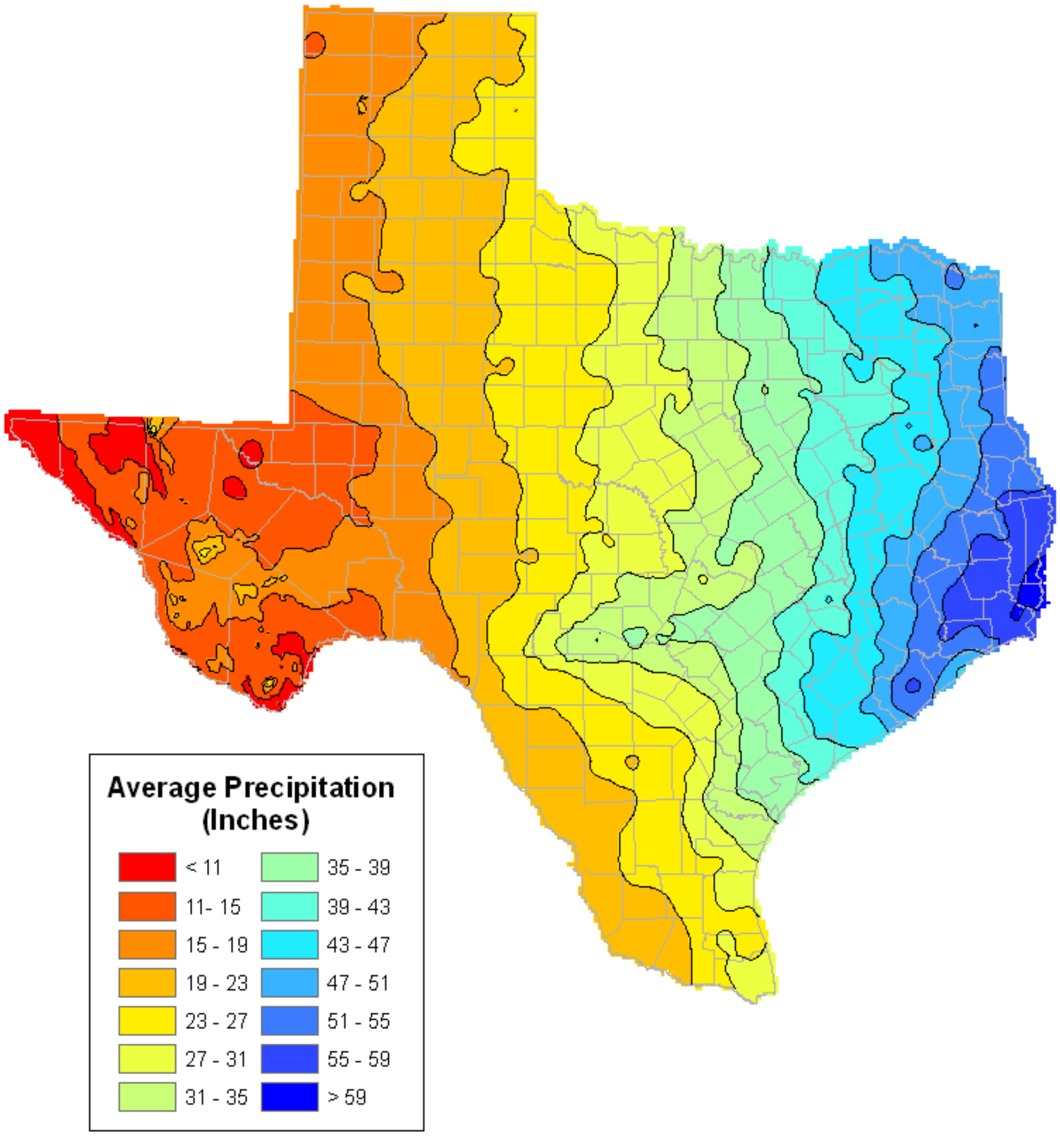
NOVEMBER
Average Monthly Precipitation
1971 - 2000



DECEMBER
Average Monthly Precipitation
1971 - 2000

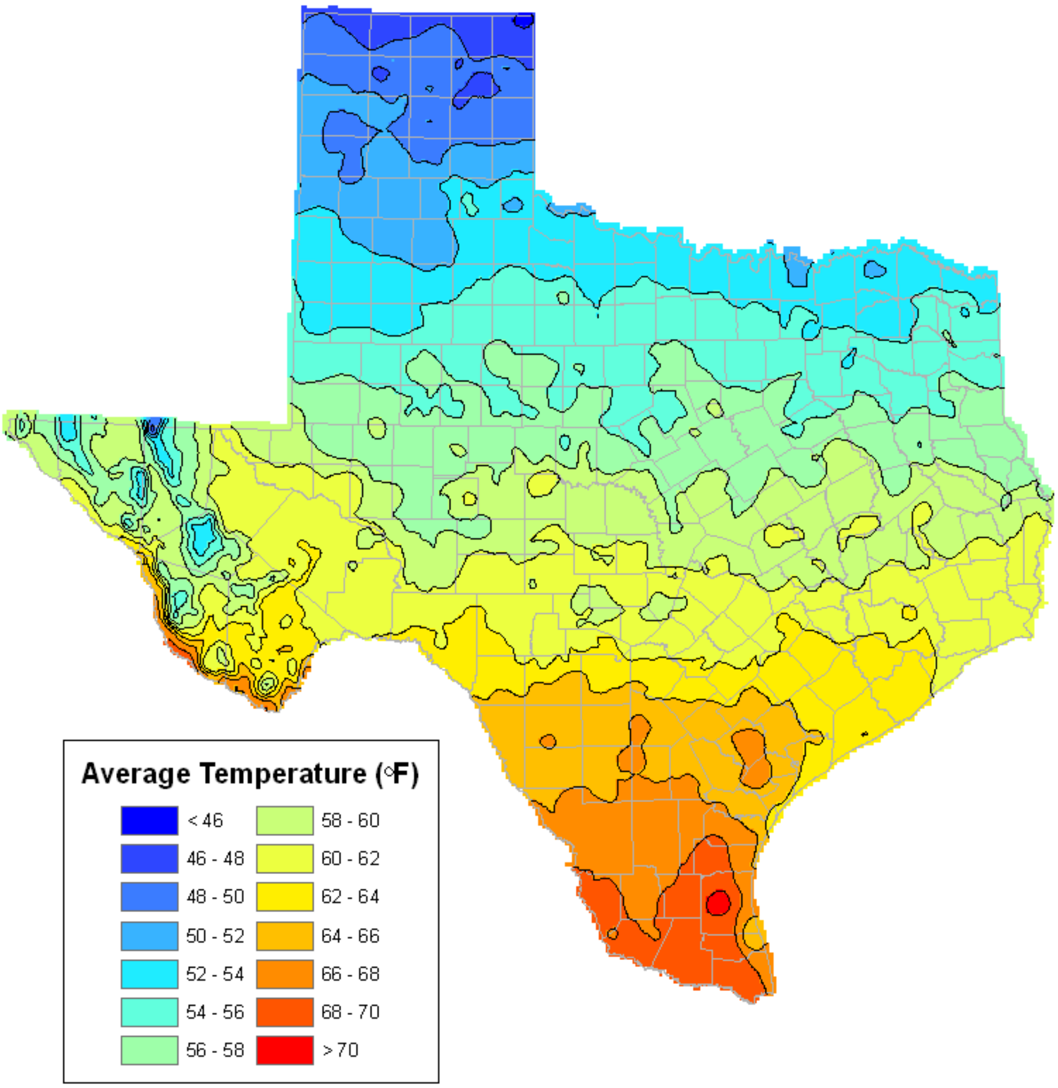


ANNUAL
Average Monthly Precipitation
1971 - 2000

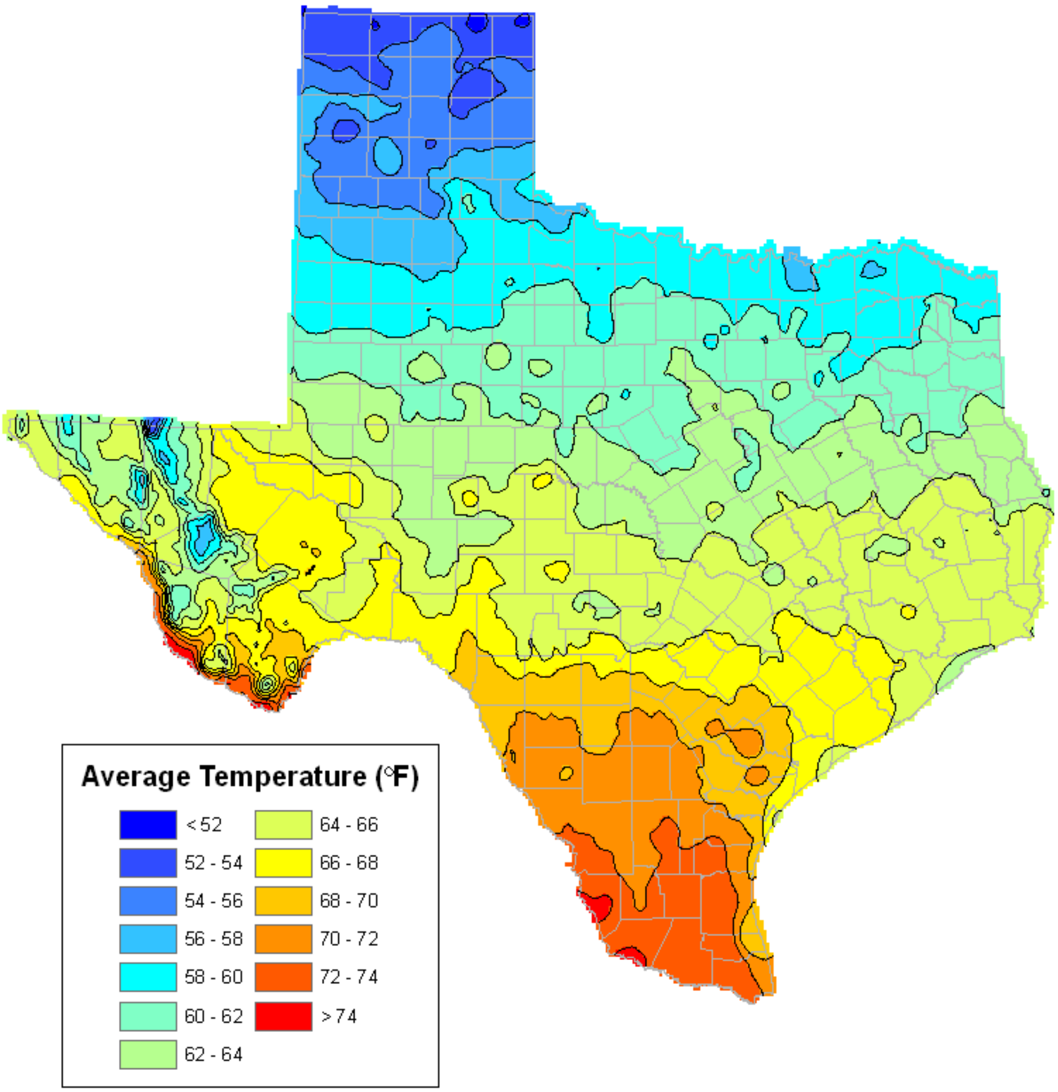


Average Monthly Maximum Temperature Maps

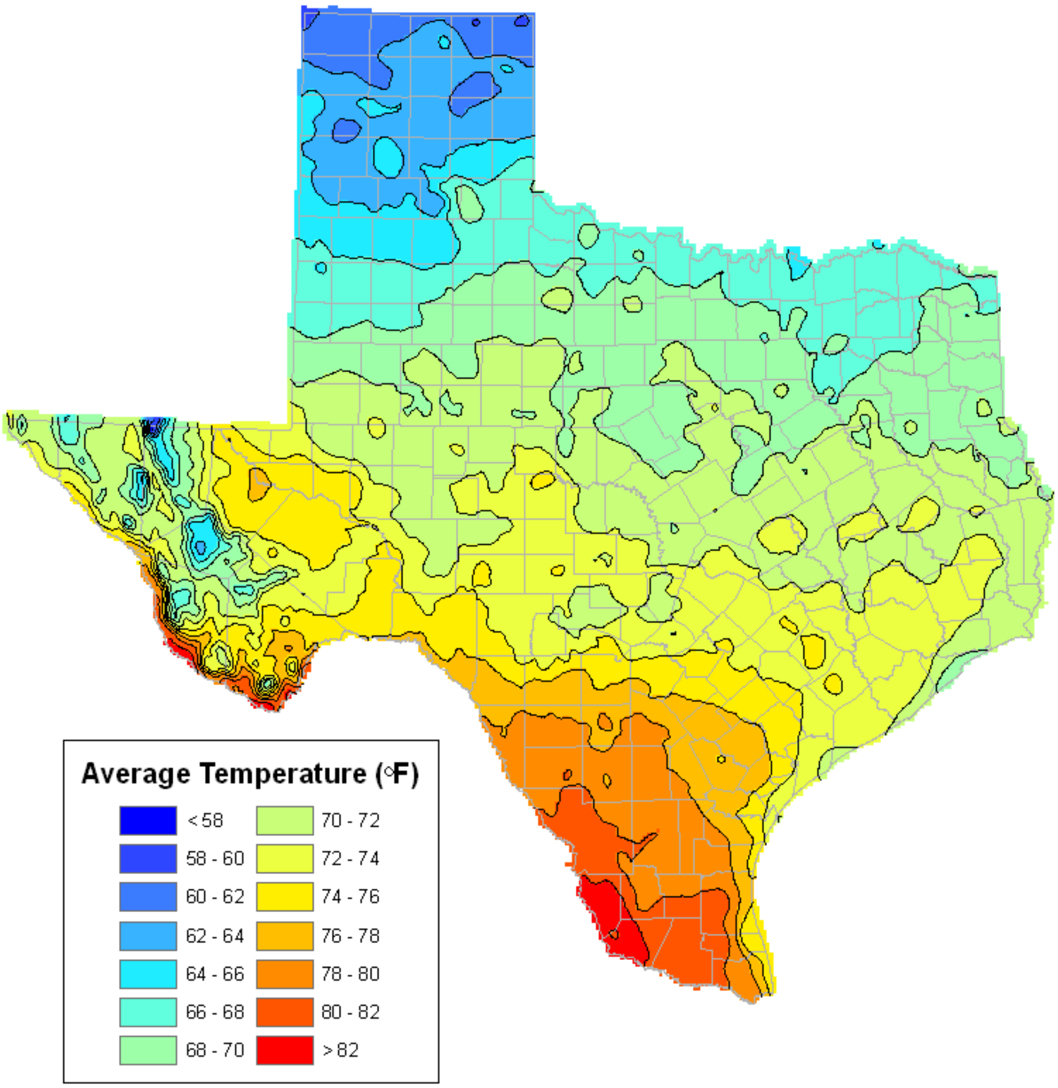
JANUARY
Average Monthly
High Temperature (°F)
1971 - 2000



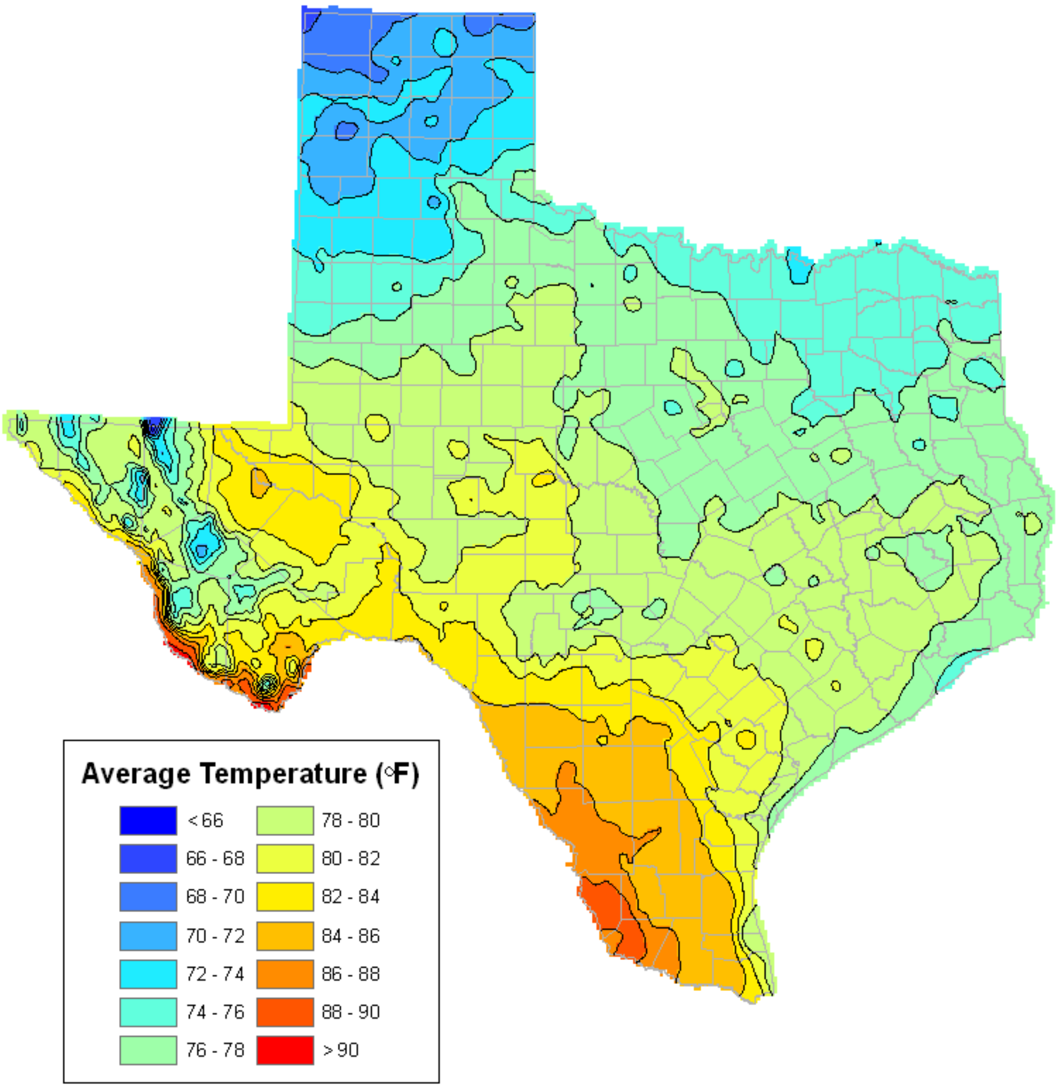
FEBRUARY
Average Monthly
High Temperature (°F)
1971 - 2000



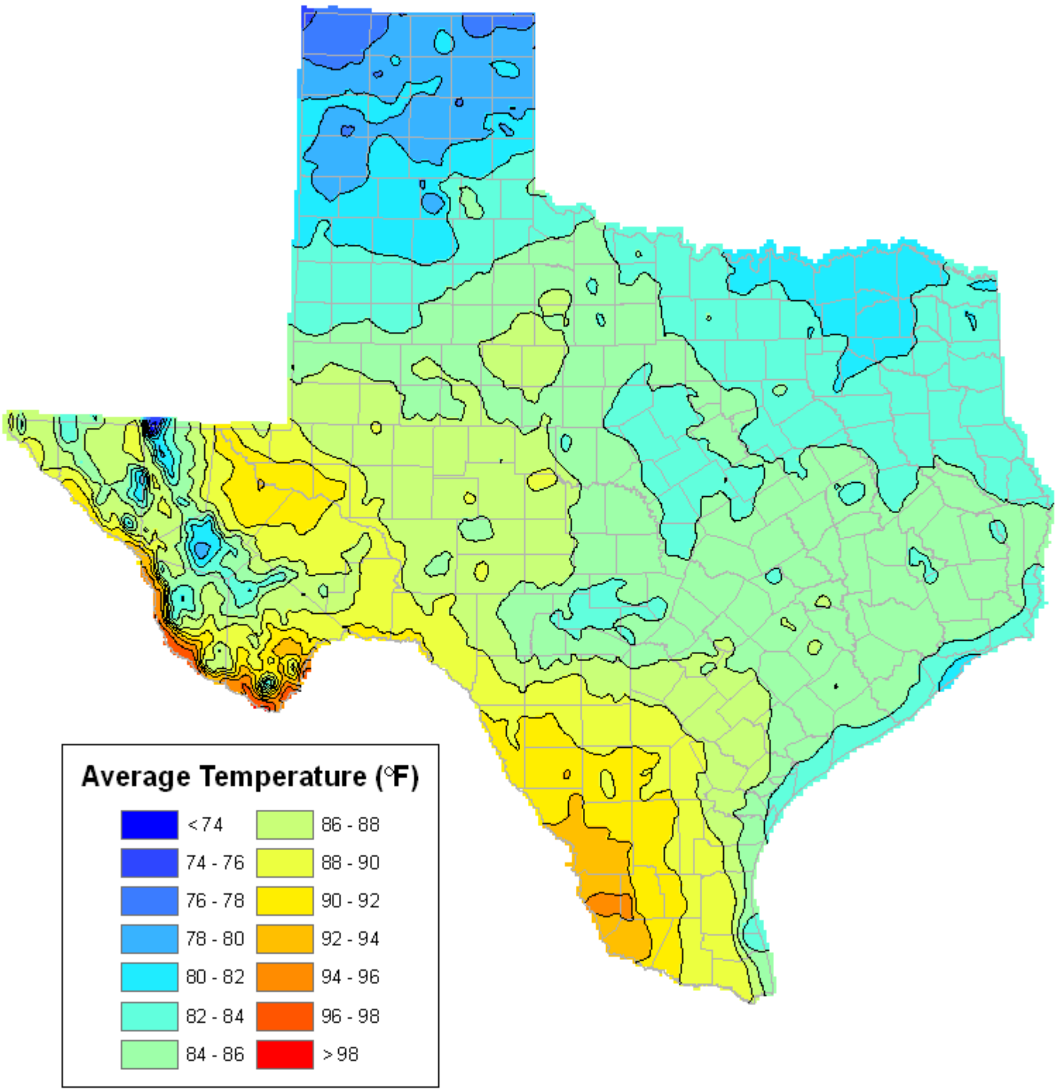
MARCH
Average Monthly
High Temperature (°F)
1971 - 2000



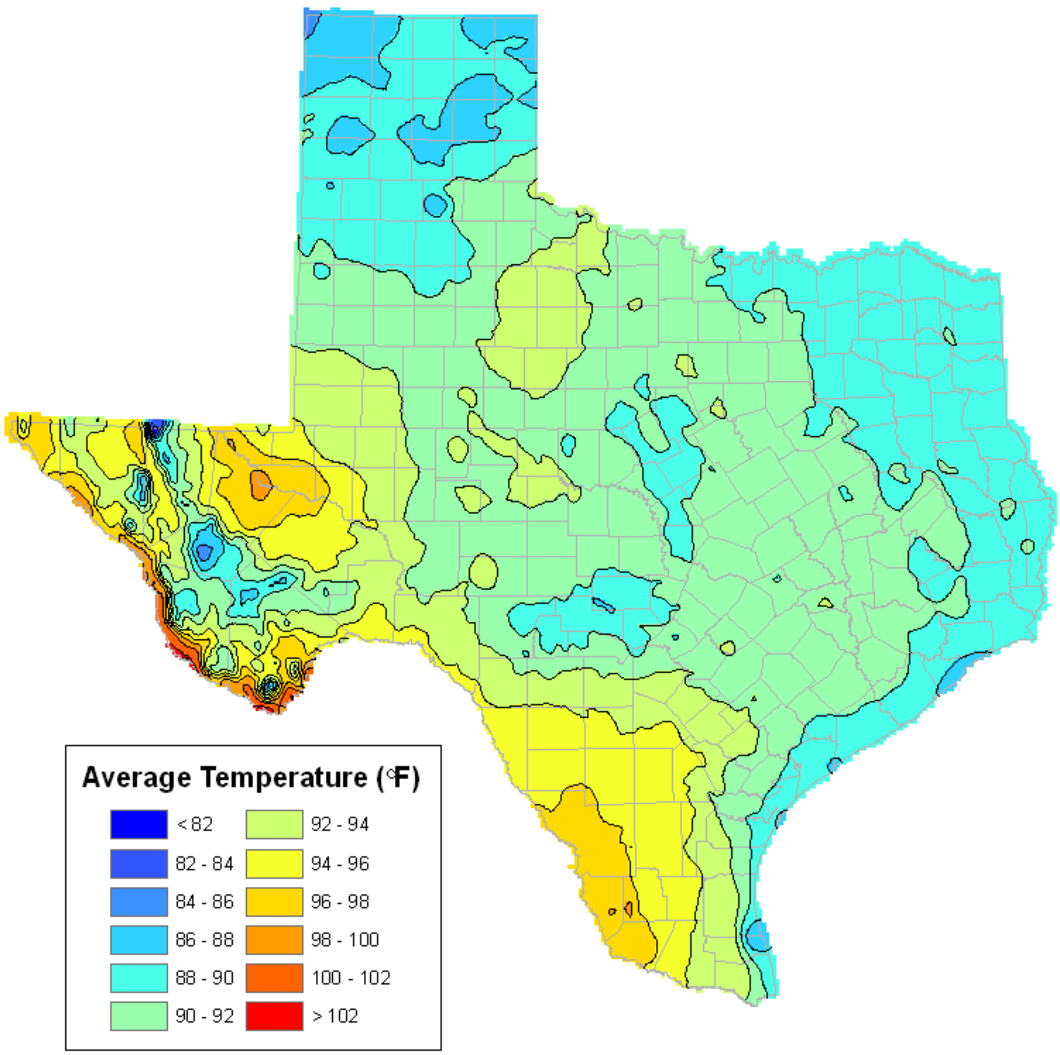
APRIL
Average Monthly
High Temperature (°F)
1971 - 2000



