CZECH TECHNICAL UNIVERSITY
IN PRAGUE

Faculty of Civil Engineering,
Department of Mapping and Cartography

Bachelor Thesis

Climate Characteristics of the Czech Republic Using ArcGIS

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Declaration

I declare that I have completed the Bachelor thesis called “Climate Characteristics of the Czech Republic Using ArcGIS “ by myself. Literature used and other references are mentioned in the references section.

In Prague on ....

Arnošt Müller

Acknowledgments

I would like to thank my teacher of Cartography and Thematic Mapping and Computer Mapping and Geographic visualization classes at Kansas State University (KSU) Dr. Shawn Hutchinson, associate professor at the Department of Geography, for his help and time for consultations. I am grateful to Richard Chubb, the GIS Application Development Manager from the Office of Mediated Education at KSU, for setting up the ArcGIS Server web application. I would like to thank my English instructor Enid Cocke for her corrections.

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Abstract

Annual 90m x 90m resolution raster datasets of mean temperatures covering the Czech Republic were created for the 1998-2007 period in ArcGIS using linear regression. Linear regression was based on correlation between dependent climate variable – mean temperature and independent variable – altitude. Altitude information was taken from a digital elevation model (DEM) acquired by the Space Shuttle Radar Topographic Mapping Mission (SRTM). Climate data were obtained from a small subset of meteorological stations (22 stations total) supervised by the Czech Hydrometeorological Institute.

Annual variation in mean temperature was visualized in an animated map and published on the Internet. Mean temperature maps were published as a web map service. This web-based environment was created using ArcGIS Server software using a web server managed by the Department of Geography at Kansas State University.

Abstrakt

Cílem této bakalářské práce bylo vytvoření klimatických map pro území České Republiky za posledních deset let (1998-2007) pomocí softwaru ArcGIS. Jako nejvhodnější metoda byla zvolena lineární regrese. Lineární regrese je v případě této práce založena na značné závislosti mezi průměrnou teplotou a nadmořskou výškou. Nadmořská výška byla získána z globálního digitálního modelu terénu (DEM) Space Shuttle Radar Topographic Mapping Mission (SRTM), který má rozlišení 90x90m. Klimatická data byla stažena z webových stránek ČHMÚ pro 22 meteorologických stanic.

Rozdíly průměrných teplot mezi jednotlivými roky jsou nejlépe patrné z GIF animace zveřejněné na internetu. Výsledná geodatabáze obsahující mapy průměrných ročních teplot a odchylky od normálu byla umístěna na server katedry geografie na Kansas State University pomocí aplikace ArcGIS Server.

Key Words

Temperature, mean temperature, annual mean temperature, climate, Czech Republic, GIS, ArcGIS, regression analysis, linear regression, DEM, SRTM, animated map.

Klíčová slova

Teplota, průměrná teplota, průměrná roční teplota, klima, Česká republika, GIS, ArcGIS, regresní analýza, lineární regrese, DMT, SRTM, animovaná mapa.

Bibliographic Card

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List of Abbreviations

ArcGIS	GIS software package from ESRI
CHMI	Czech Hydrometeorological Institute
DEM	Digital elevation model
EROS	Earth Resources Observation and Science
ESRI	Environmental Systems Research Institute, Inc.
GEOTOPO30	Global DEM at 30 arc seconds (1-km) resolution
GIS	Geographic information system
IDW	Inverse distance weighting
IDWA	Inverse distance weighted averaging
KML	Keyhole Markup Language
NASA	National Aeronautics and Space Administration
NGA	National Geospatial-Intelligence Agency
PRISM	Parameter-elevation Regressions on Independent Slopes Model
RMS	Root mean square, also called the quadratic mean
SRTM	Space Shuttle Radar Topography Mission
USGS	U.S. Geological Survey

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1 Introduction

Understanding spatial variation in climate is essential in many scientific disciplines such as agriculture, ecology, hydrology, forest management and others. The topic of global change in climate has been a matter of growing concern not only for many researchers, but also for politicians, and the public for the last decade. There is a relevant study of global climate change elaborated by Czech Hydrometeorological Institute for the Ministry of Environment of the Czech Republic in 2003. It was published in the form of a web page (http://www.chmi.cz/cc/inf/index.html) in the Czech language.

Climate data are measured by meteorological stations, which are situated at discrete locations, also called sampled sites. Climate maps covering extensive areas with unmeasured locations (or unsampled sites) are produced using one of many available spatial interpolation techniques. An exhaustive comparison of eight different interpolation methods for temperature estimation can be found in a conference paper by F. C. Collins.