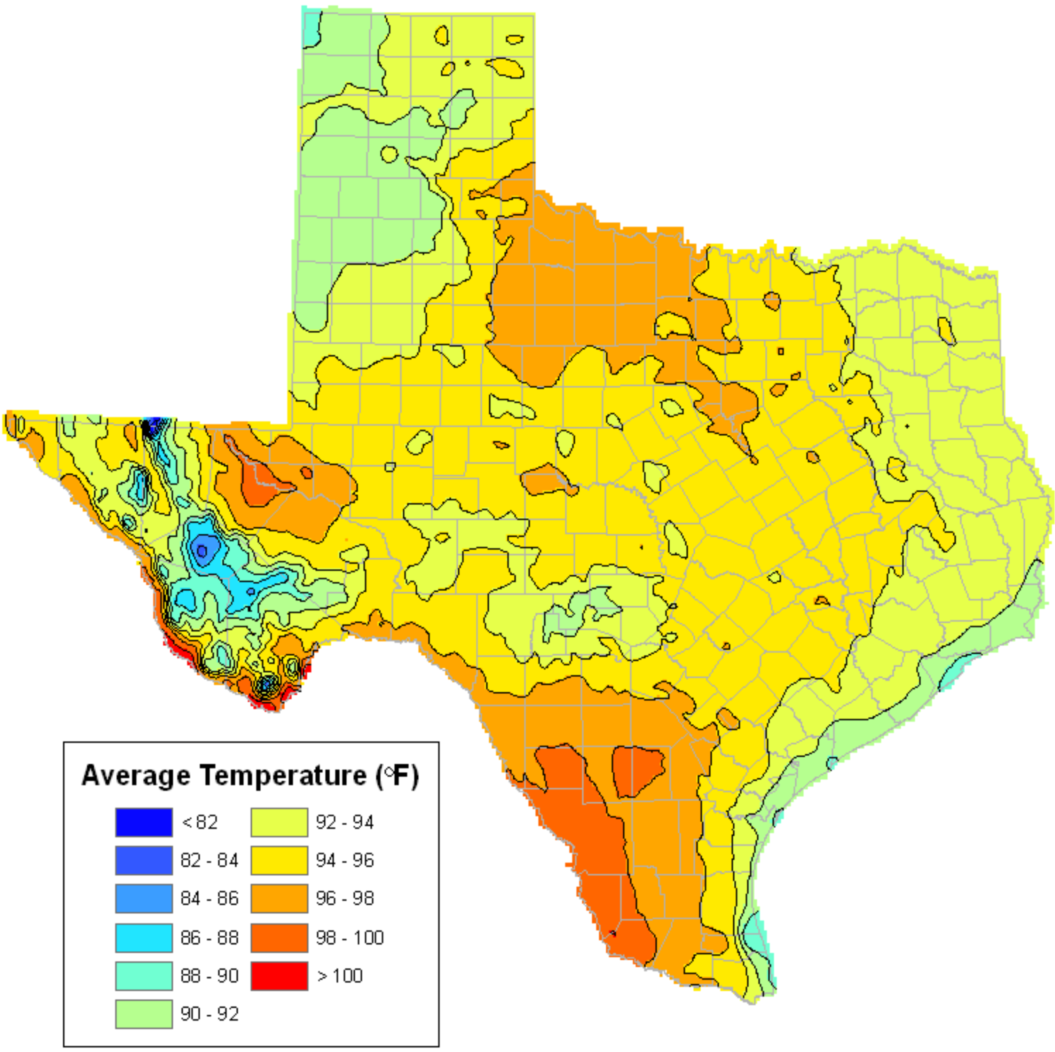
MAY
Average Monthly
High Temperature (°F)
1971 - 2000



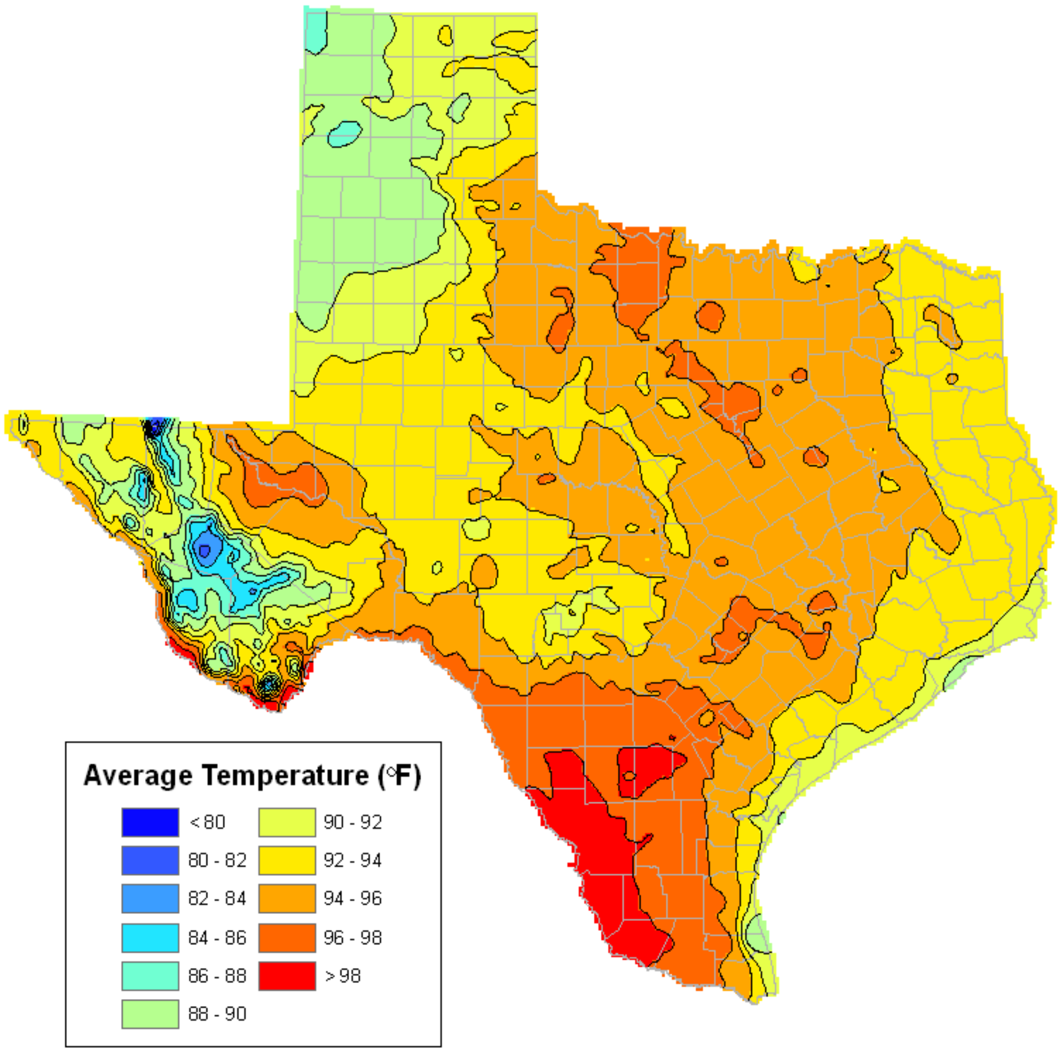
JUNE
Average Monthly
High Temperature (°F)
1971 - 2000



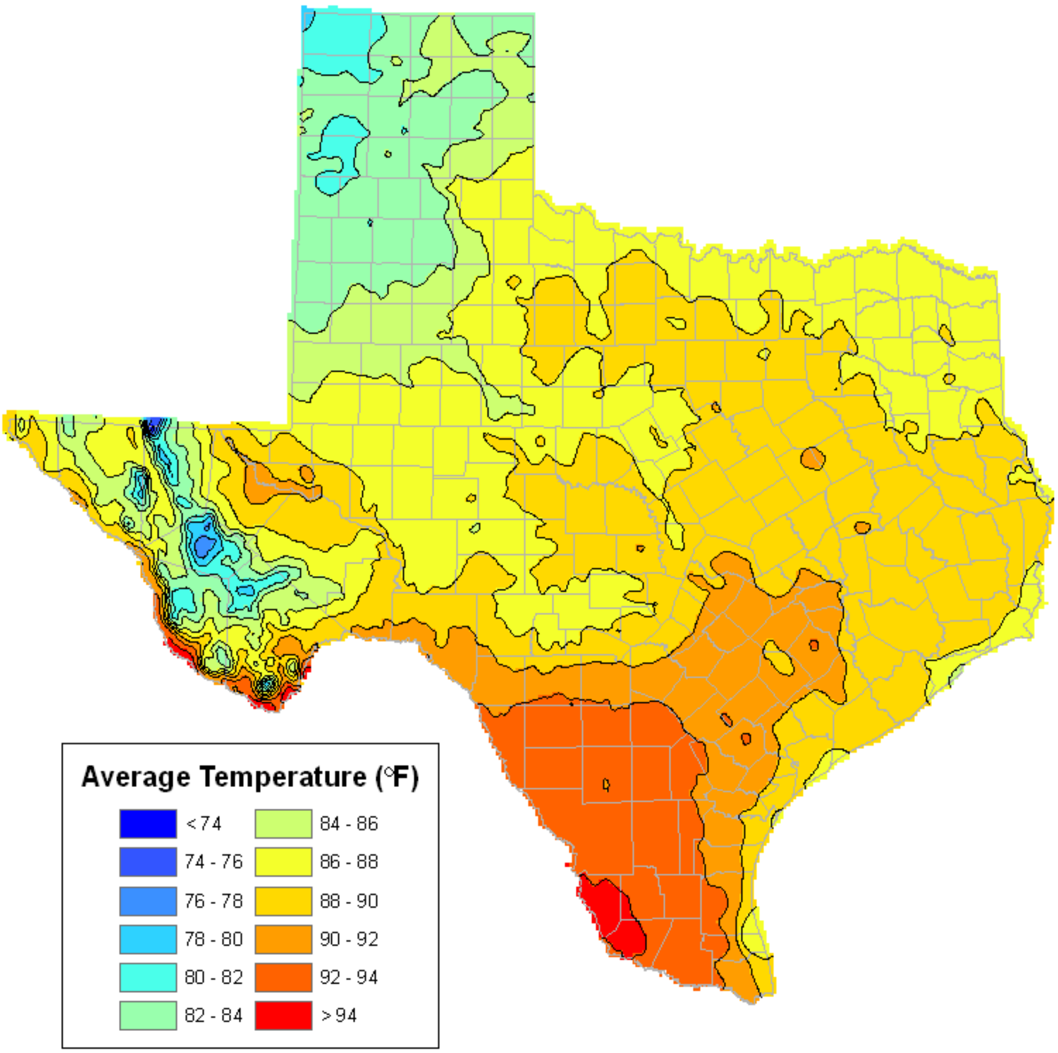
JULY
Average Monthly
High Temperature (°F)
1971 - 2000



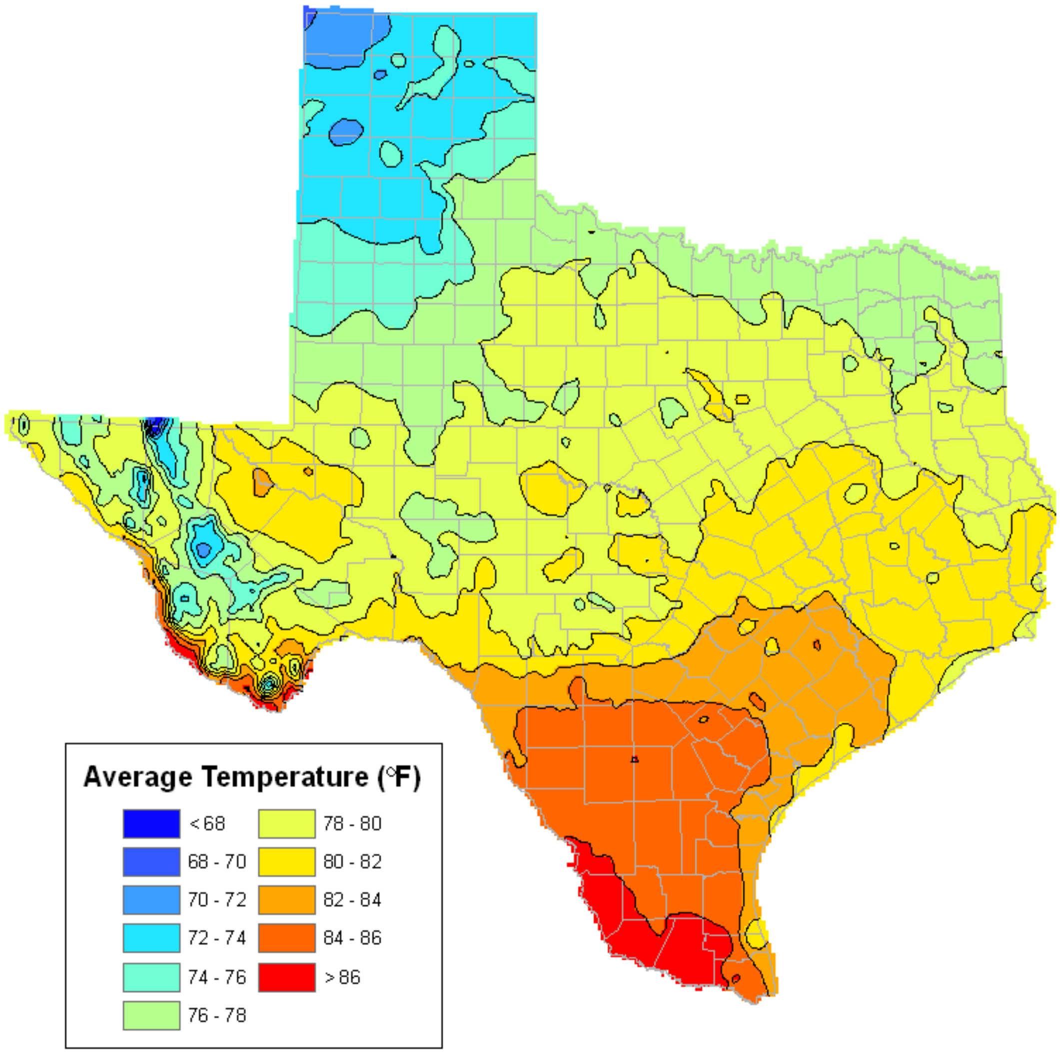
AUGUST
Average Monthly
High Temperature (°F)
1971 - 2000



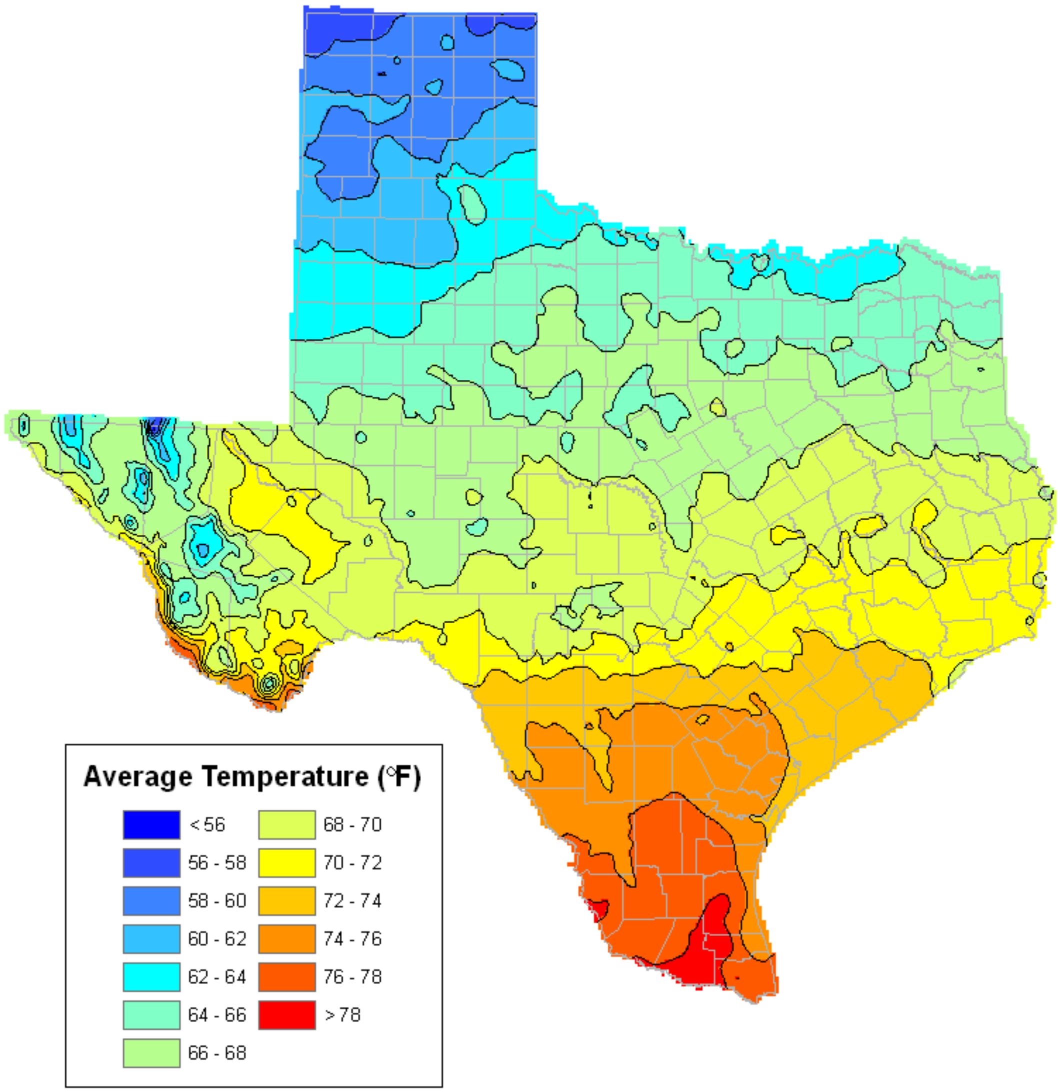
SEPTEMBER
Average Monthly
High Temperature (°F)
1971 - 2000



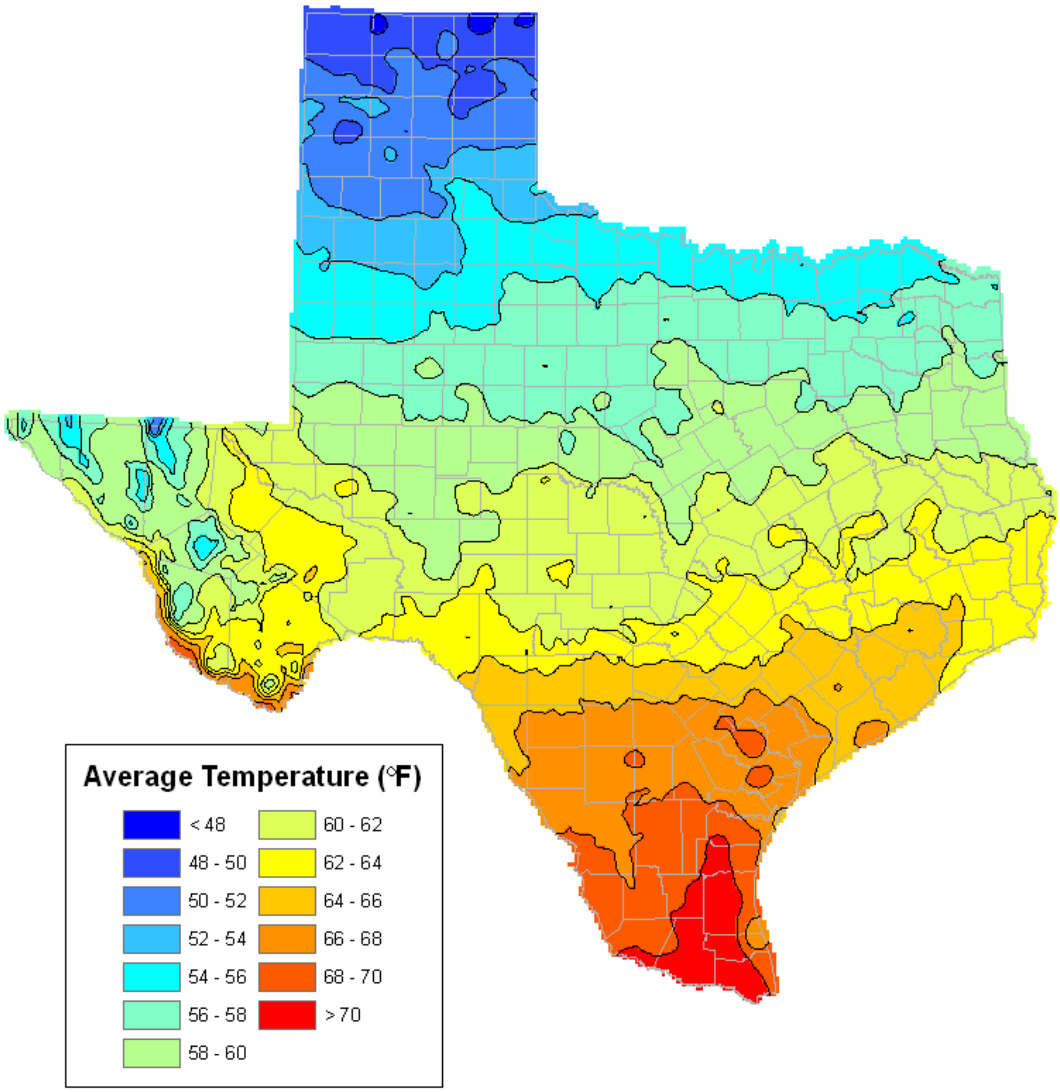
OCTOBER
Average Monthly
High Temperature (°F)
1971 - 2000



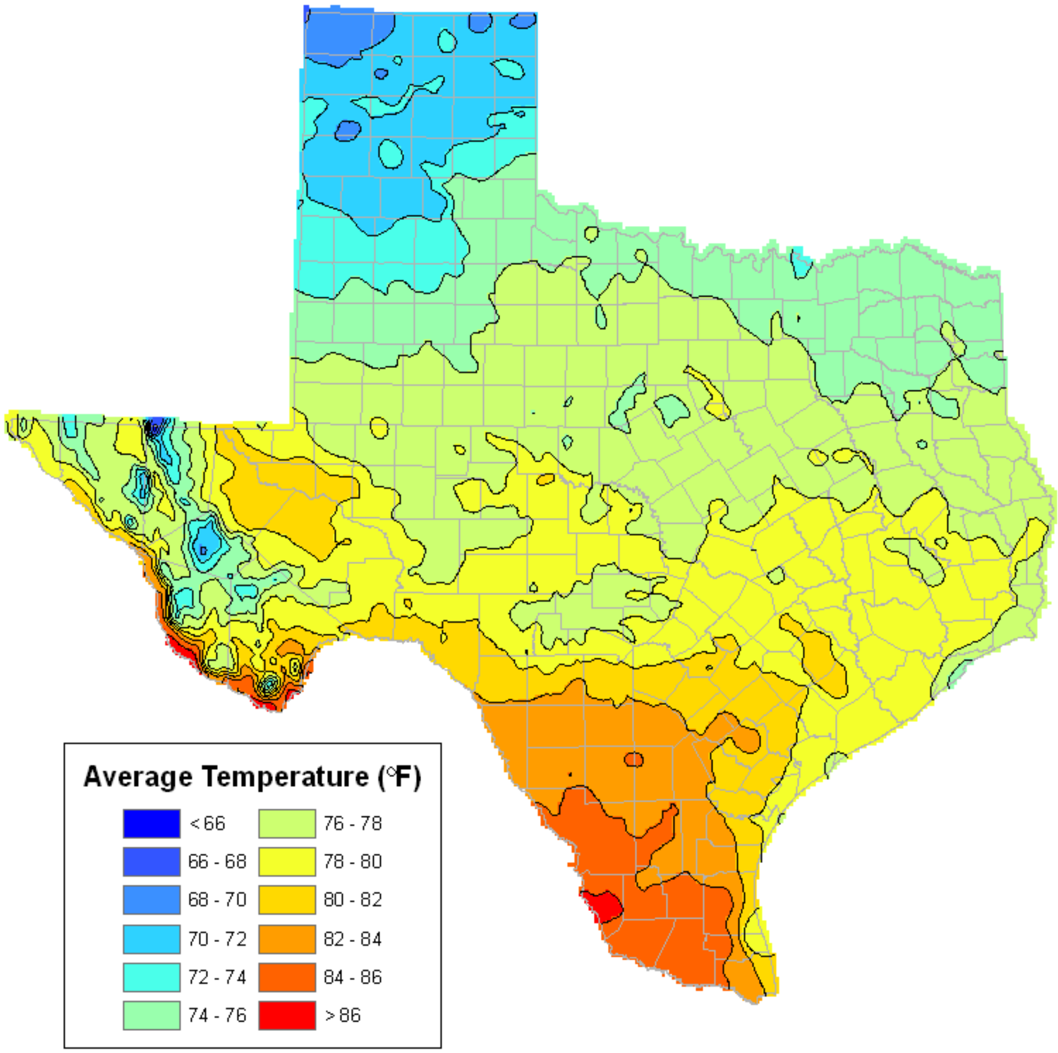
NOVEMBER
Average Monthly
High Temperature (°F)
1971 - 2000



DECEMBER
Average Monthly
High Temperature (°F)
1971 - 2000

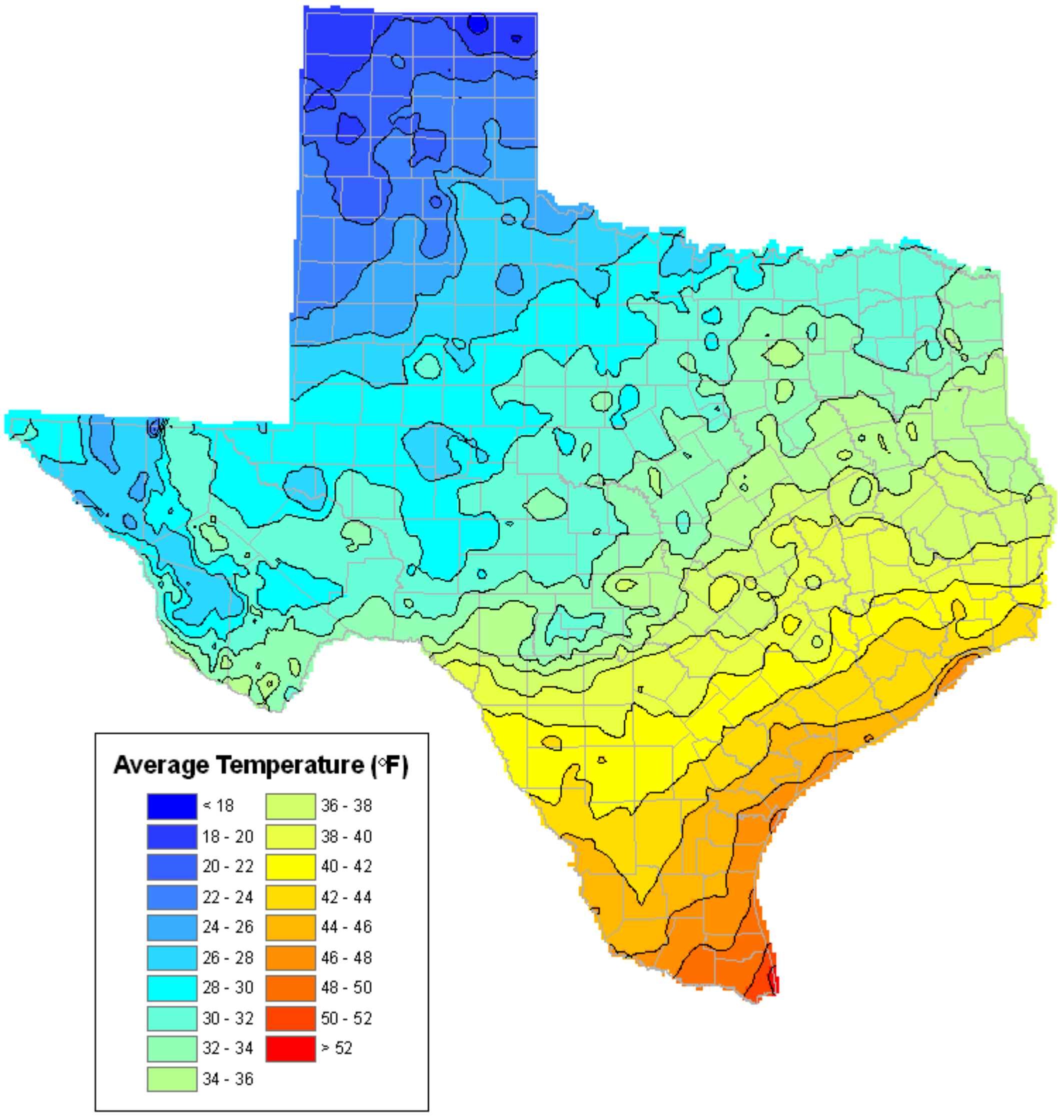


ANNUAL
Average Monthly
High Temperature (°F)
1971 - 2000

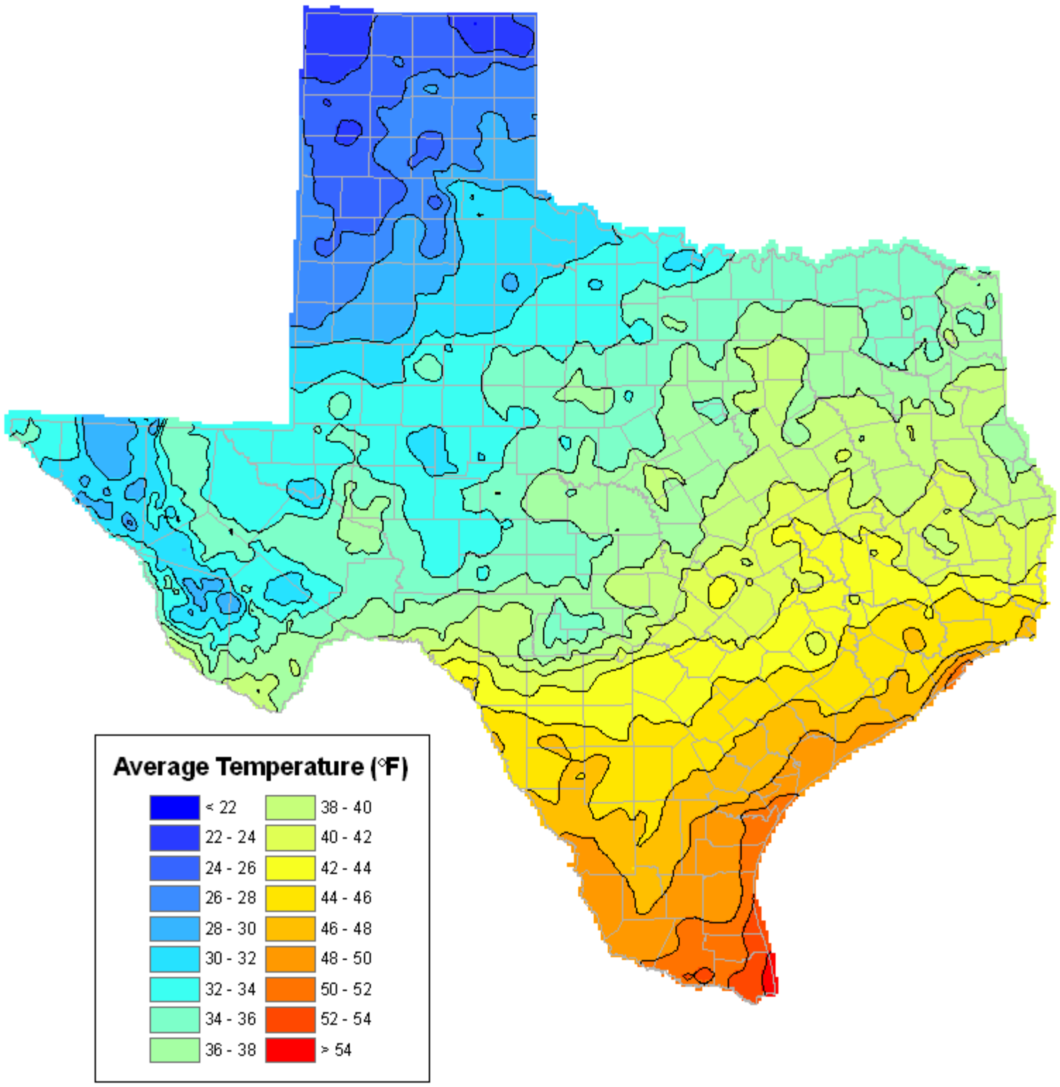


Average Monthly Minimum Temperature Maps

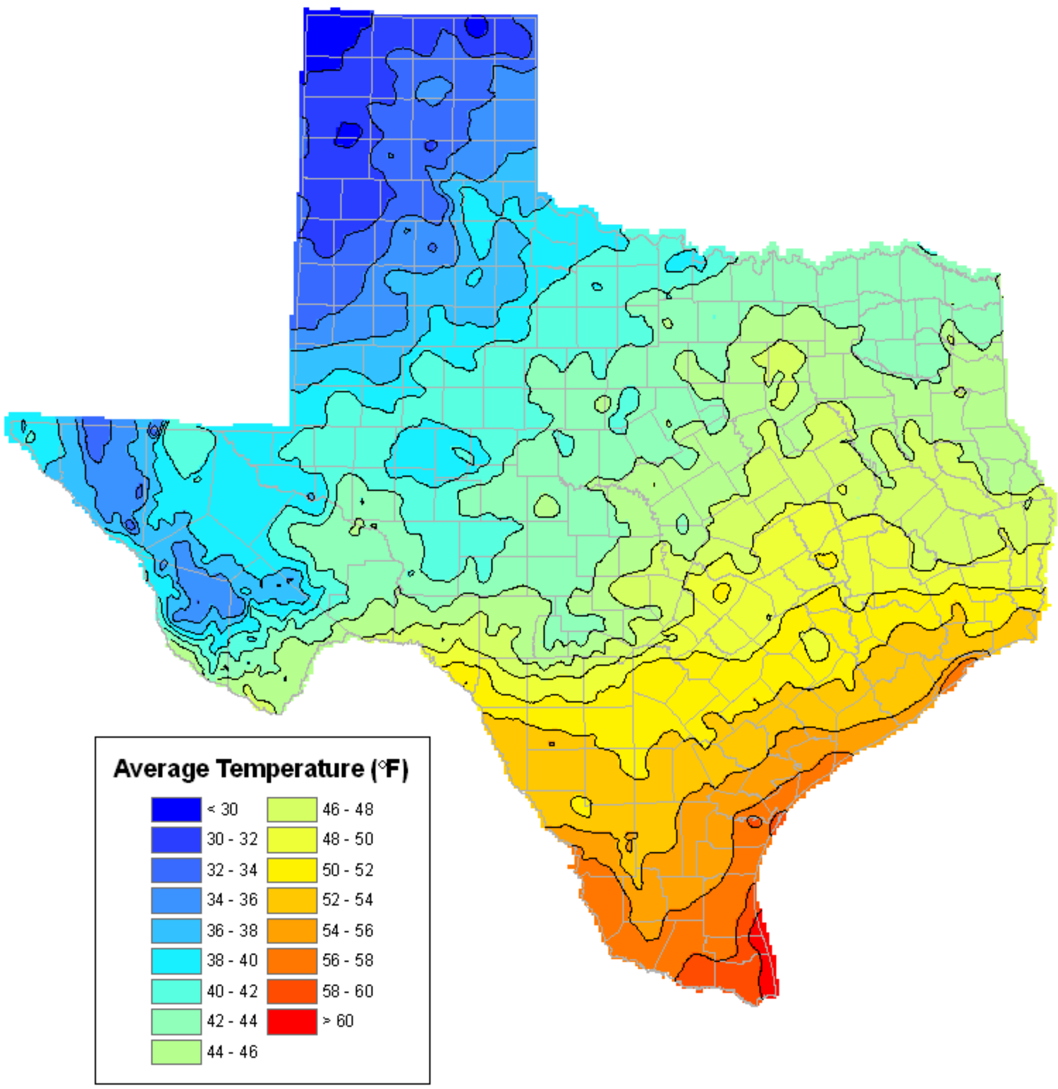
JANUARY
Average Monthly
Low Temperature (°F)
1971 - 2000



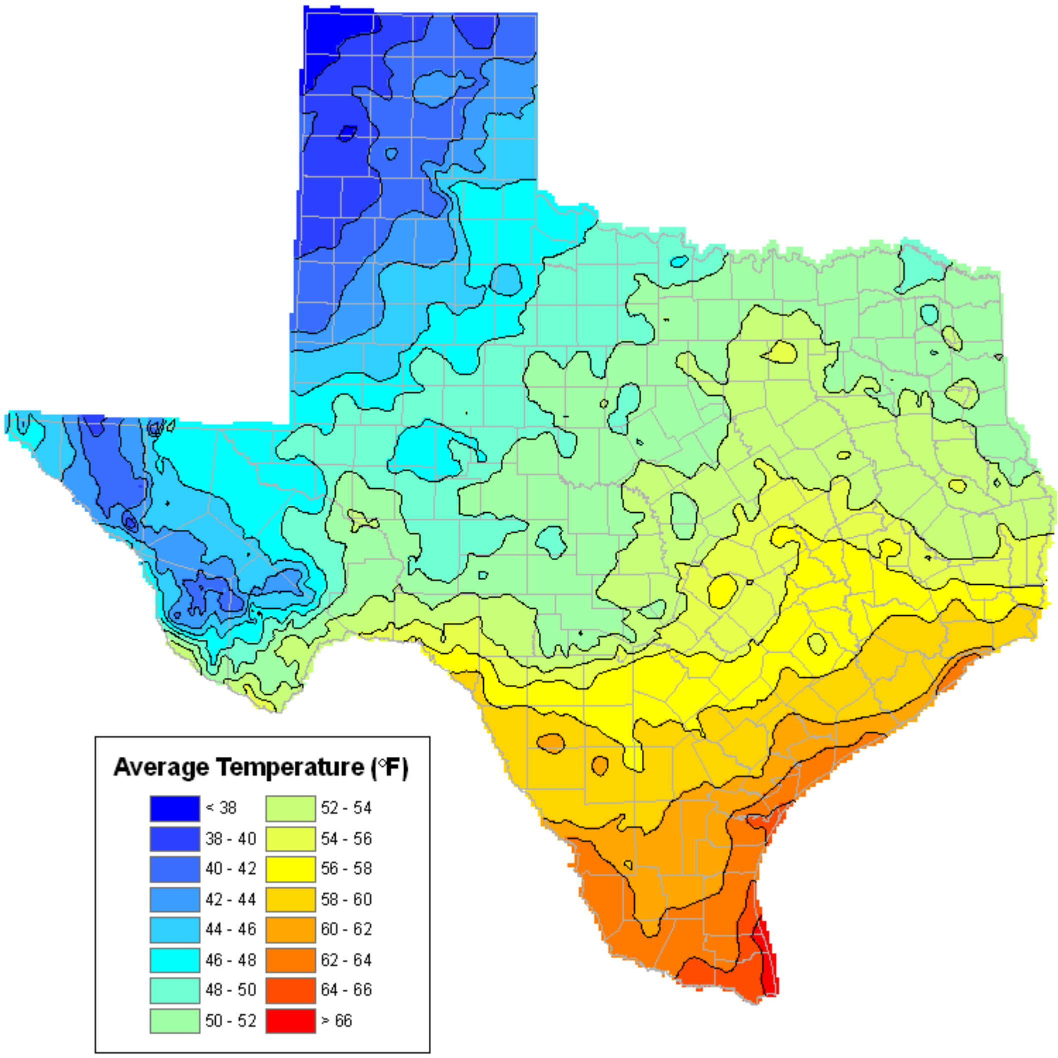
FEBRUARY
Average Monthly
Low Temperature (°F)
1971 - 2000



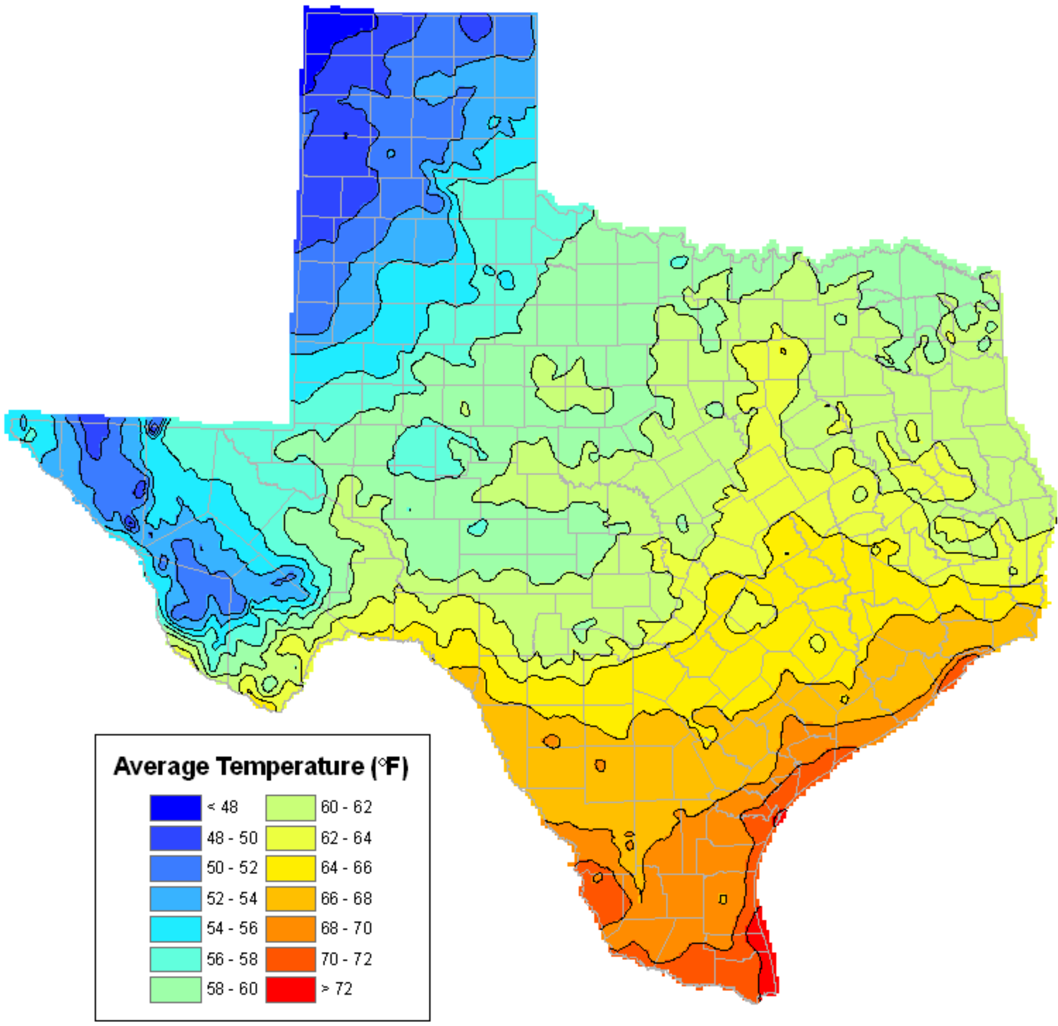
MARCH
Average Monthly
Low Temperature (°F)
1971 - 2000



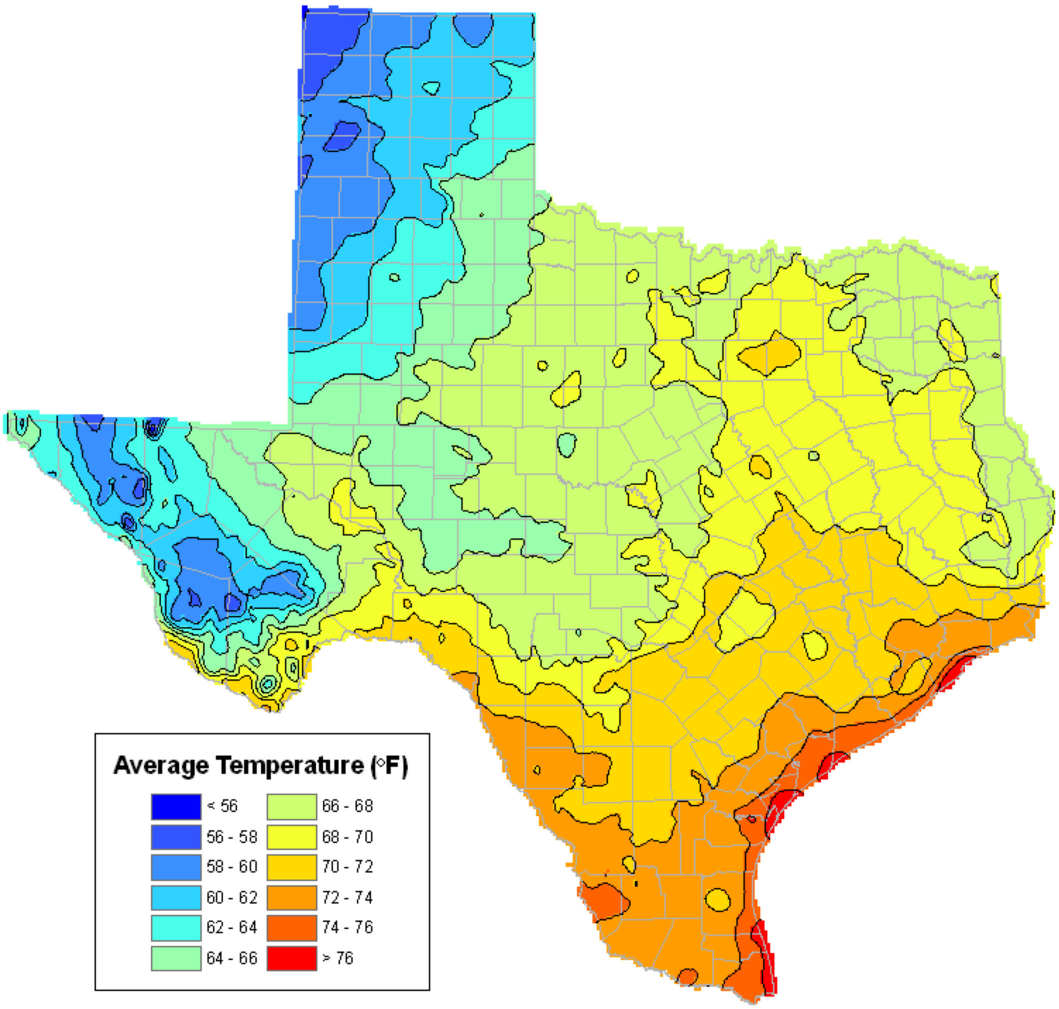
APRIL
Average Monthly
Low Temperature (°F)
1971 - 2000



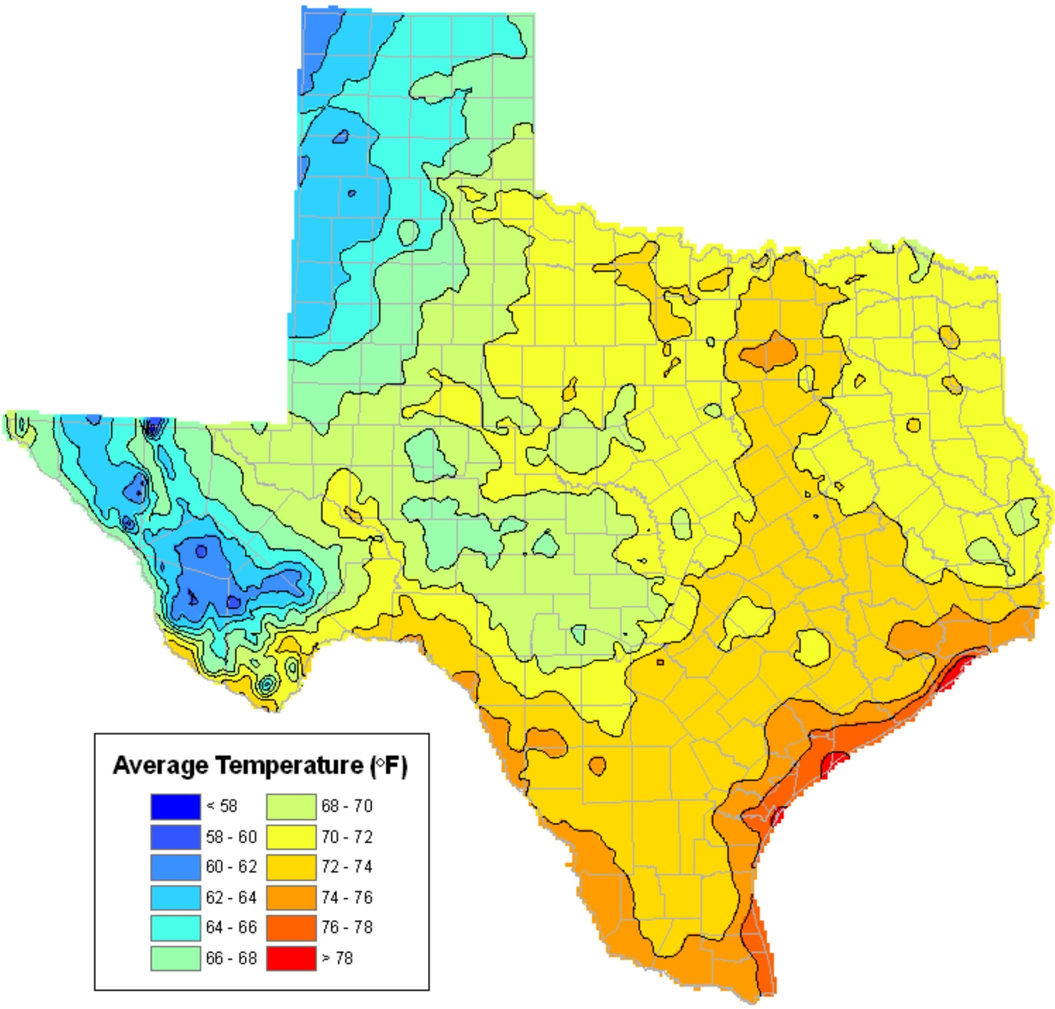
MAY
Average Monthly
Low Temperature (°F)
1971 - 2000