Geographic information systems (GIS) are powerful modeling and mapping tools not only in agricultural research, natural resource management, but also in studying weather. (Hartkamp et al.) In applied climatology, climate mapping associated with GIS has made rapid progress. The demand for climatological data on a regular grid is increasing as ecological and hydrological models become increasingly linked to GIS that spatially represent and manipulate model output. (Daly, Neilson and Phillips 140-157) Accurate temperature estimates are also critical in the calibration of satellite sensors. (Collins and Bolstad)

1.1 Past and Recent Works

There has been a variety of different approaches for mapping climate using GIS and DEM. A well established project called PRISM was created at Oregon State University. PRISM stands for Parameter-elevation Regressions on Independent Slopes Model. Its goal is to produce the most innovative and sophisticated climate maps available anywhere. According to PRISM Group, "PRISM is a knowledge-based system that uses point measurements of precipitation, temperature, and other climate elements to produce continuous, digital coverages. PRISM coverages are used with GIS to construct maps and perform many types of analysis."

Recently in 2007, Luis Rodríguez-Lado et. al. proved that multiple regression technique for mapping air temperature of the State of São Paulo, Brazil is an accurate method. The correlation between the climate dependent variables, with latitude and altitude as independent variables was significant. They used $0.5km$ digital elevation model (DEM) in GIS.

C. J . Willmott and K. Matsuura talk about "smart interpolators" in estimating annually averaged air temperature in the United States. There are two basic approaches: climatologically aided interpolation and topographically informed interpolation. Smart interpolation includes both interpolation techniques by incorporating spatially high-resolution DEM, an average environmental lapse rate, and another high-resolution long-term average temperature field. Smart interpolators can reduce time-averaged air temperature interpolation errors significantly. (Willmott and Matsuura 2577-2586)

David P. Brown and Andrew C. Comrie modeled winter temperature and precipitation in Arizona and New Mexico, USA for the period 1961-1990. They used regression models at $1km$ resolution for the varying topography of the Southwest of the United States.

The Czech Climate Atlas was published by the Czech Hydrometeorological Institute (CHMI) in 2007. Besides the atlas, CHMI also runs the climate predicting model "Aladin" (http://www.chmi.cz/meteo/ov/aladin/).

1.2 Objectives

The primary idea behind this thesis was to create thematic maps using the ArcGIS 9.2 software (ESRI, Redlands, CA) that shows one of the basic climate variables for the Czech Republic: Mean temperature for the last ten years. There wasn't enough time to study precipitation because precipitation is more difficult to model and predict than temperature. Modeling precipitation requires more complex models with more input data, for example slope and aspect, solar radiation, continentality, clouds characteristic and others.

The goal set for this thesis was to create accurate digital thematic maps that could be made available on the Internet. Alternative cartographic techniques would be used in an attempt to create cartographically correct maps that are more aesthetically pleasing than similar maps produced and published by the Czech Hydrometeorological Institute (CHMI) on its web site (http://www.chmi.cz/meteo/ok/infklime.html). In contrast to maps by CHMI this thesis only works with a small portion of the CHMI climate data, which is provided for free. For that reason reaching better accuracy than CHMI maps is impossible. The second task for this work was to visualize the change in temperature annually and to publish those maps as an ArcGIS Server application on the Internet.

2 Study Area

The Czech Republic is located in the center of Europe, sharing borders with Germany, Austria, Slovakia, and Poland. It occupies an area of almost 79 000 km^2 (about 30 500$miles^2$) and has variable elevations ranging from 115 to 1602 meters above the Baltic Sea level.