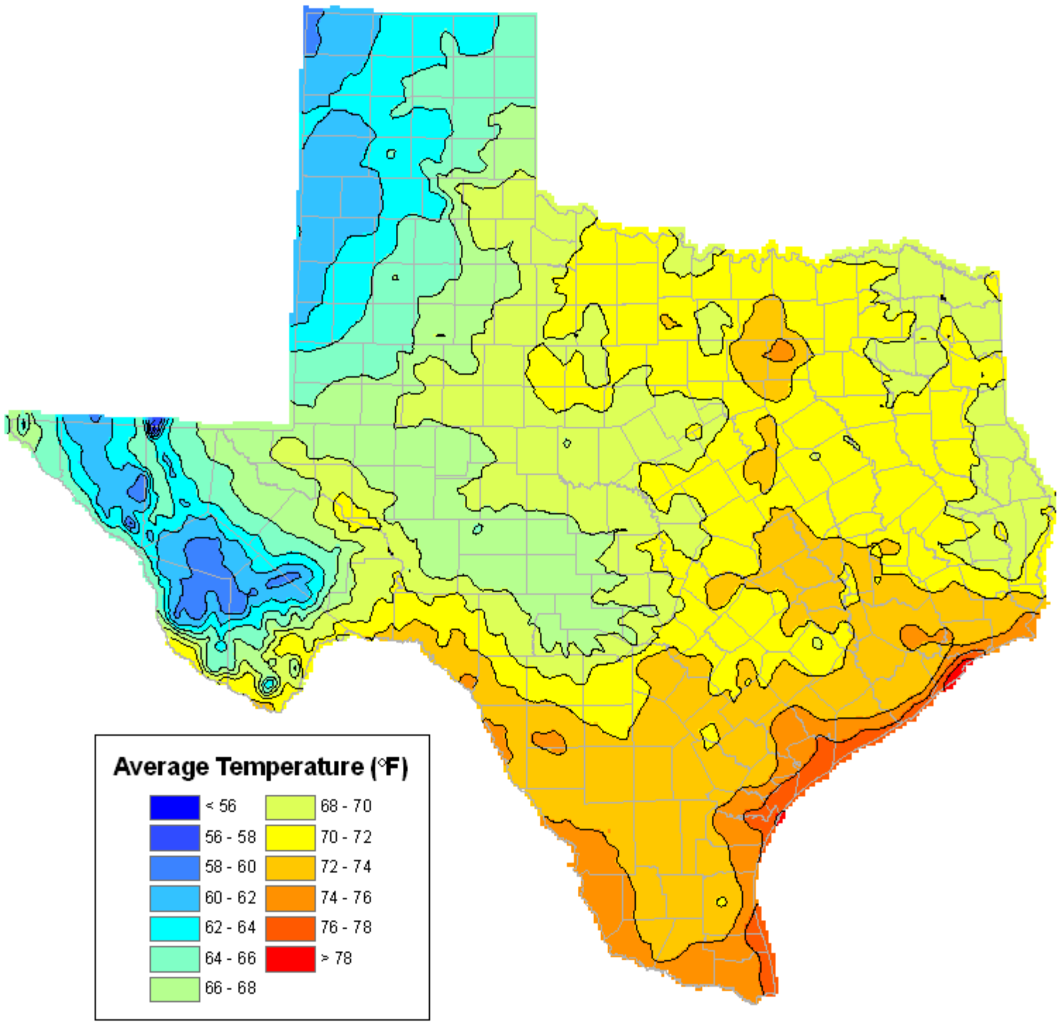
JUNE
Average Monthly
Low Temperature (°F)
1971 - 2000



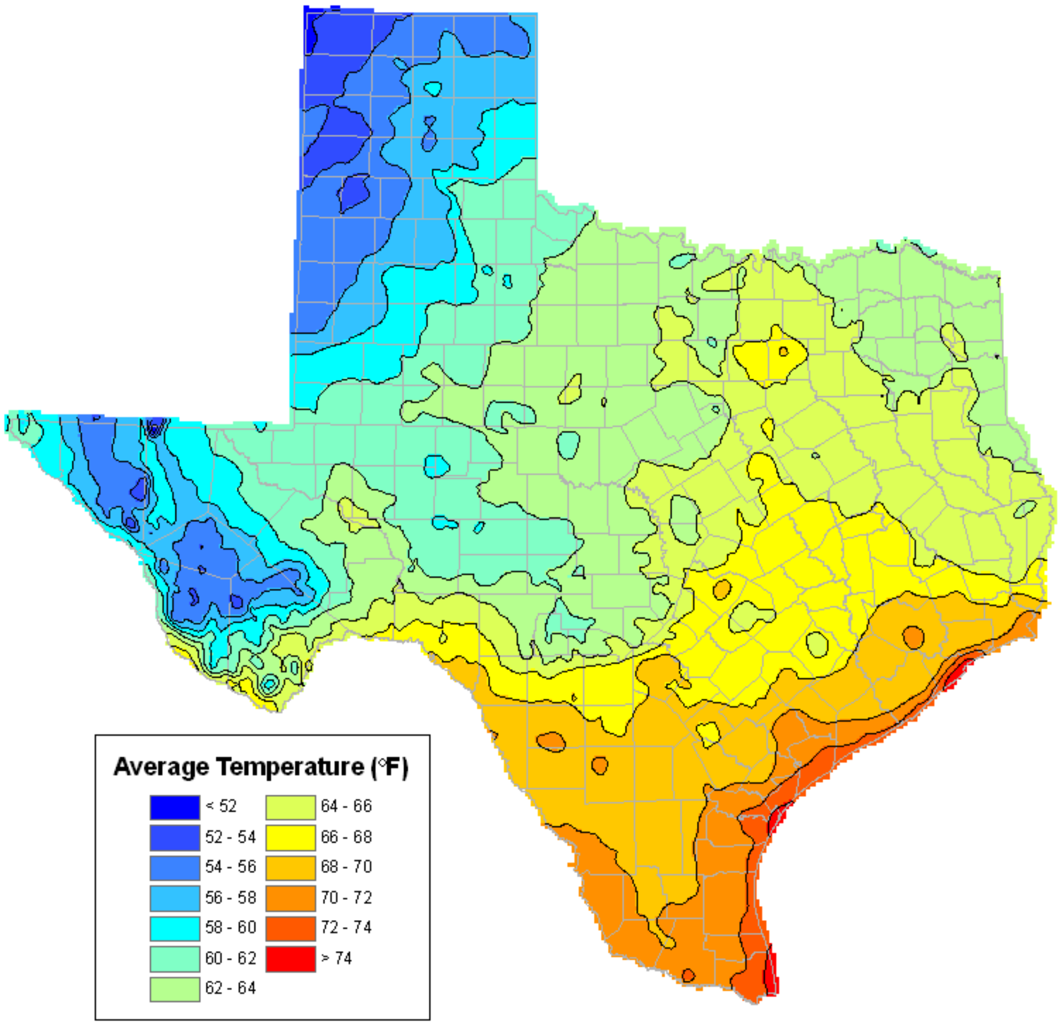
JULY
Average Monthly
Low Temperature (°F)
1971 - 2000



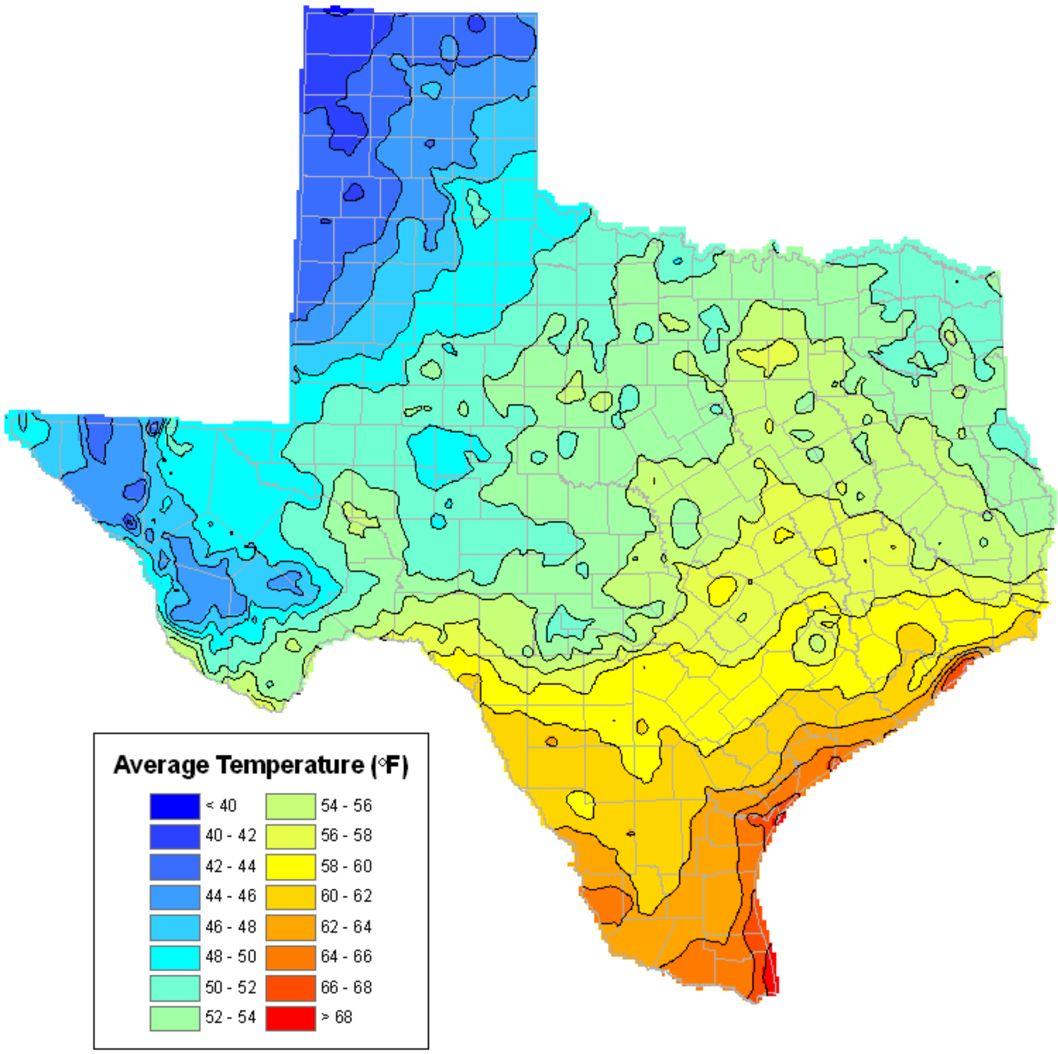
AUGUST
Average Monthly
Low Temperature (°F)
1971 - 2000



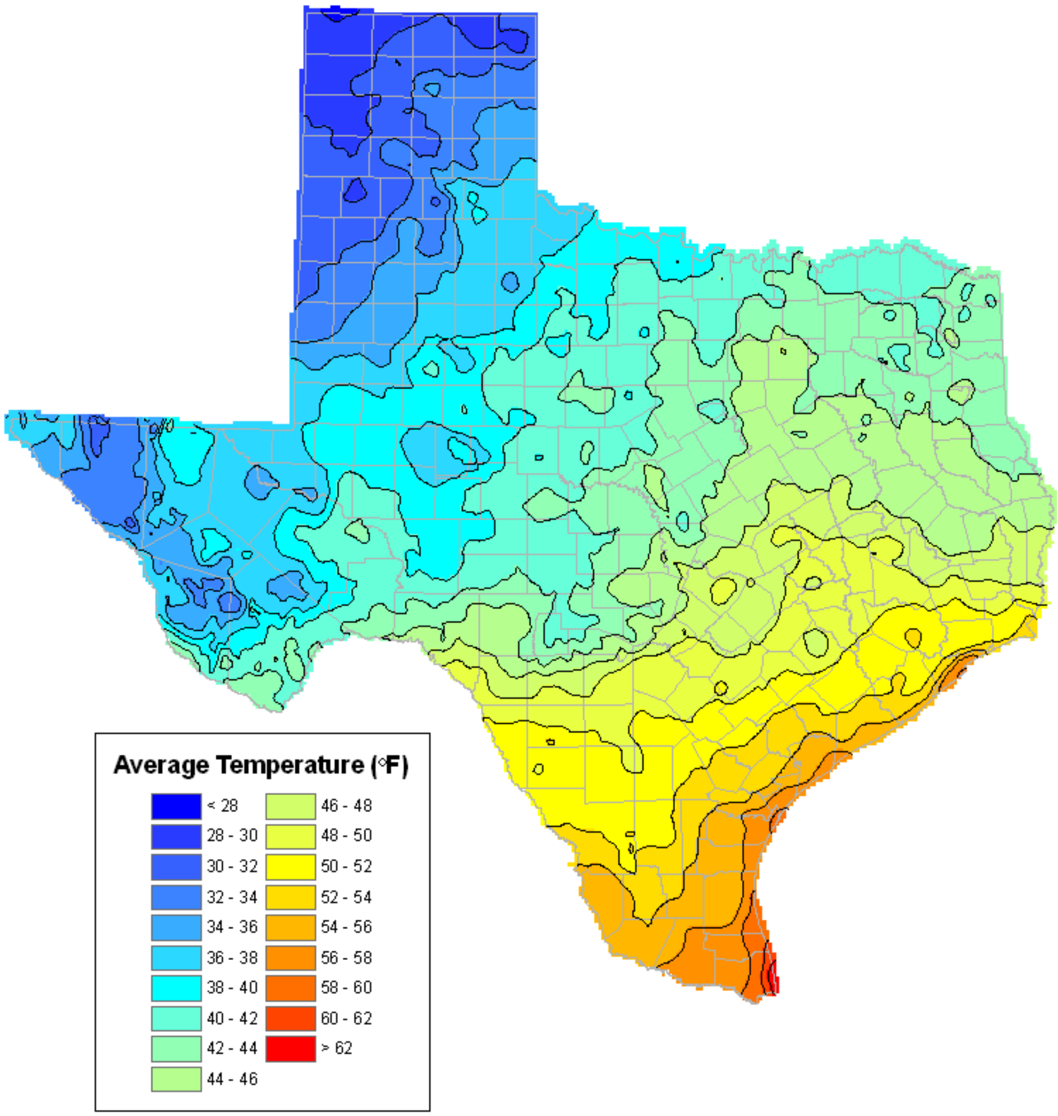
SEPTEMBER
Average Monthly
Low Temperature (°F)
1971 - 2000



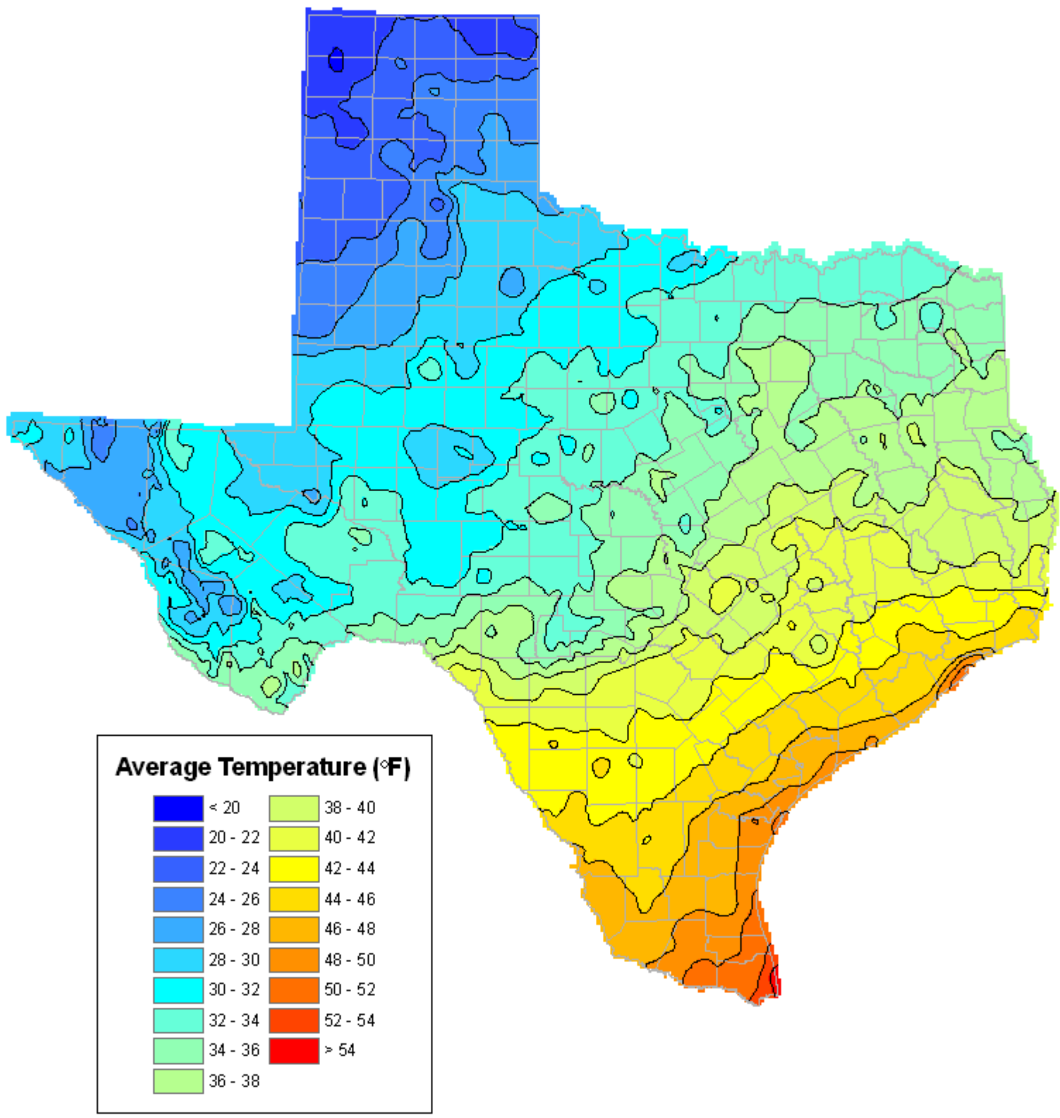
OCTOBER
Average Monthly
Low Temperature (°F)
1971 - 2000



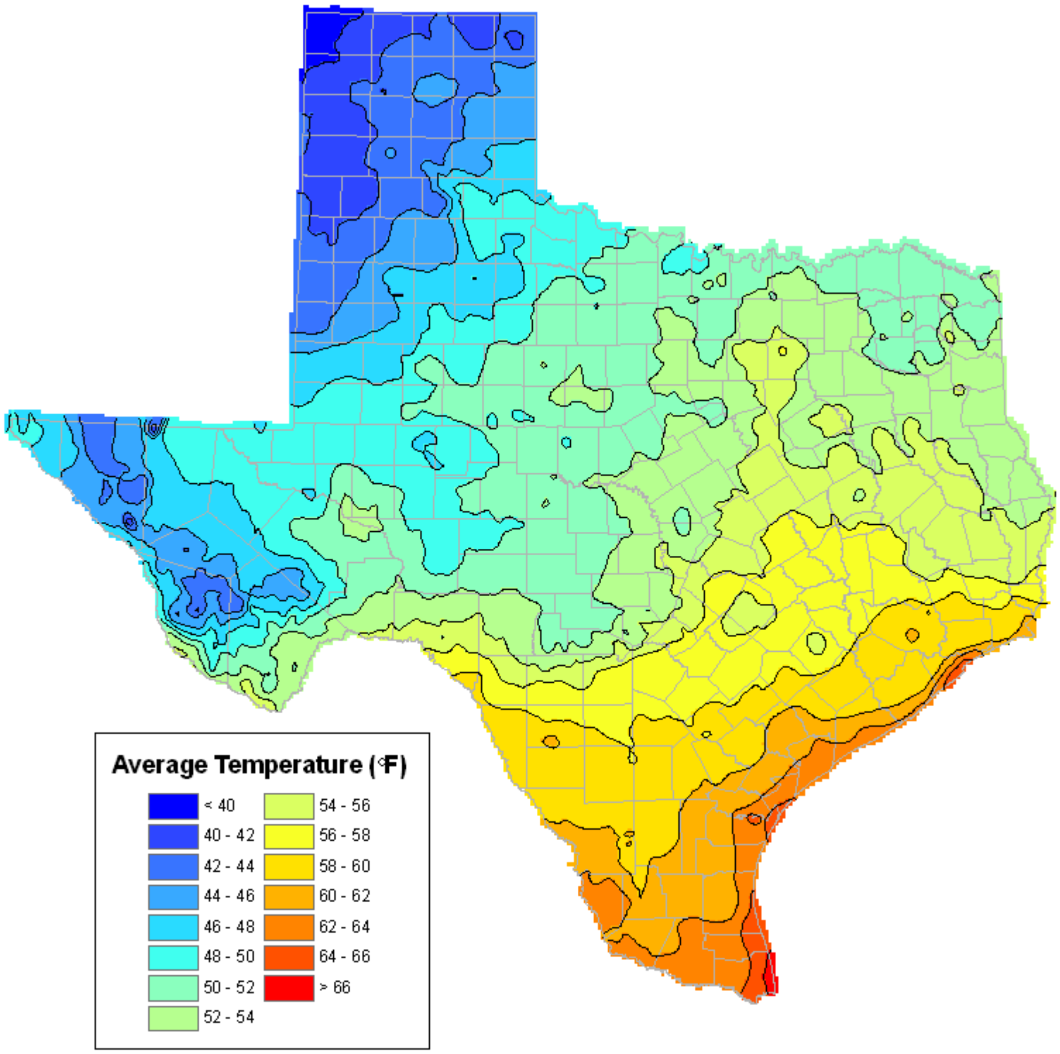
NOVEMBER
Average Monthly
Low Temperature (°F)
1971 - 2000



DECEMBER
Average Monthly
Low Temperature (°F)
1971 - 2000

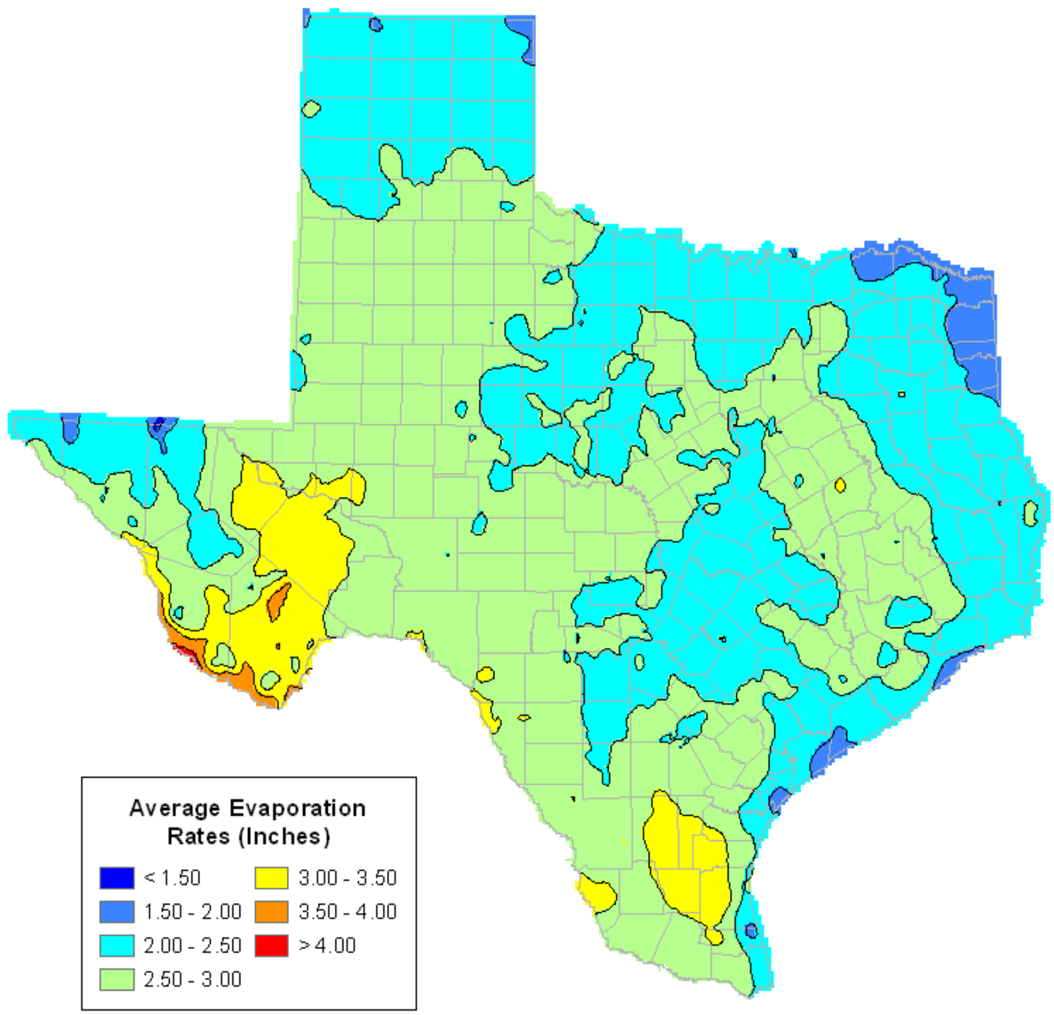


ANNUAL
Average Monthly
Low Temperature (°F)
1971 - 2000

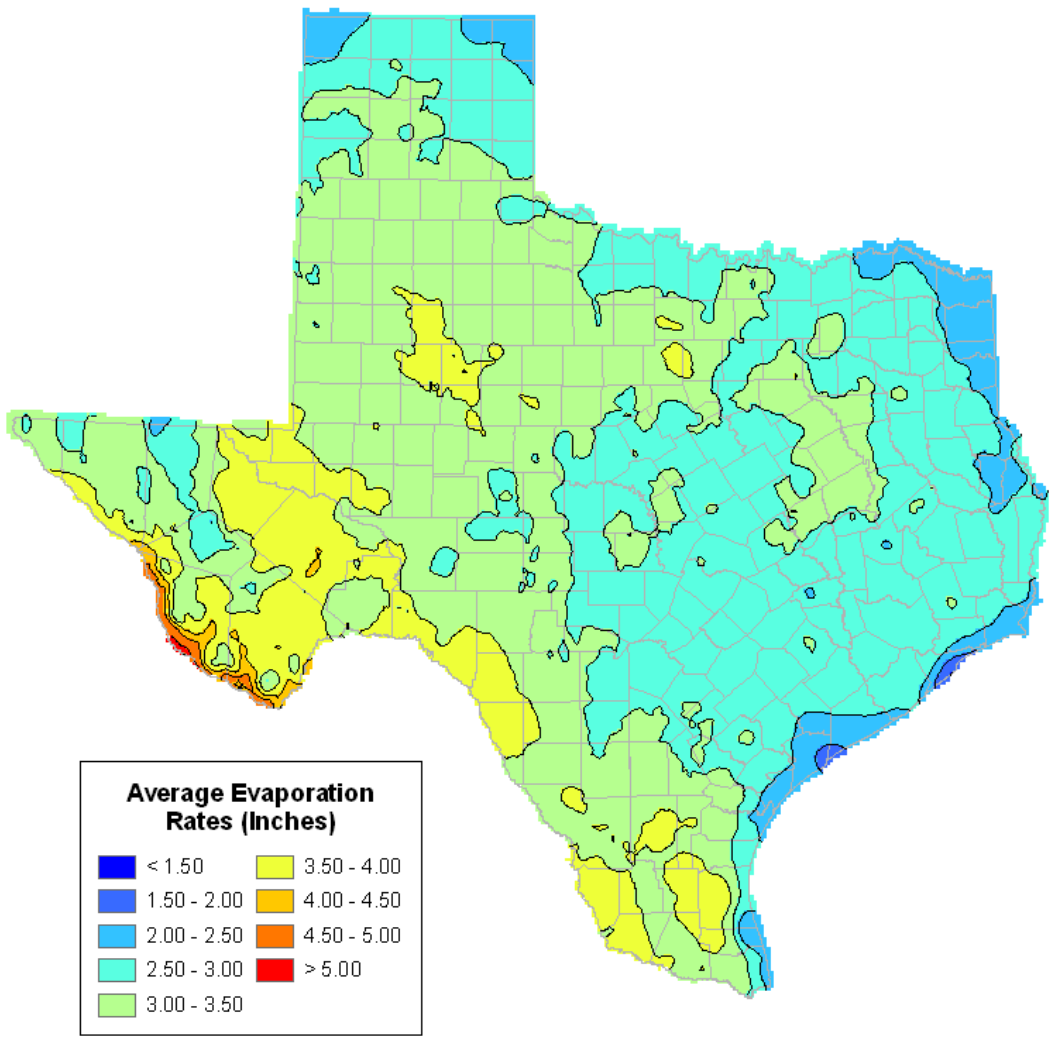


Average Monthly Lake Evaporation Maps

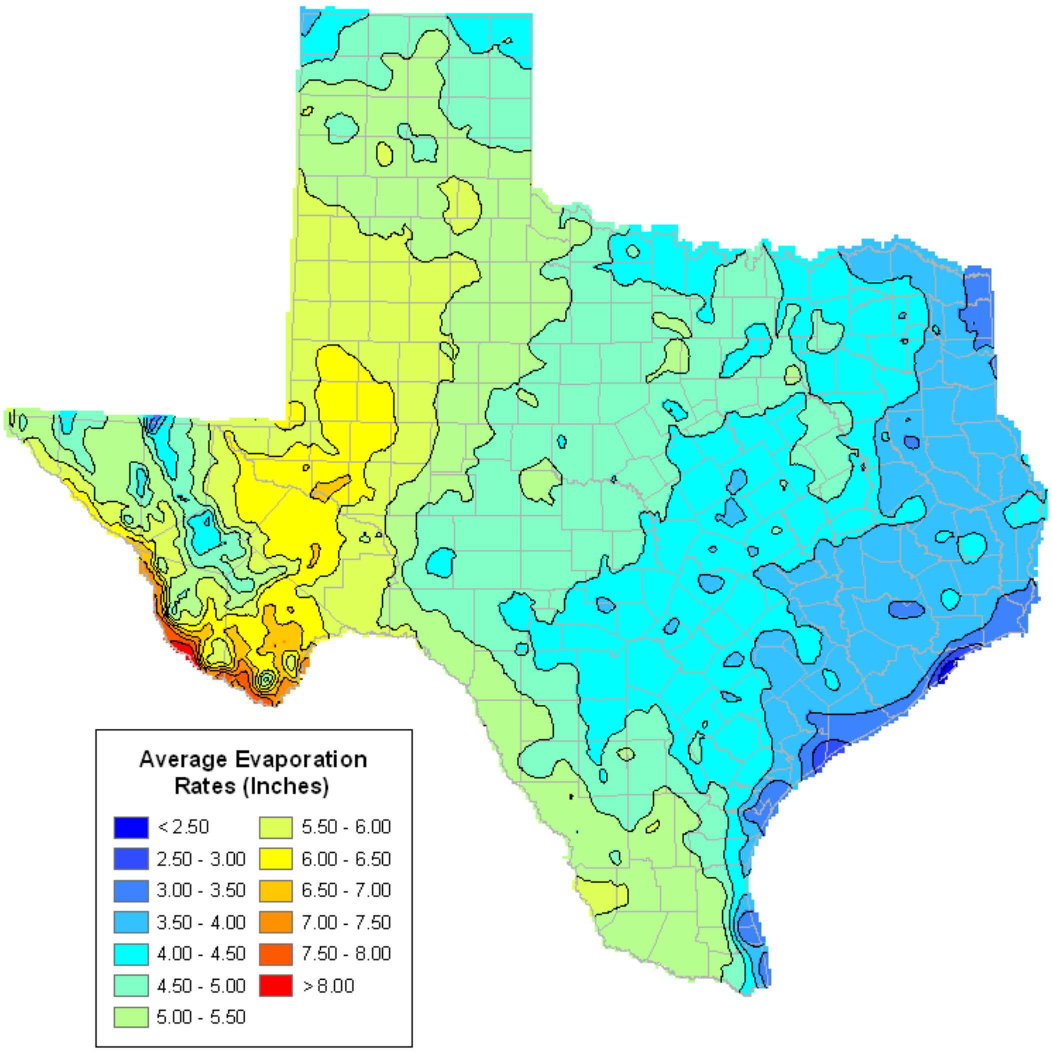
JANUARY
Average Monthly Gross Lake
Surface Evaporation Rates
In Inches, 1971 - 2000



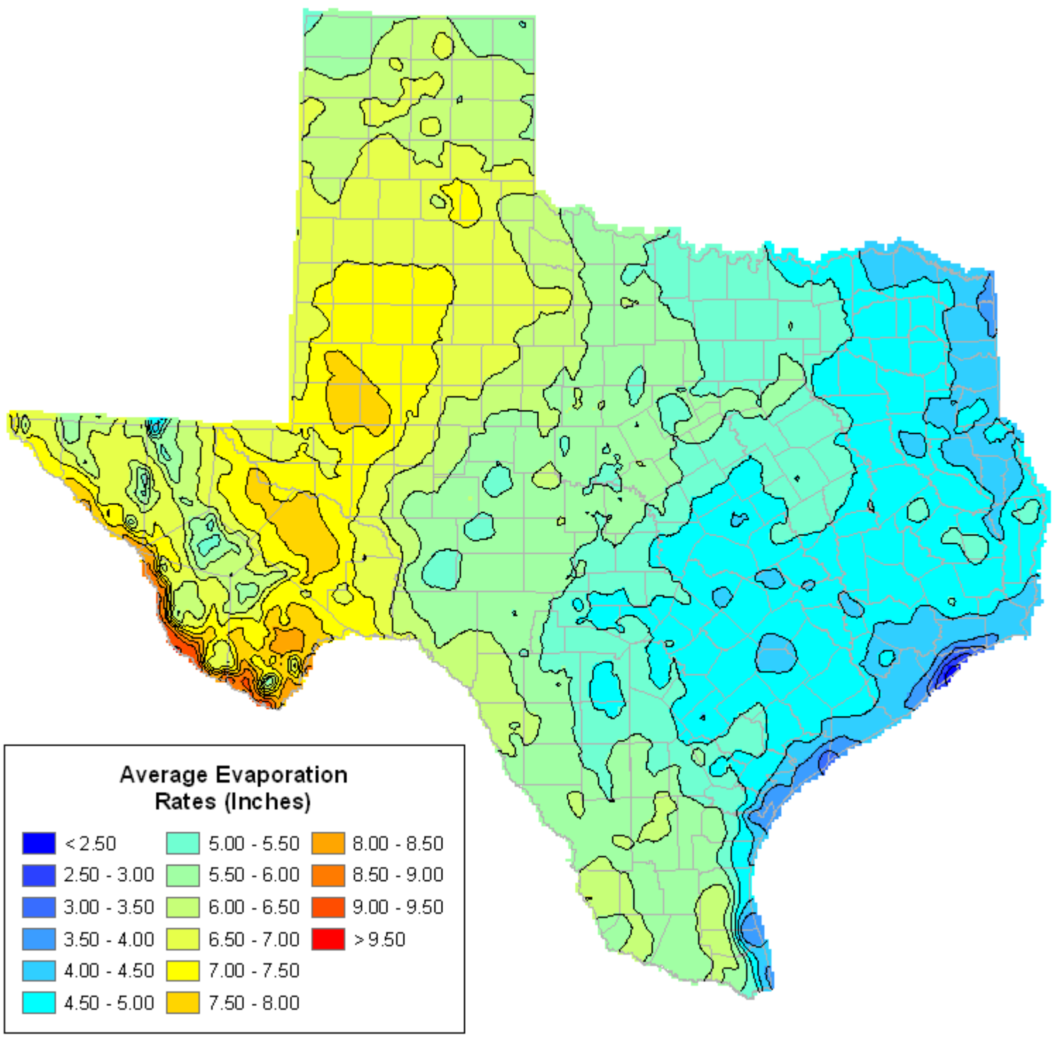
FEBRUARY
Average Monthly Gross Lake
Surface Evaporation Rates
In Inches, 1971 - 2000



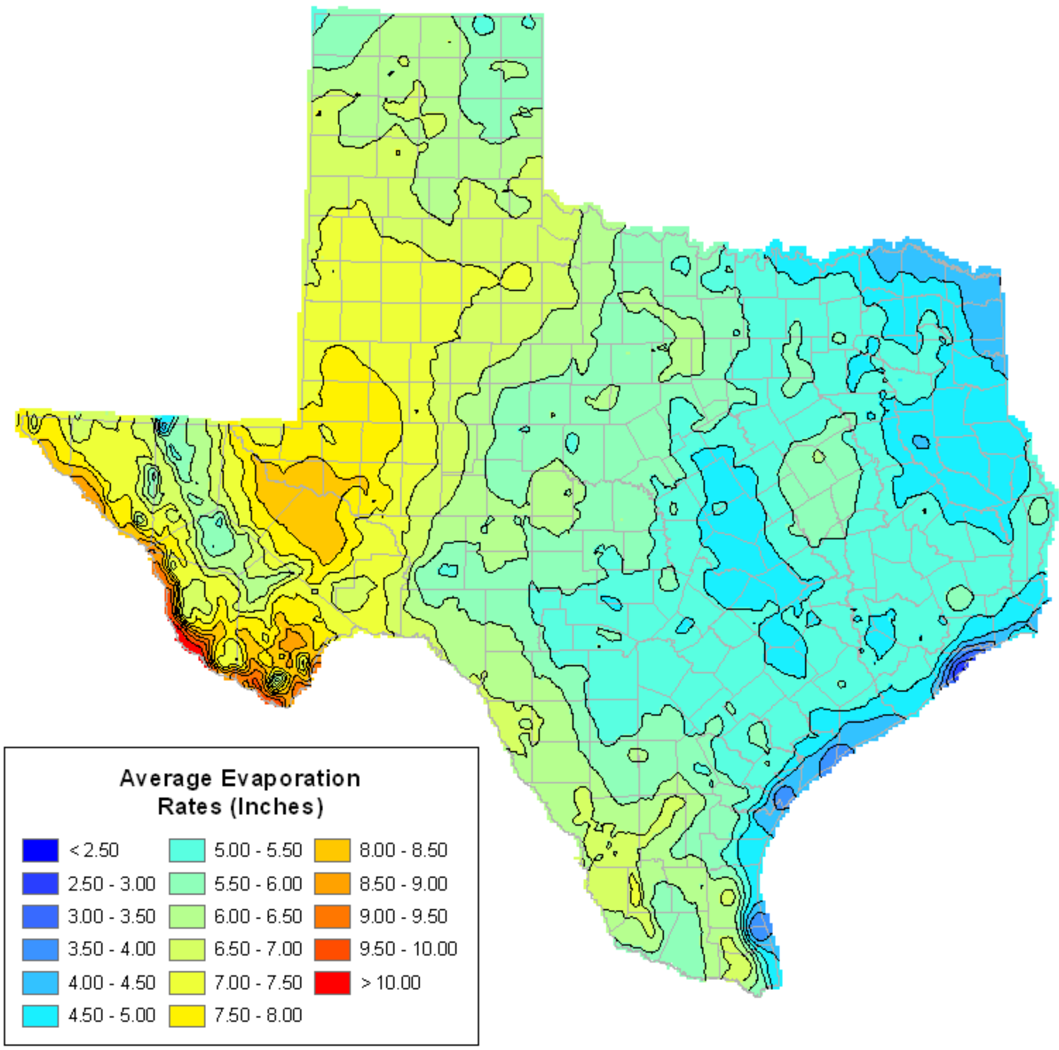
MARCH
Average Monthly Gross Lake Surface Evaporation Rates
In Inches, 1971 - 2000



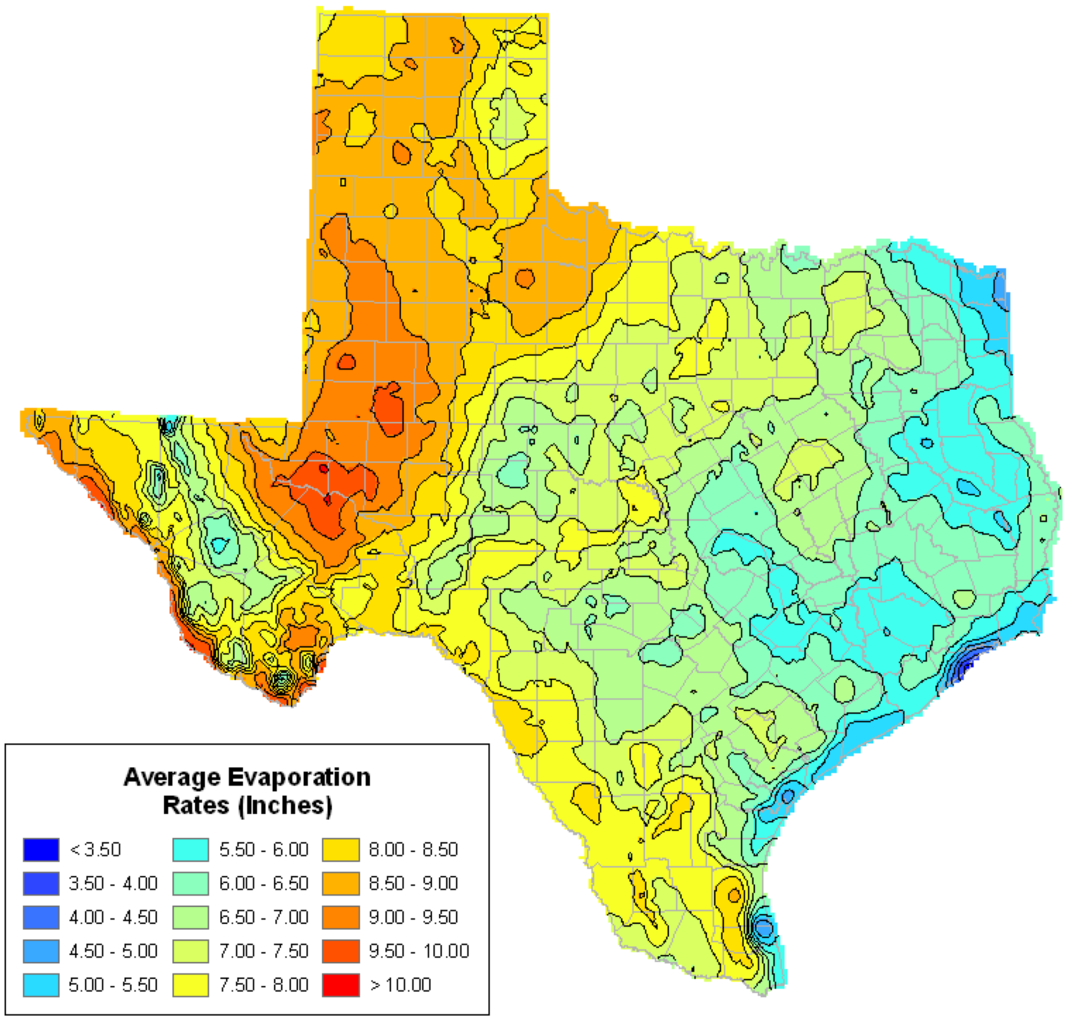
APRIL
Average Monthly Gross Lake
Surface Evaporation Rates
In Inches, 1971 - 2000



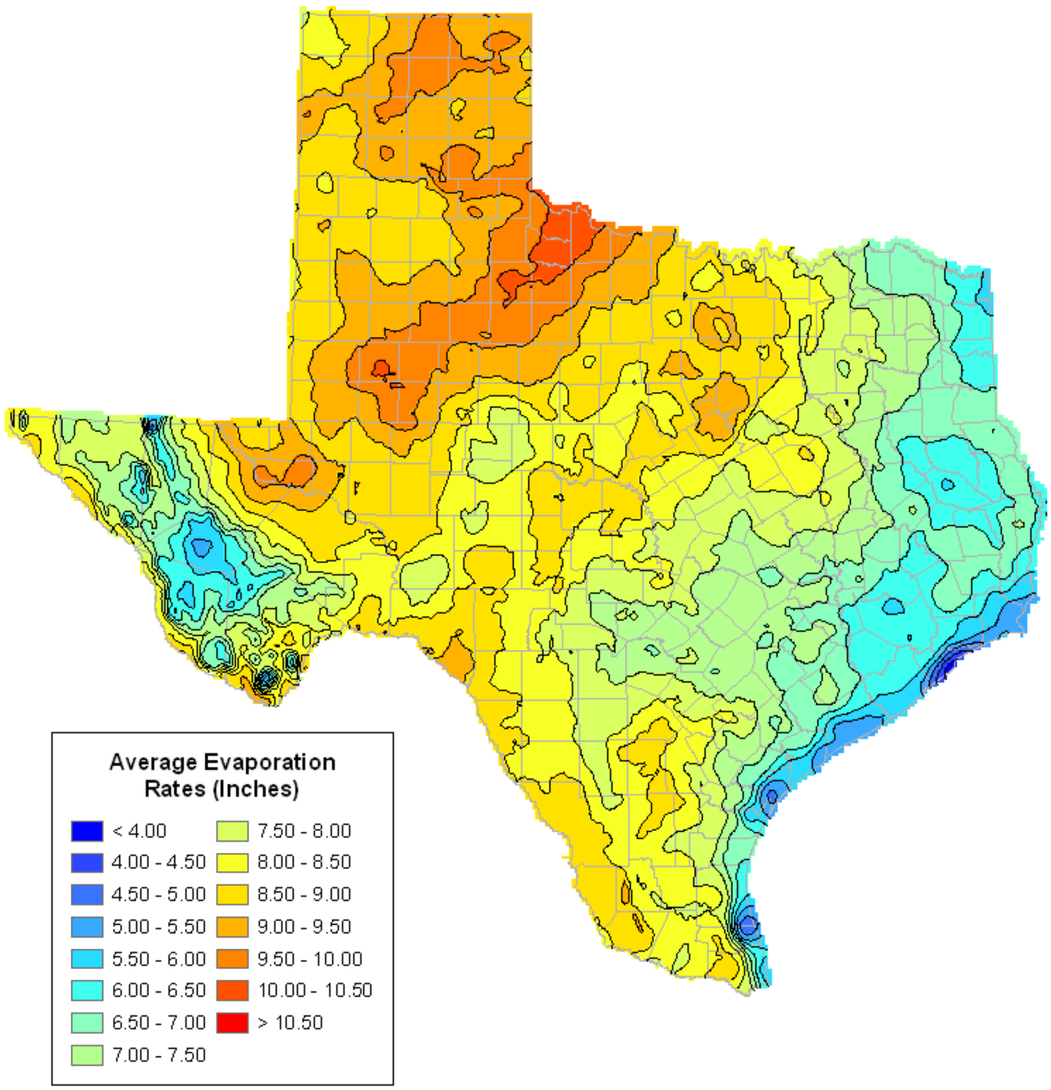
MAY
Average Monthly Gross Lake
Surface Evaporation Rates
In Inches, 1971 - 2000



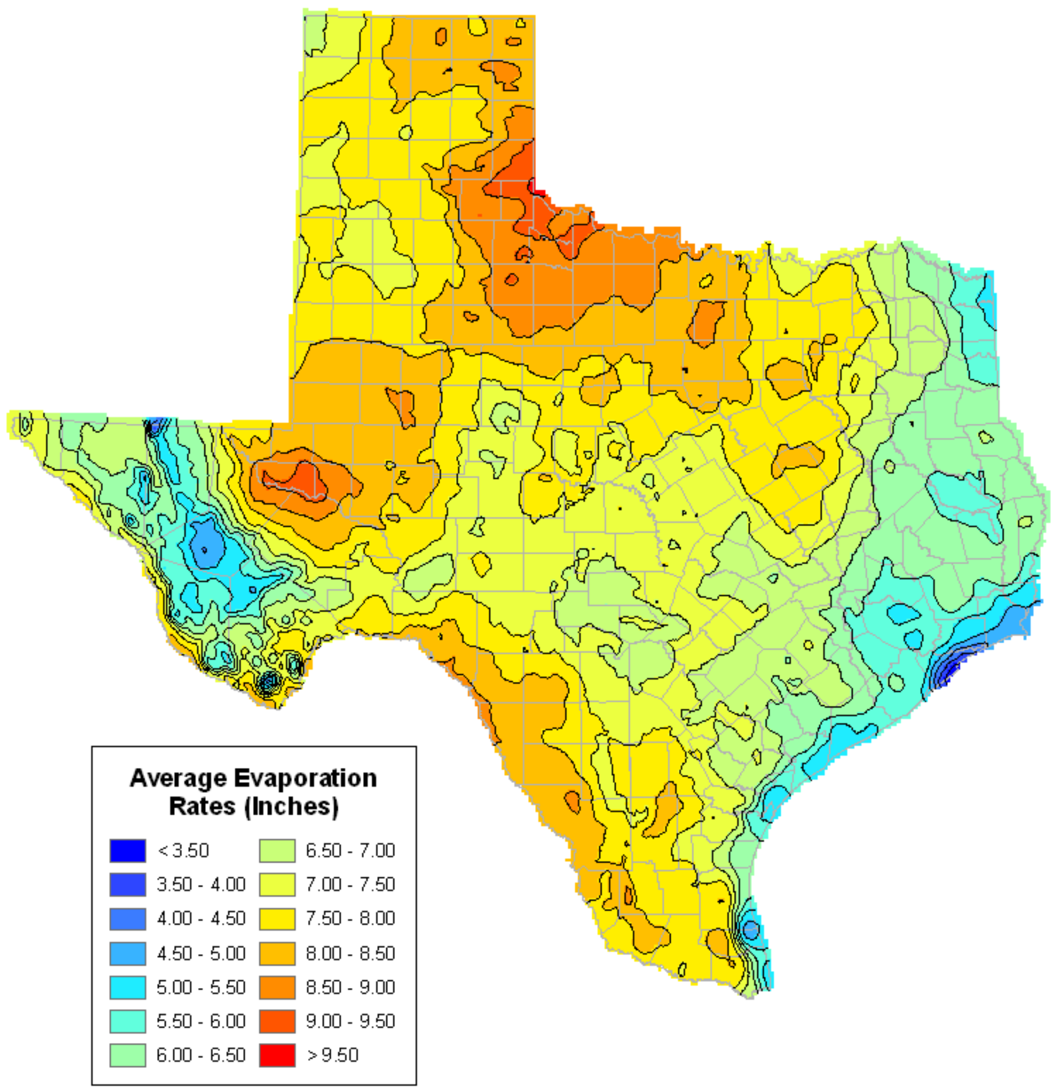
JUNE
Average Monthly Gross Lake
Surface Evaporation Rates
In Inches, 1971 - 2000



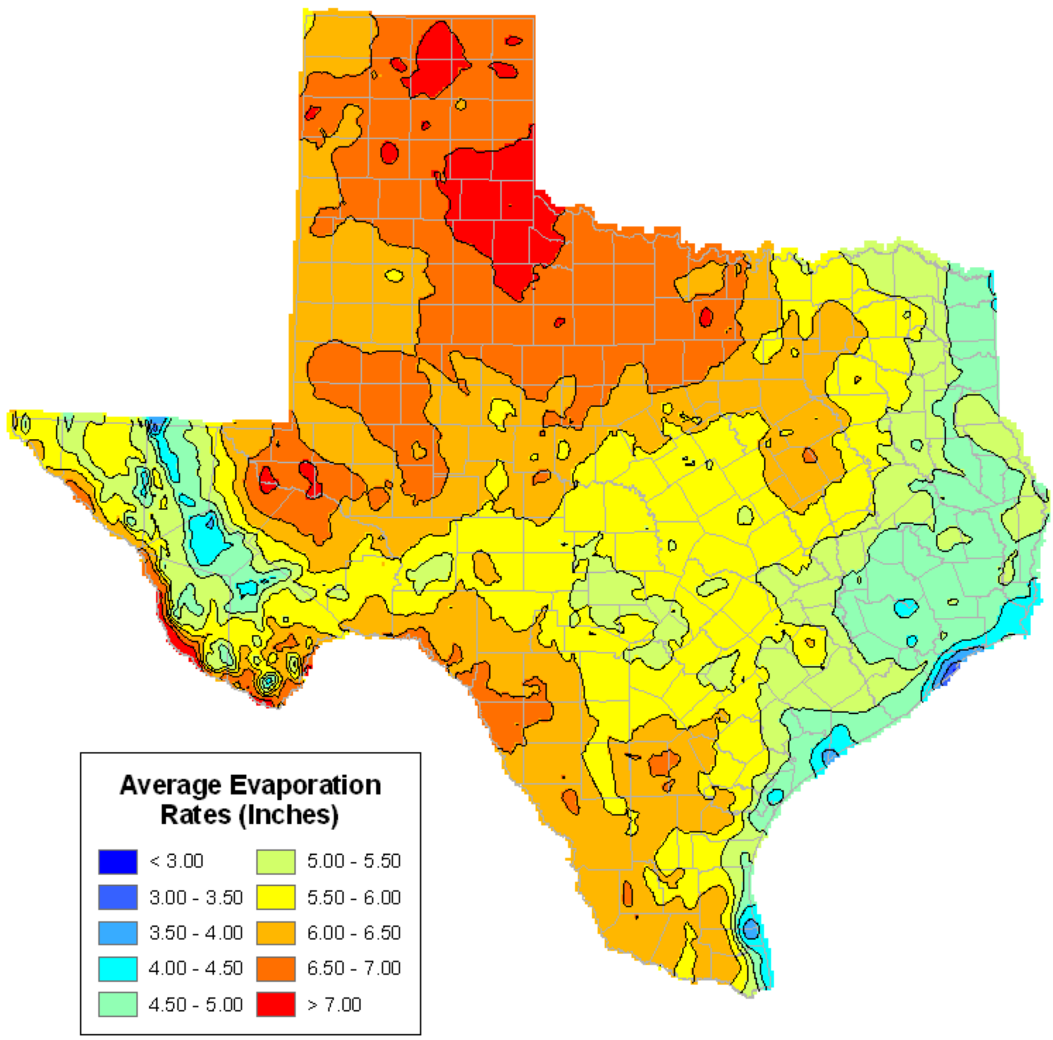
JULY
Average Monthly Gross Lake
Surface Evaporation Rates
In Inches, 1971 - 2000



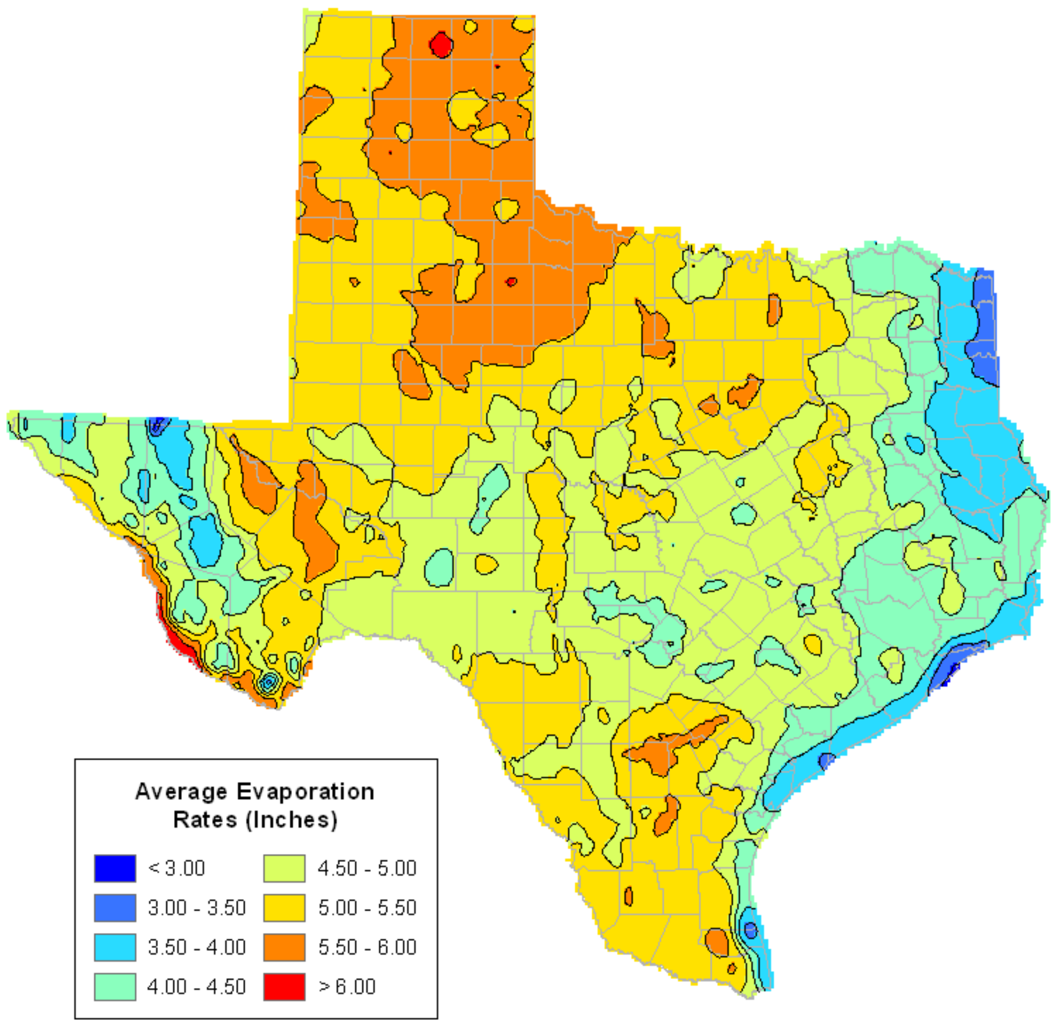
AUGUST
Average Monthly Gross Lake
Surface Evaporation Rates
In Inches, 1971 - 2000



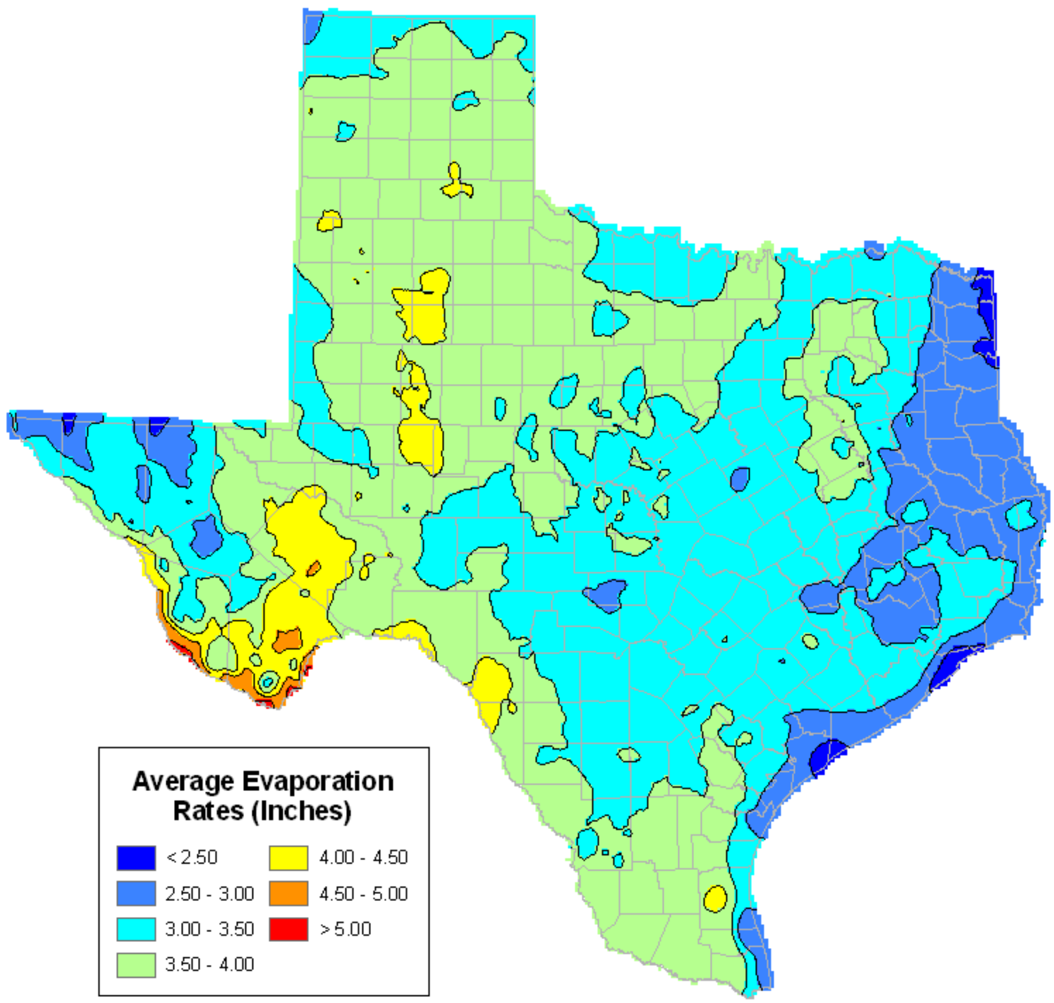
SEPTEMBER
Average Monthly Gross Lake Surface Evaporation Rates
In Inches, 1971 - 2000



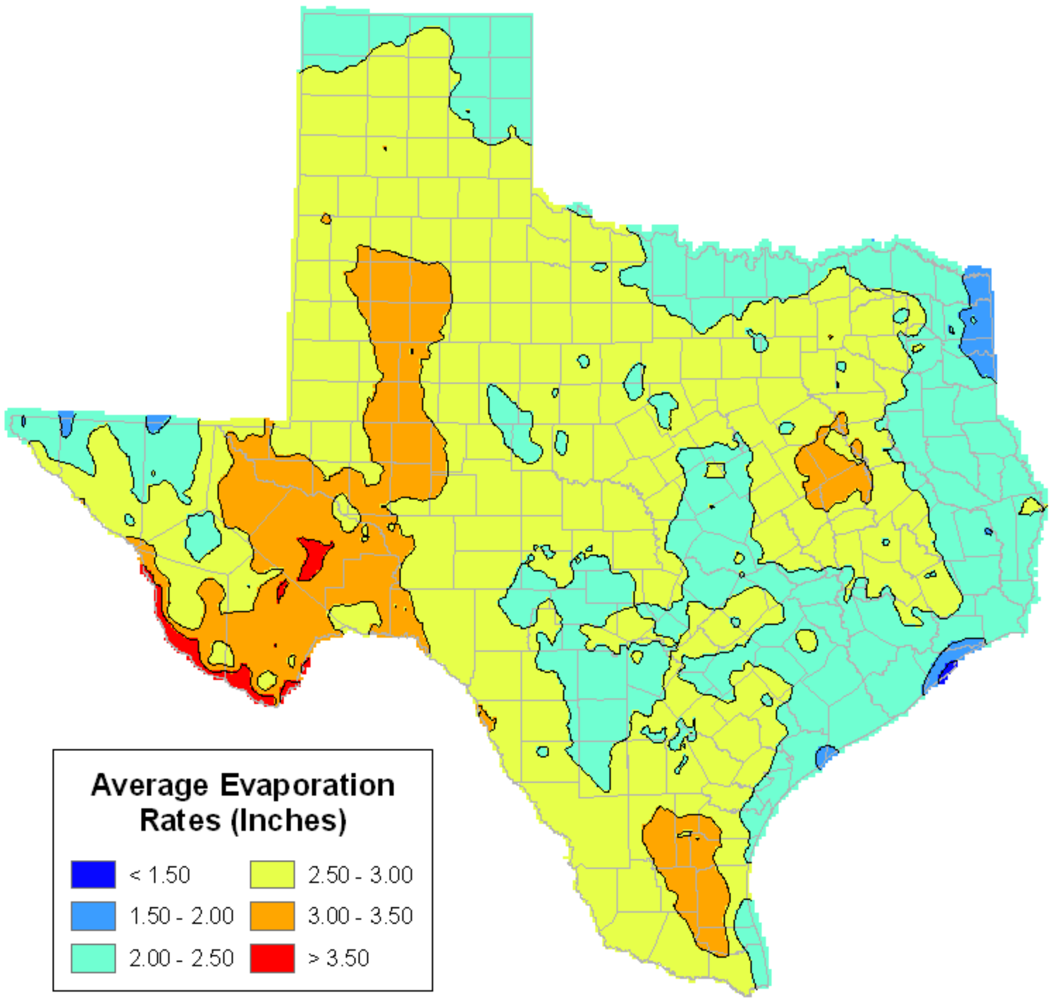
OCTOBER
Average Monthly Gross Lake
Surface Evaporation Rates
In Inches, 1971 - 2000



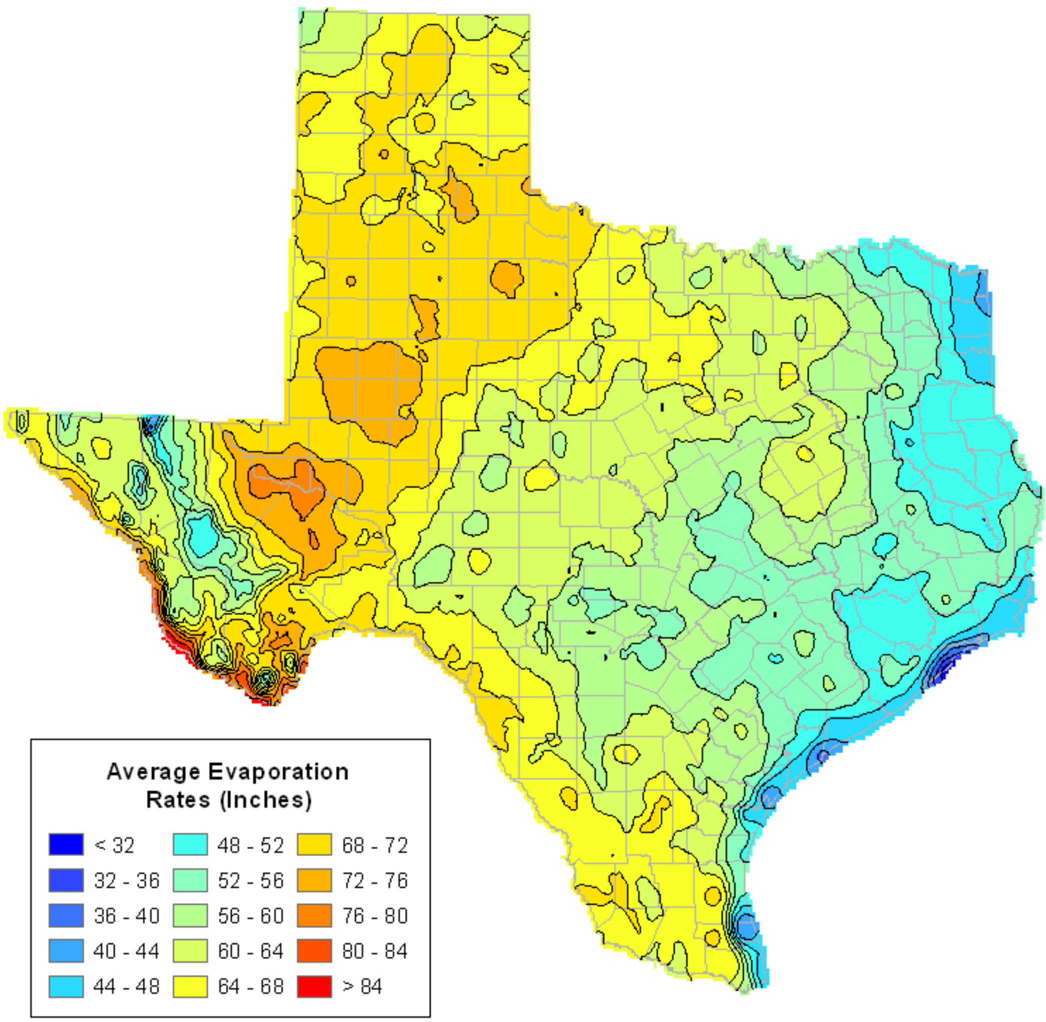
NOVEMBER
Average Monthly Gross Lake
Surface Evaporation Rates
In Inches, 1971 - 2000



DECEMBER
Average Monthly Gross Lake
Surface Evaporation Rates
In Inches, 1971 - 2000



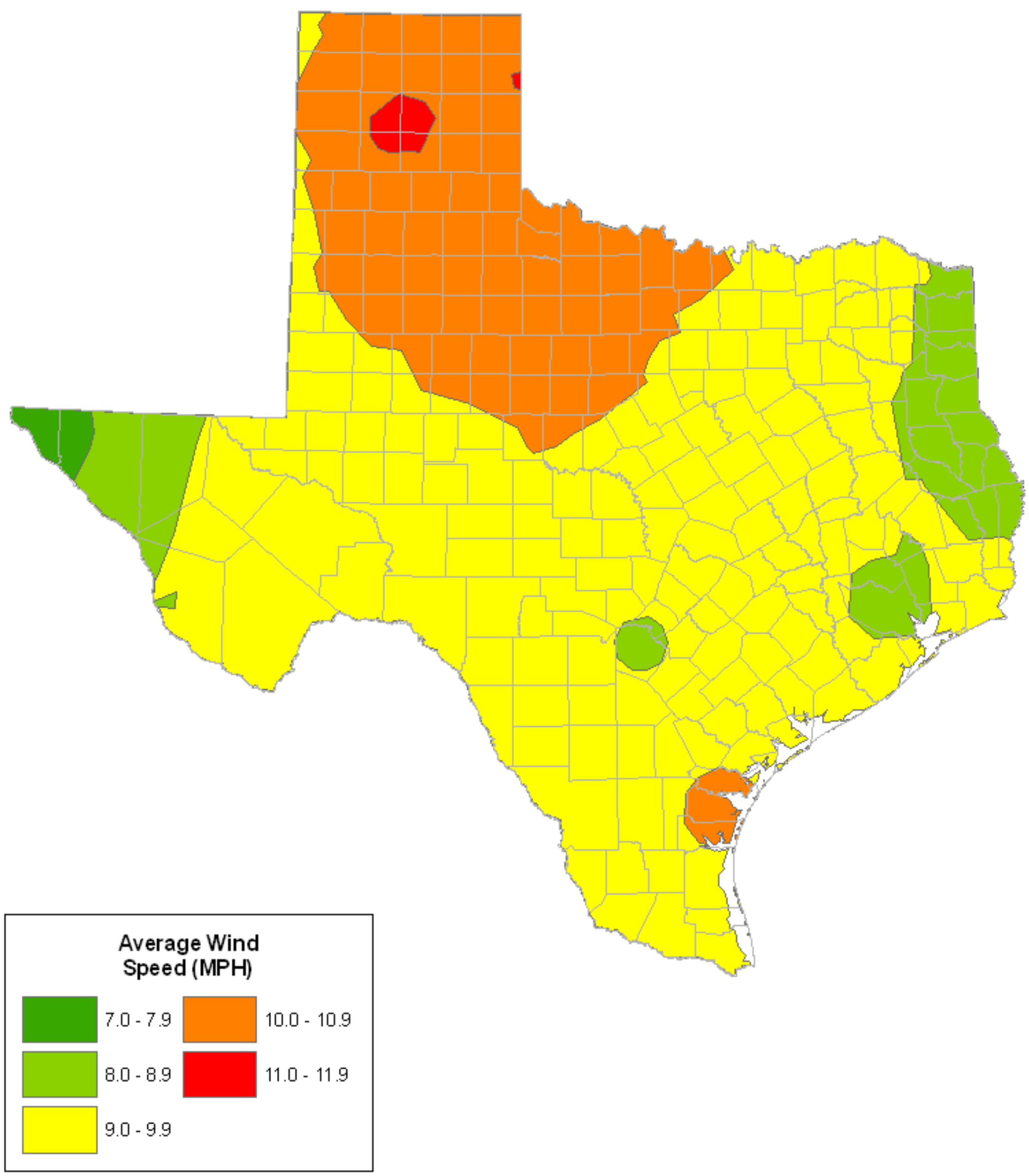
ANNUAL
Average Monthly Gross Lake
Surface Evaporation Rates
In Inches, 1971 - 2000



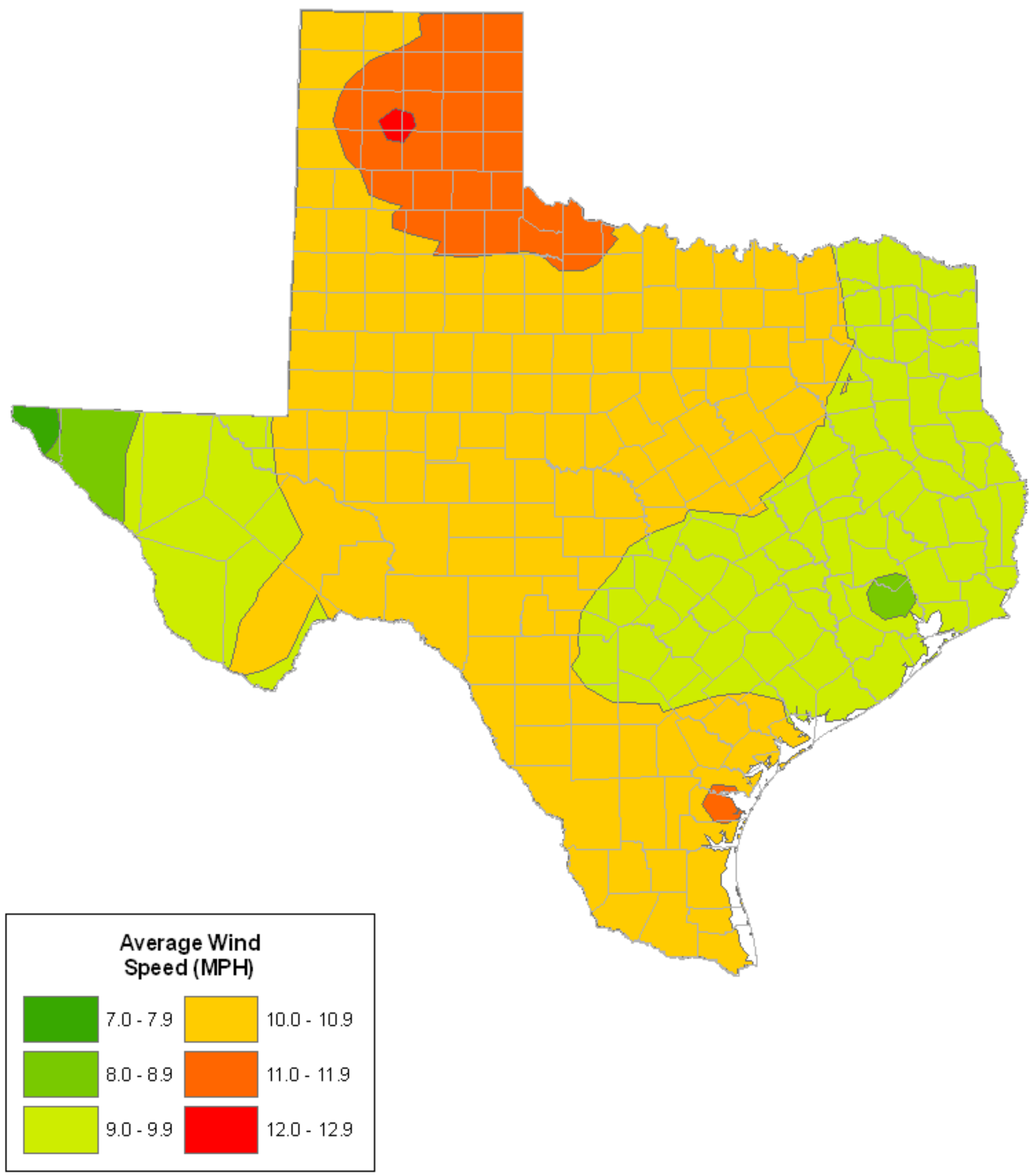
Average Monthly Wind Speed Maps

Based on the longest available records of wind speed between 1961 and 1990, contour maps of monthly and annual average wind speed were available from the NCDC CLIMAPS dataset (http://cdo.ncdc.noaa.gov/cgi-bin/climaps/climaps.pl). These contour maps were clipped for Texas and reproduced in this section.

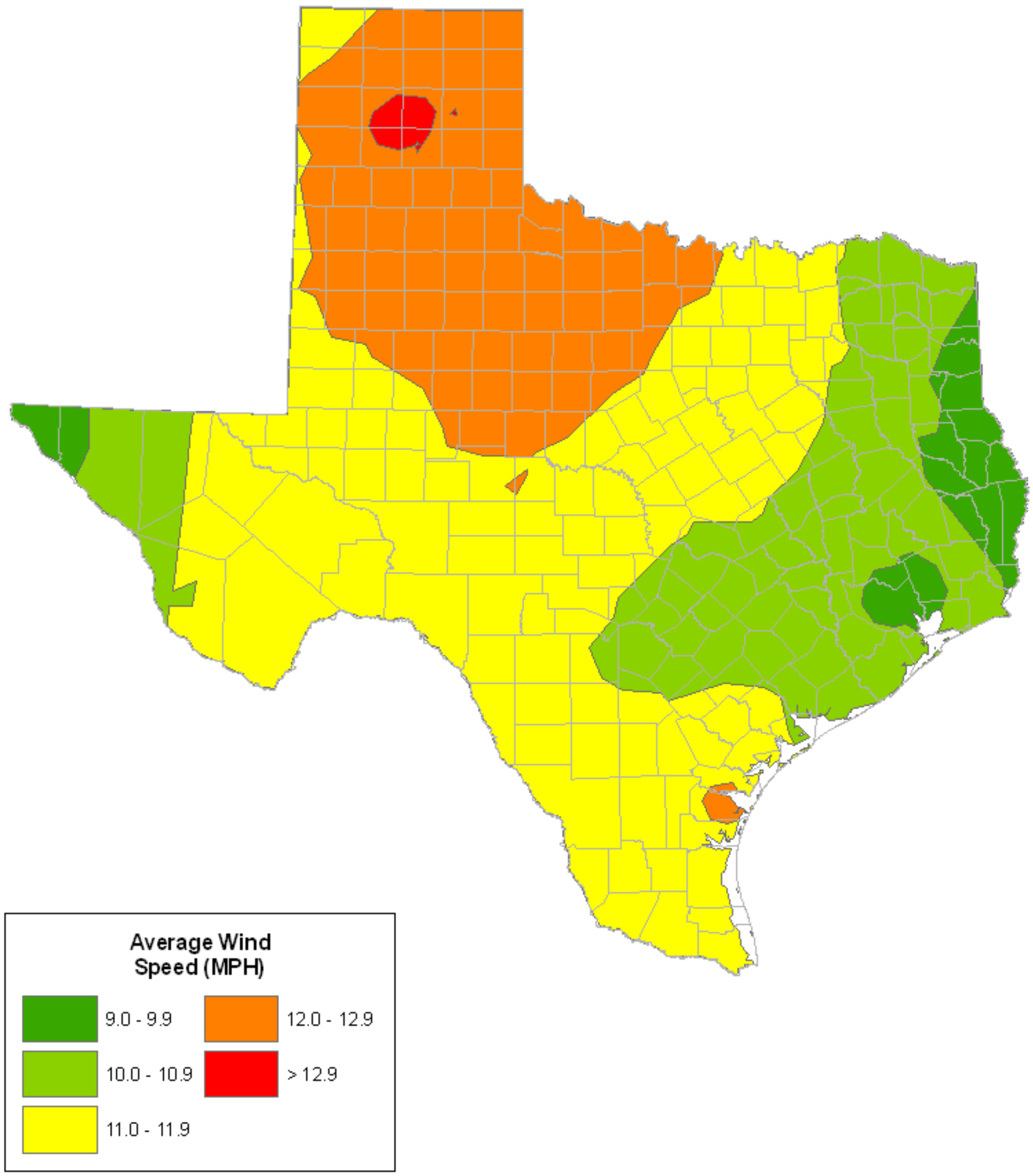
JANUARY
Average Monthly Wind Speeds
In Miles Per Hour, 1961 - 1990



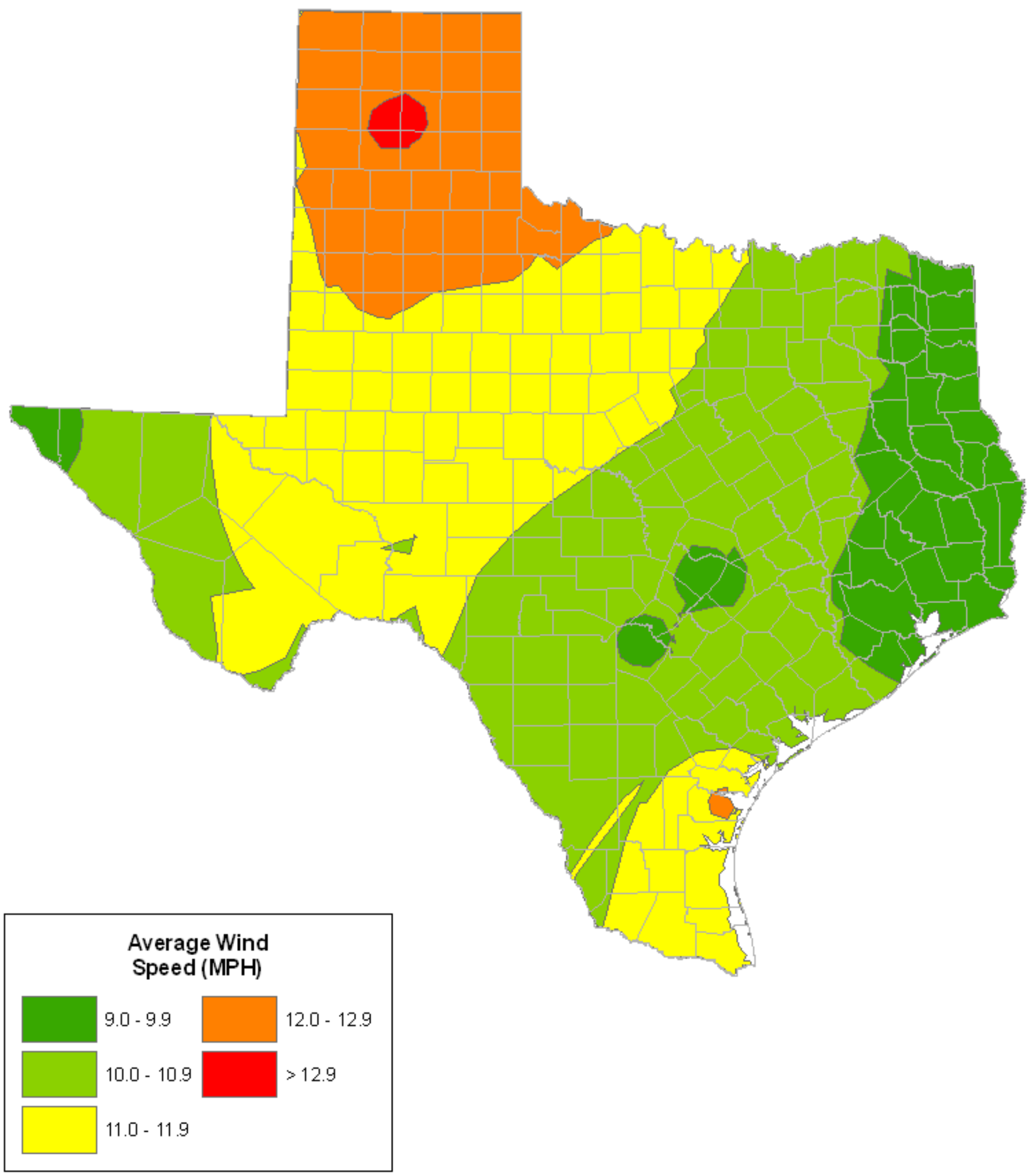
FEBRUARY
Average Monthly Wind Speeds
In Miles Per Hour, 1961 - 1990



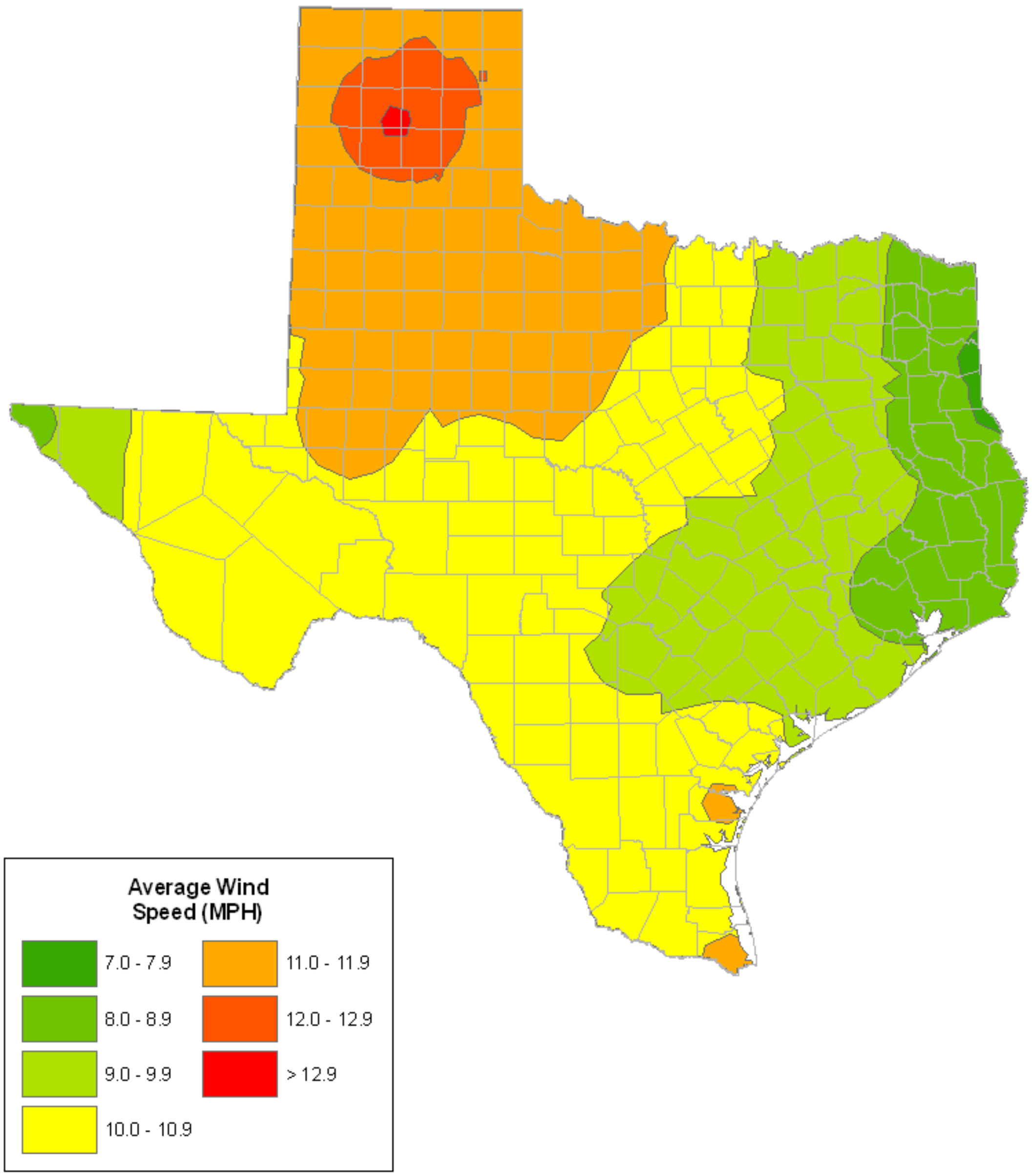
MARCH
Average Monthly Wind Speeds
In Miles Per Hour, 1961 - 1990



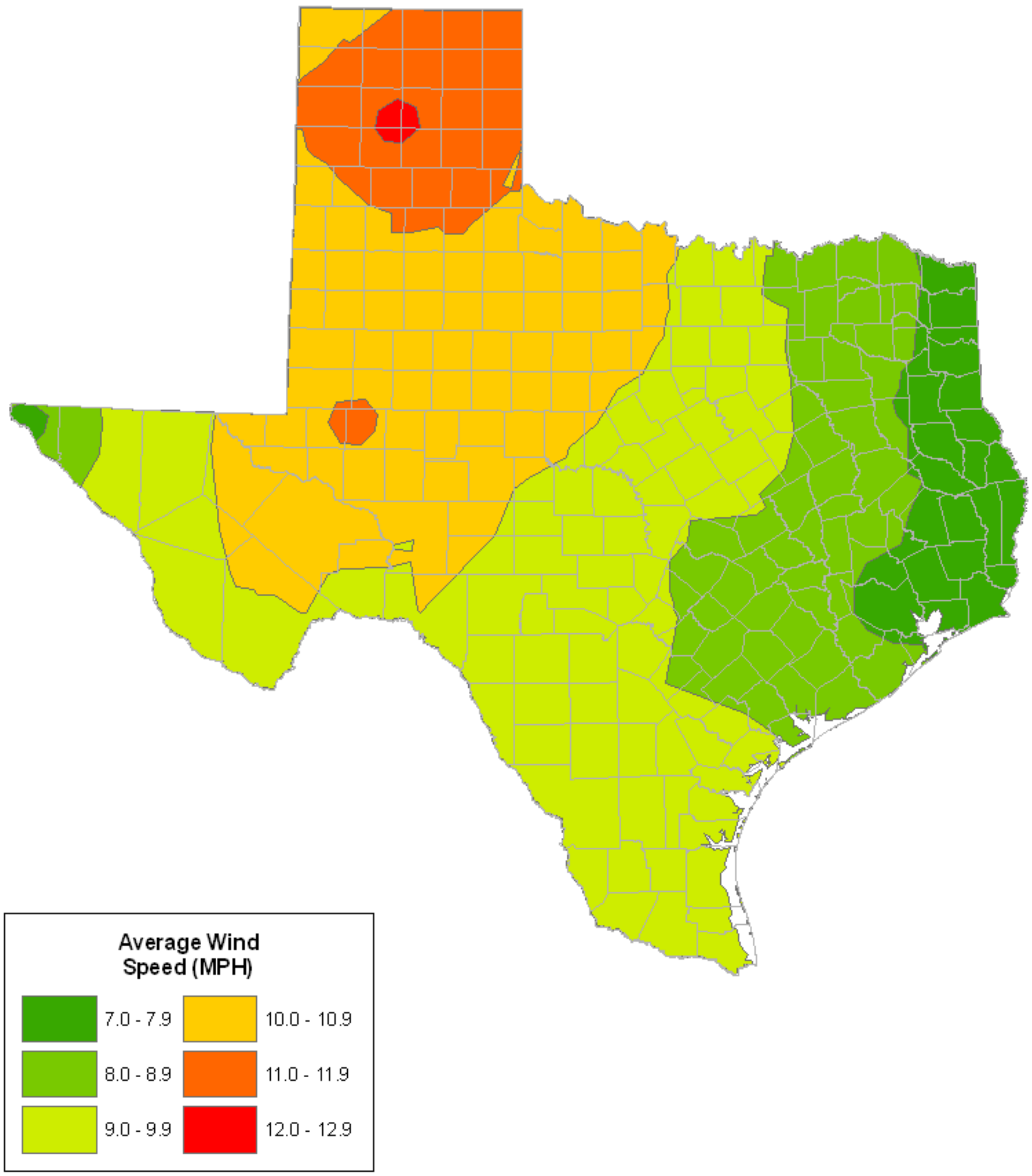
APRIL
Average Monthly Wind Speeds
In Miles Per Hour, 1961 - 1990



MAY
Average Monthly Wind Speeds
In Miles Per Hour, 1961 - 1990



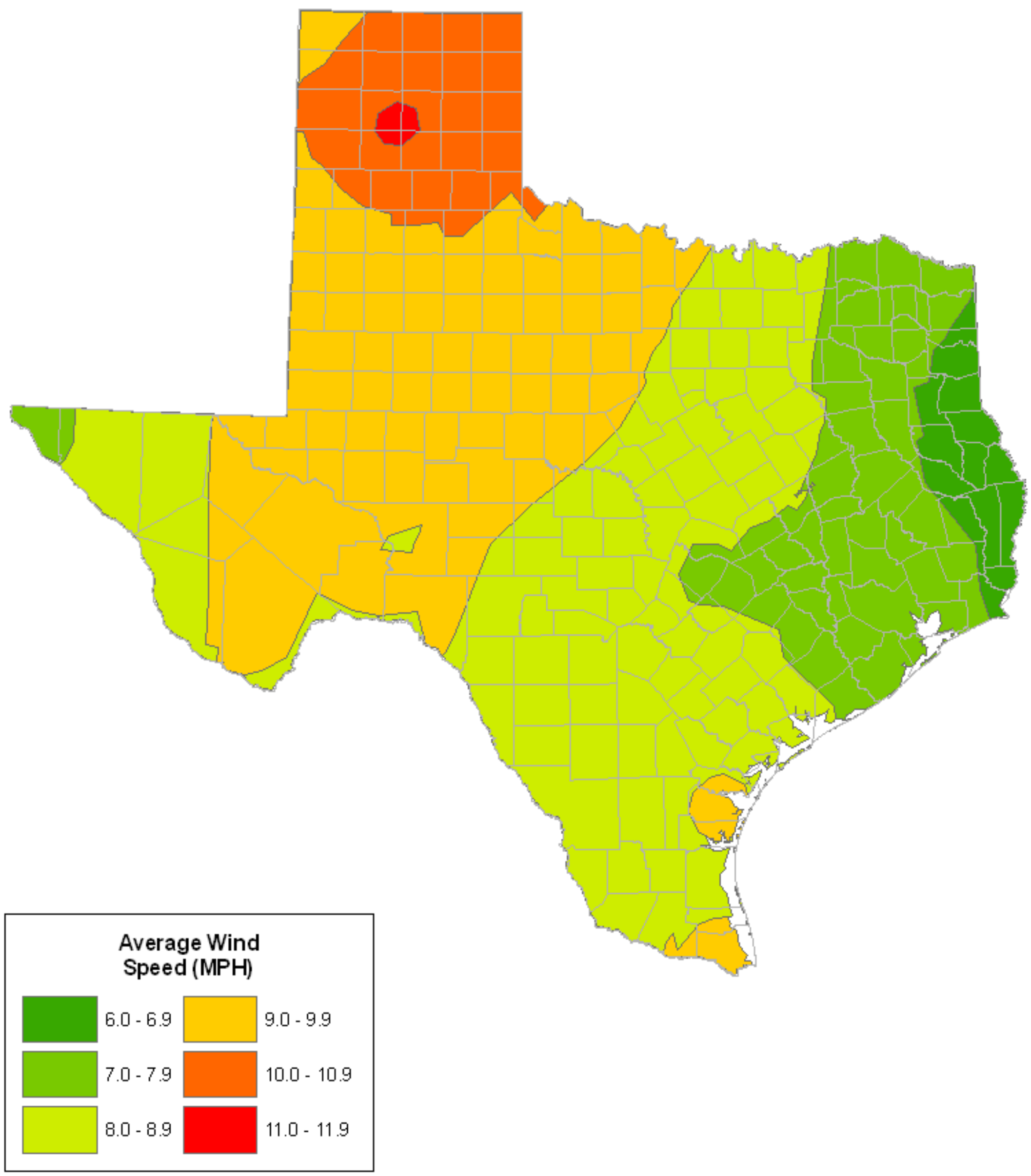
JUNE
Average Monthly Wind Speeds
In Miles Per Hour, 1961 - 1990



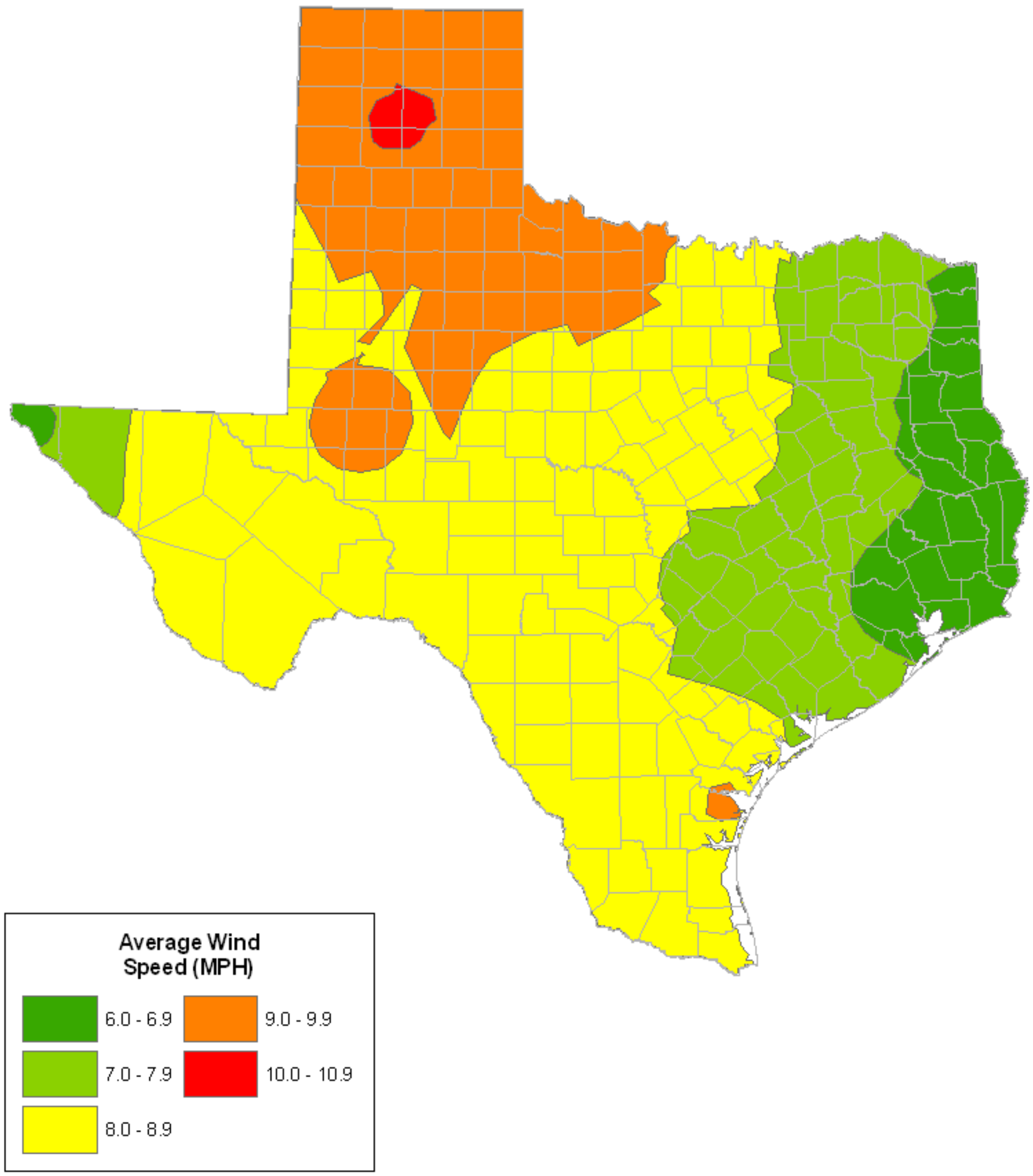
JULY

Average Monthly Wind Speeds

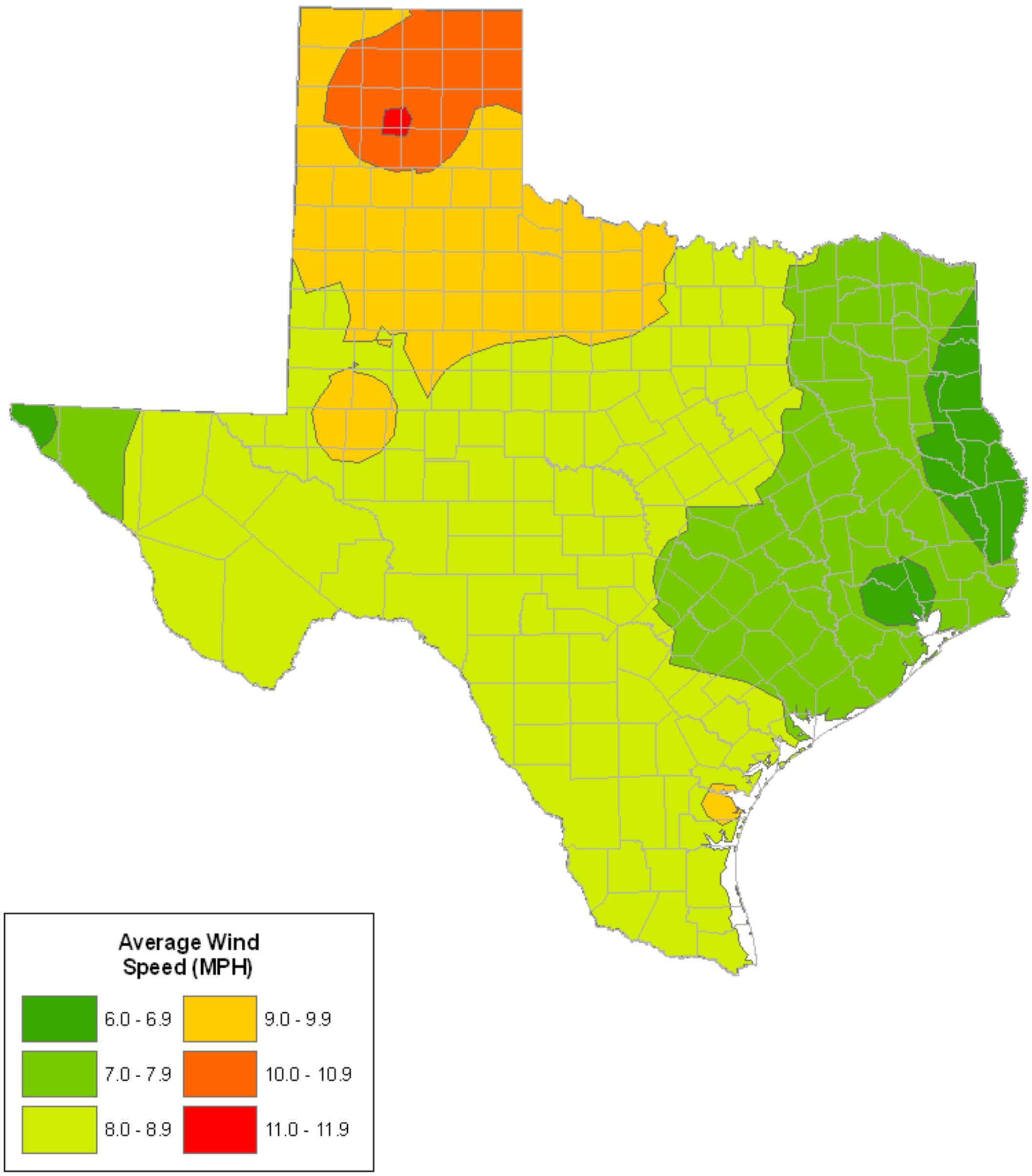
In Miles Per Hour, 1961 - 1990



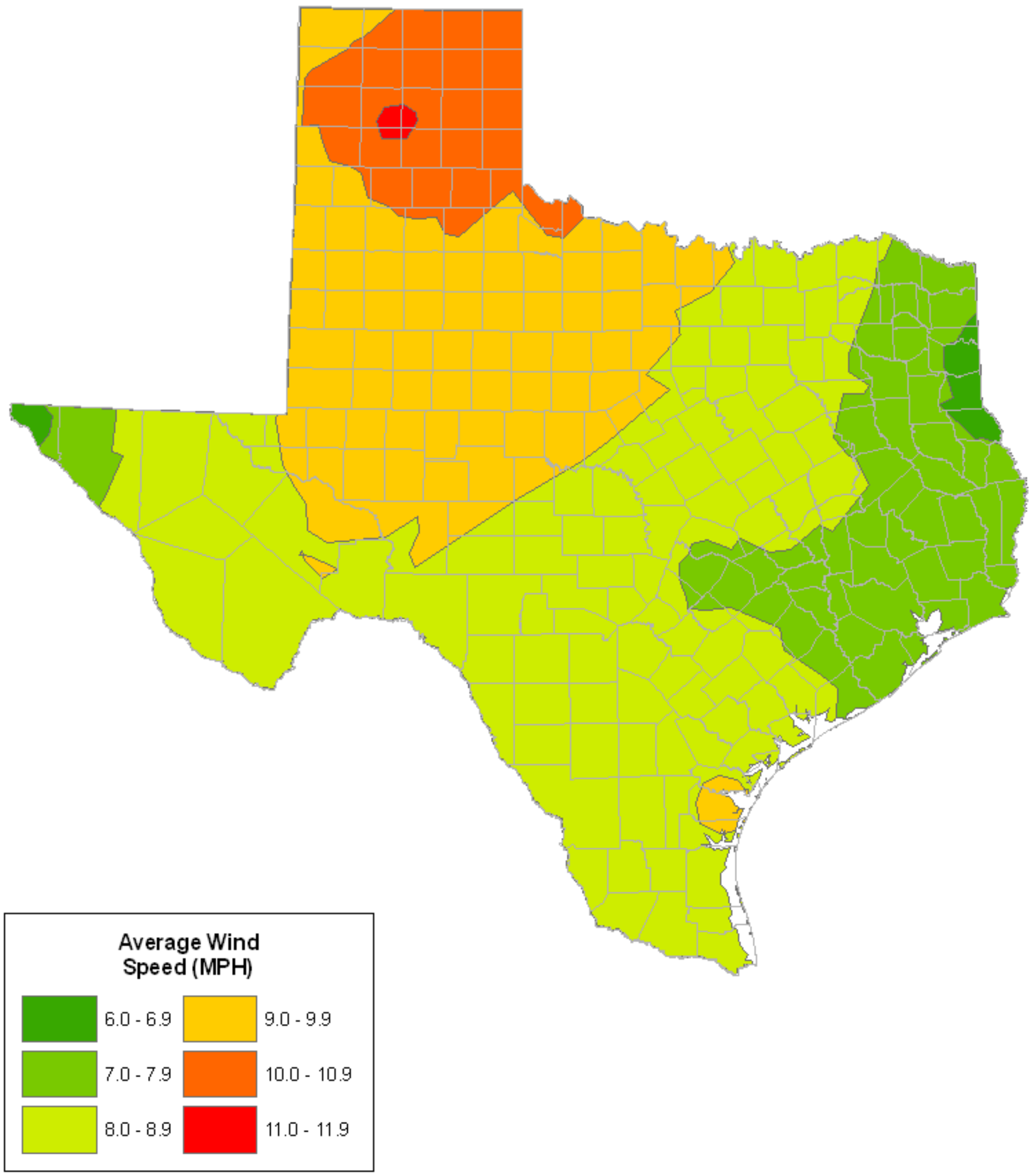
AUGUST
Average Monthly Wind Speeds
In Miles Per Hour, 1961 - 1990



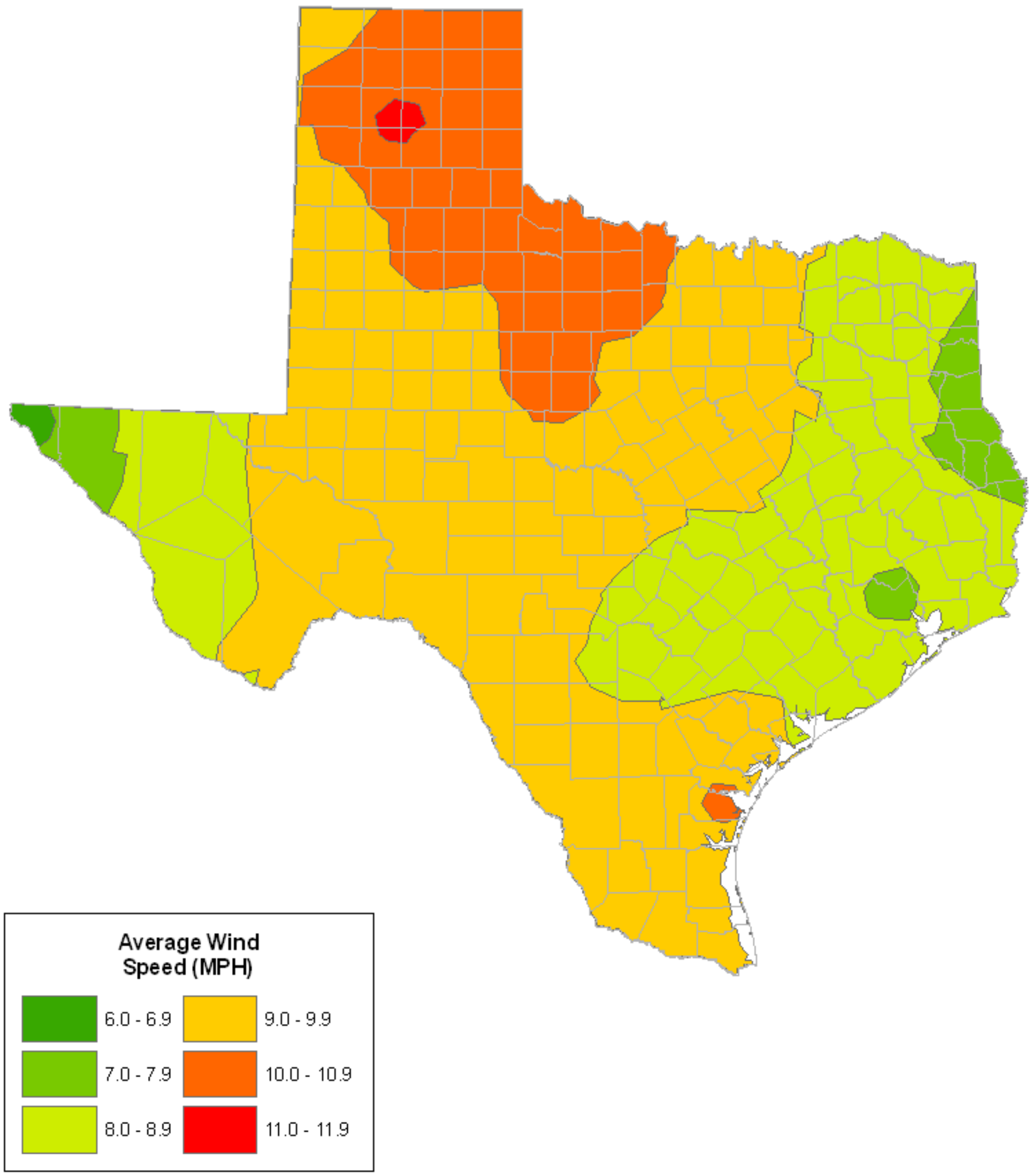
SEPTEMBER
Average Monthly Wind Speeds
In Miles Per Hour, 1961 - 1990



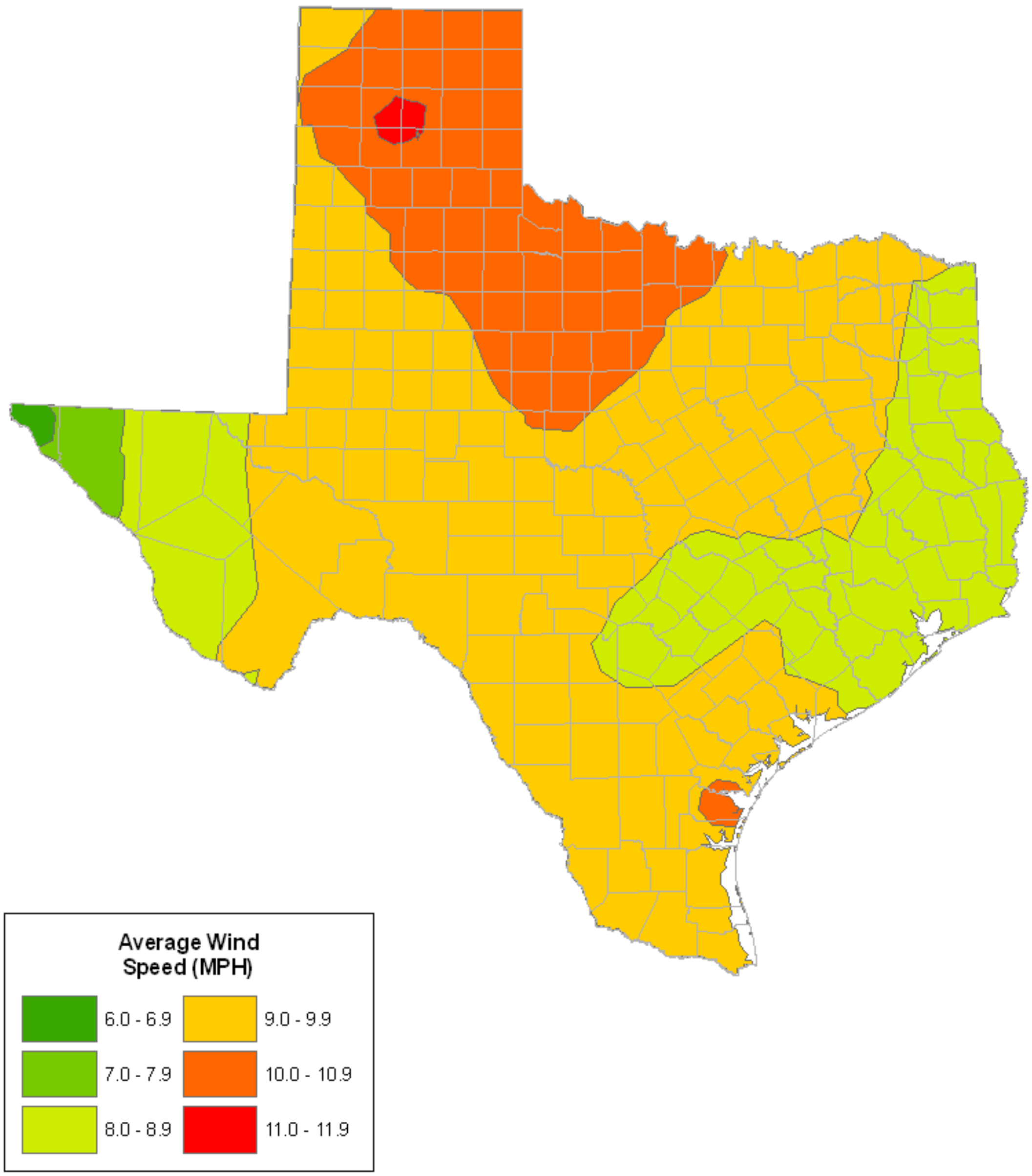
OCTOBER
Average Monthly Wind Speeds
In Miles Per Hour, 1961 - 1990



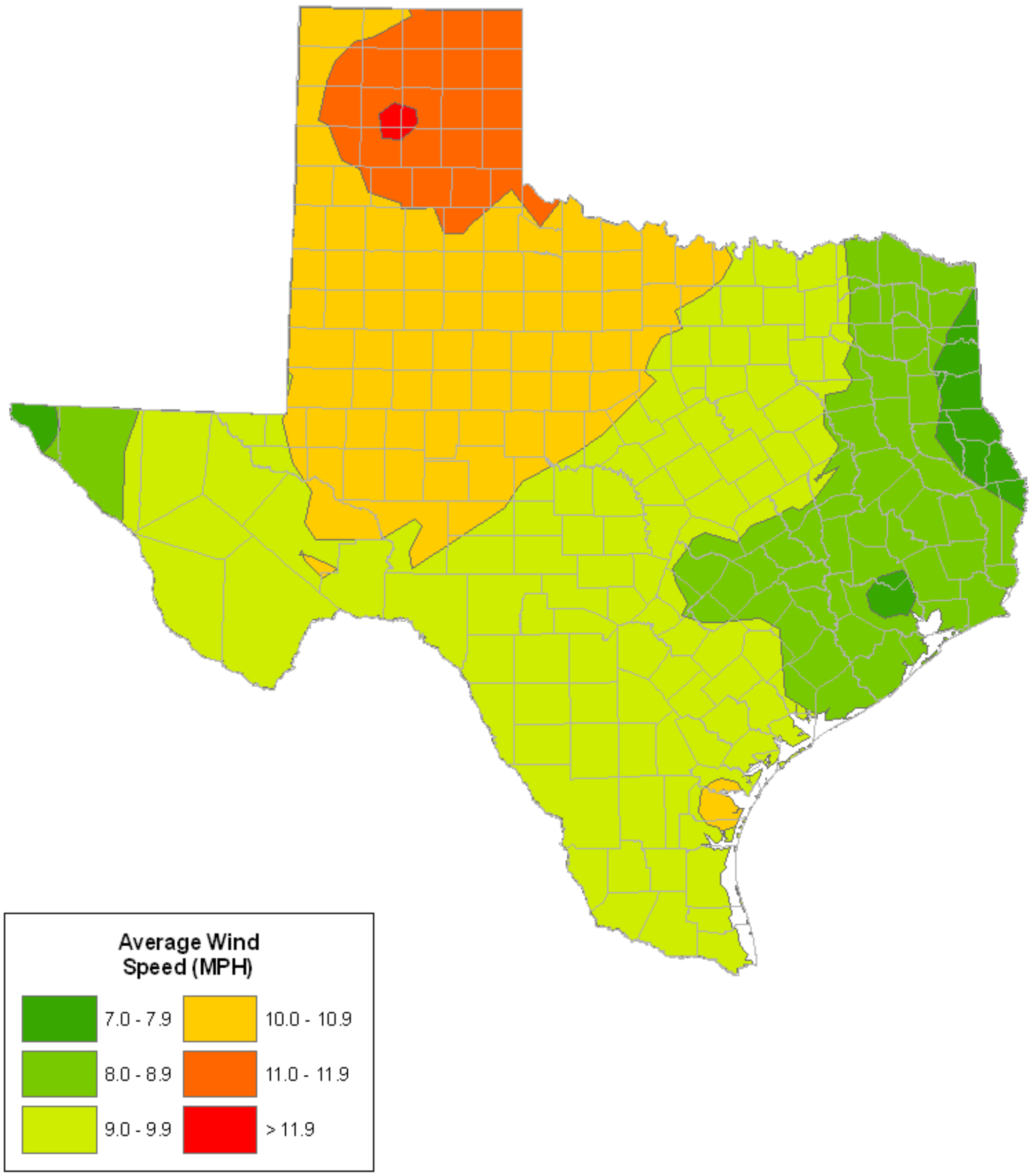
NOVEMBER
Average Monthly Wind Speeds
In Miles Per Hour, 1961 - 1990



DECEMBER
Average Monthly Wind Speeds
In Miles Per Hour, 1961 - 1990



ANNUAL
Average Annual Wind Speeds
In Miles Per Hour, 1961 - 1990

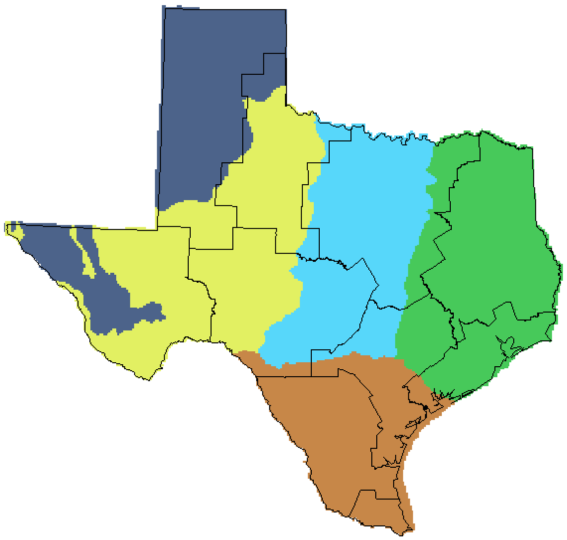


Appendix B

Thirty year monthly means (1971-2000) of precipitation, maximum and minimum temperature, dew point temperature and mean monthly wind speed (60 data layers) were used to identify unique climatic zones of varying size across Texas. In order to identify the unique climatic zones, each climatic parameter was normalized using the maximum and minimum values of the climatic parameters to make sure that the resultant data layer was unit less. Using these 60 layers of information the Iterative Self-Organizing Data Analysis Technique (ISODATA) (Tou and Gonzalez, 1974) was used to find clusters with unique climatic properties. This clustering algorithm identifies unique patterns of temporal variations in the five climatic parameters and then assigns each pixel to a unique class iteratively until about 95% of the pixel does not change classes within subsequent iterations. The procedure was used to classify Texas into 5, 10, 25 and 50 different climatic classes. Appendix B contain illustrations of these climatic divisions along with an overlay of the NCDC's 10 climatic division (image on the left) along with the new climatic division boundaries corrected to align with county political boundaries (image on the right) based on the dominant climatic zone of the county. It is interesting to note that the 10 climatic zones produced by ISODATA are different from the current NCDC climatic divisions, except for the High-Plains climatic division.

Texas Climatic Divisions

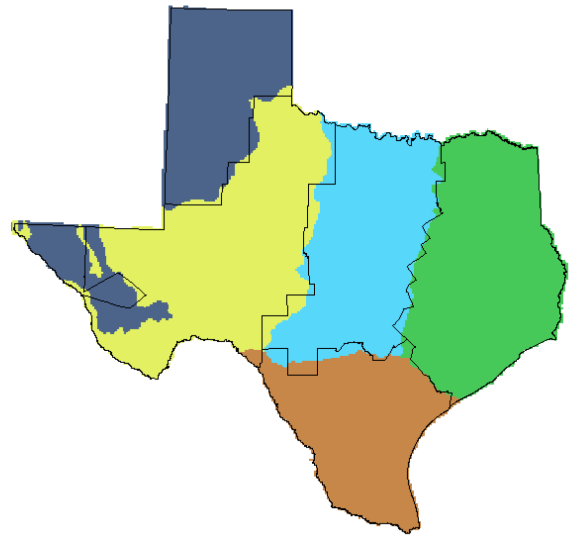
5 Divisions



Note: New climatic divisions along with an overlay of the NCDC's 10 climatic division boundary (Figure 12)

Texas Climatic Divisions

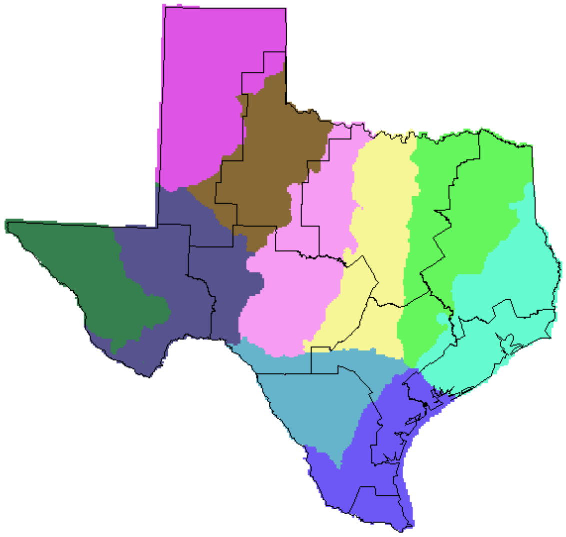
5 Divisions



Note: Climatic division boundaries approximated
to match with county boundaries based
on the dominant climatic division of the county

Texas Climatic Divisions

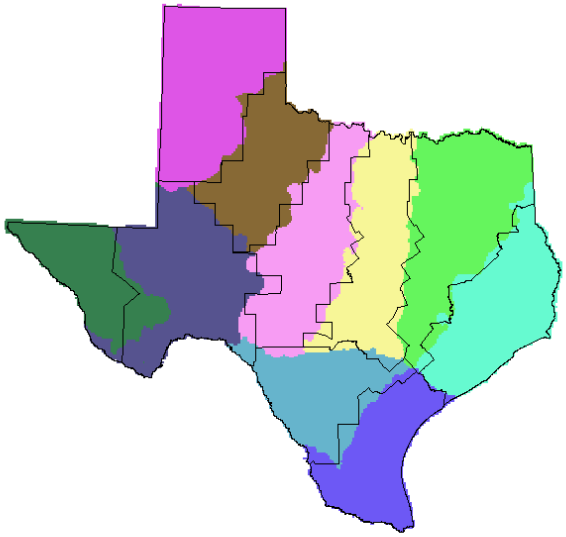
10 Divisions



Note: New climatic divisions along with an overlay of the NCDC's 10 climatic division boundary (Figure 12)

Texas Climatic Divisions

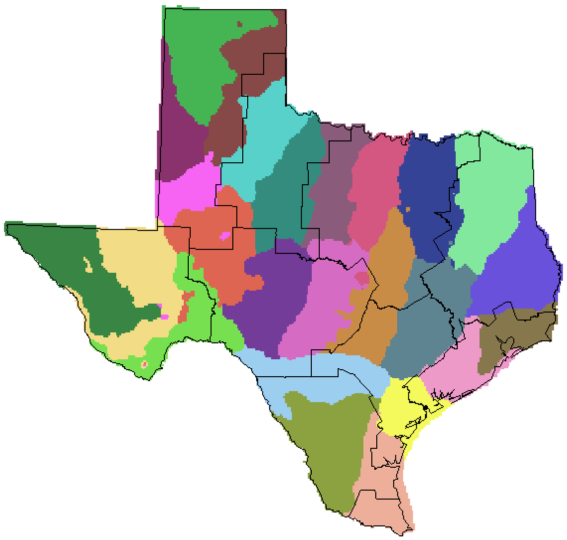
10 Divisions



Note: Climatic division boundaries approximated to match with county boundaries based on the dominant climatic division of the county

Texas Climatic Divisions

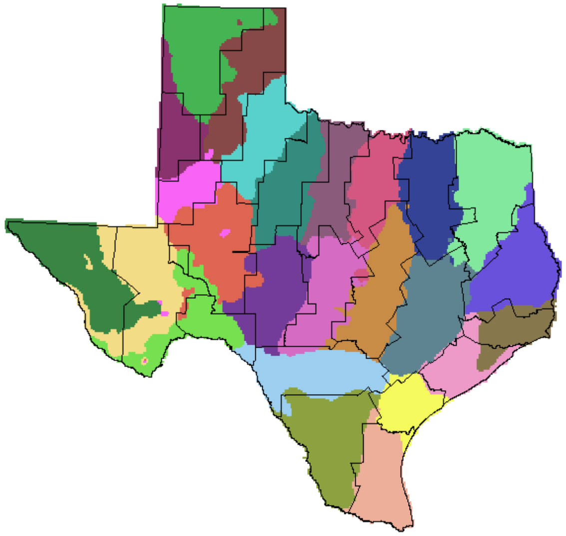
25 Divisions



Note: New climatic divisions along with an overlay of the NCDC's 10 climatic division boundary (Figure 12)

Texas Climatic Divisions

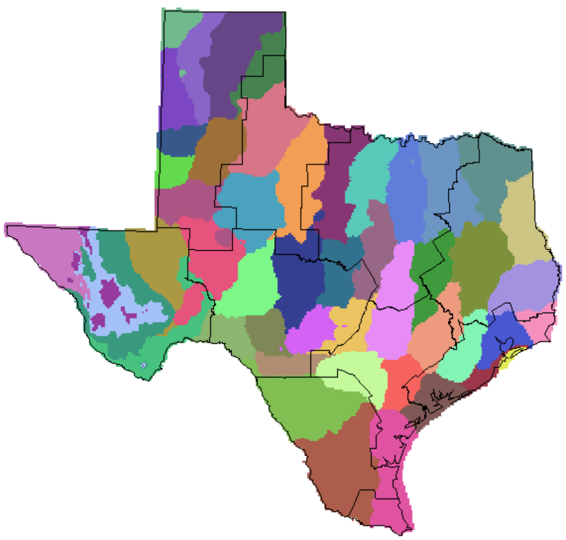
25 Divisions



Note: Climatic division boundaries approximated to match with county boundaries based on the dominant climatic division of the county

Texas Climatic Divisions

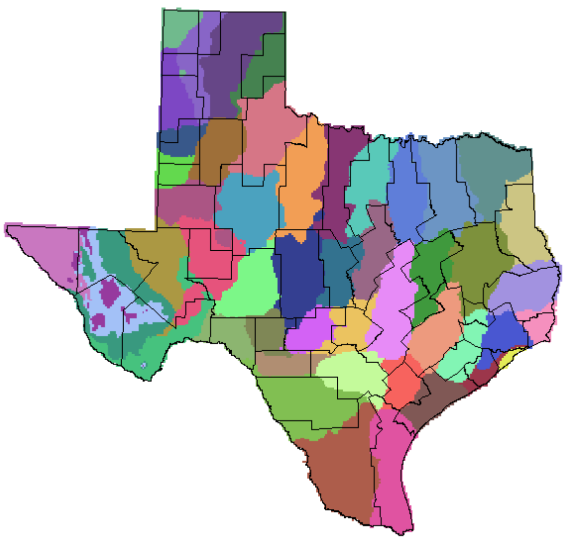
50 Divisions



Note: New climatic divisions along with an overlay of the NCDC's 10 climatic division boundary (Figure 12)

Texas Climatic Divisions

49 Divisions



Note: Climatic division boundaries approximated
to match with county boundaries based
on the dominant climatic division of the county