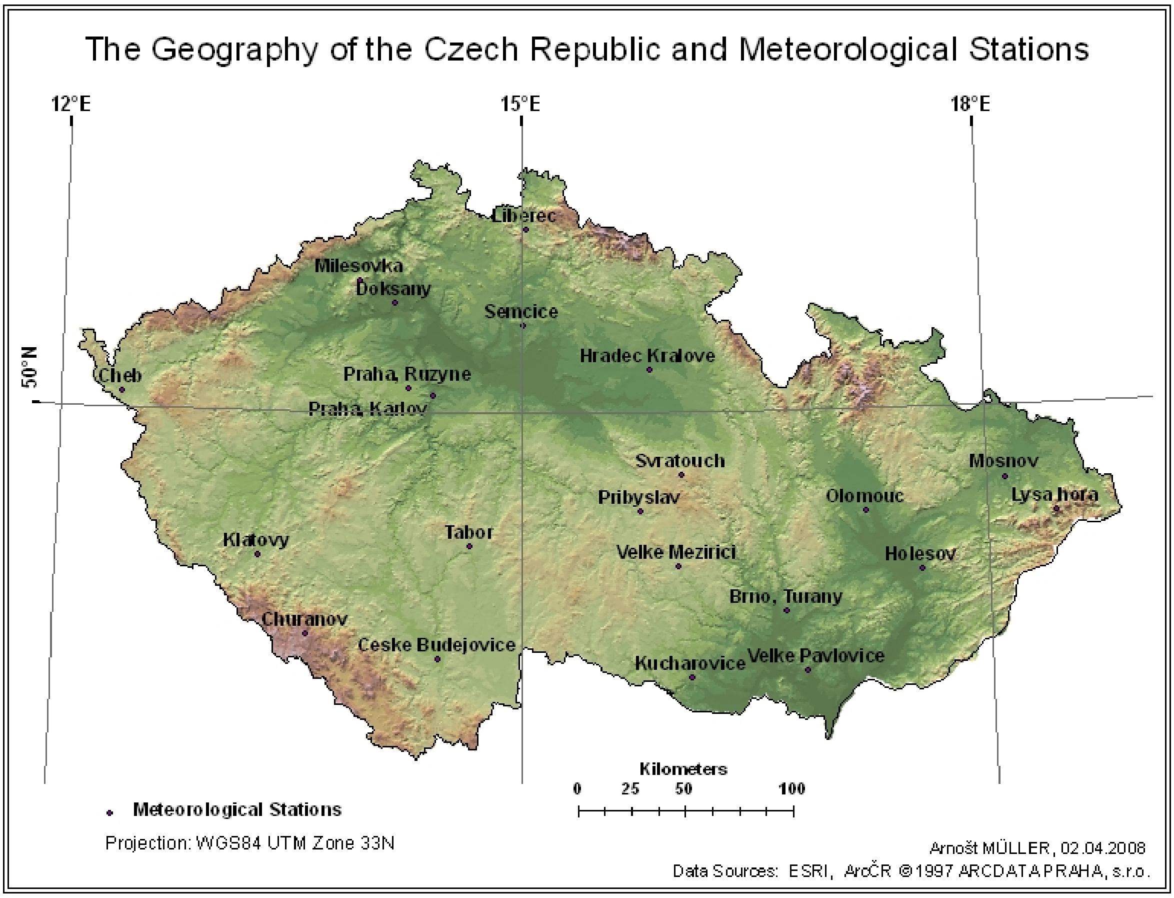

Figure 1: Local geography and 22 meteorological stations used for interpolation.

2.1 Climate Characteristics of the Czech Republic

The climate of the Czech Republic is influenced by both the continental and the ocean climate. It is characterized by winds blowing from the west, intense cyclonical activity and relatively high precipitation. The influence of ocean climate is more distinctive in Bohemia in the West, while the continental influence increases in Moravia and Silesia in the East. Higher continental influence with east or north-east winds causes warmer, dry summers and stronger, colder winters. Variation in altitude has larger influence on both climate and weather in the Czech Republic. There are 52 817 km^2 (66.97% of total area) in altitudes lower than 500m, 25 222 km^2 (31.98%) between 500 and 1 000m and only 827 km^2 (1.05%) higher than 1 000m. The mean altitude of the Czech Republic is 430m. ("Česká republika.")

Precipitation on the wind facing sides of the mountains reaches up to 1 500mm per year, areas (for example region Žatecko and part of central Bohemia) lying in a precipitation shadow receive less than 500mm per year. Mean winter temperature in January is between -7°C in the mountains and 0°C in lowlands. Mean summer temperature oscillates between 7°C in the highest altitudes and 20°C in Prague and South Moravia.

In 2007, the Climate Atlas of the Czech Republic was published by CHMI. It contains "the most comprehensive processing of climate characteristics on the territory of the Czech Republic within the period of 1961–2000…The Climate Atlas of the Czech Republic features all of this in a friendly form with well-arranged maps and graphs with easy-to-understand comments in both Czech and English language." ("Climate Atlas of the Czech Republic.") However, the Climate Atlas of the Czech Republic is only available in a printed form. One of the goals of this project was set to visualize variation in temperature and to make climate maps accessible on the web for everybody.

CHMI also provides a limited number of maps on its website. Annual climate map (an example for year 1998 in Figure 2) published on the web site of CHMI is cartographically incomplete and lacks compelling aesthetic features. For example, more classes should be used for the temperature categories shown. The long-term mean temperature map in Figure 3 is cartographically correct, has more classes, but the color schema is not distinctive.

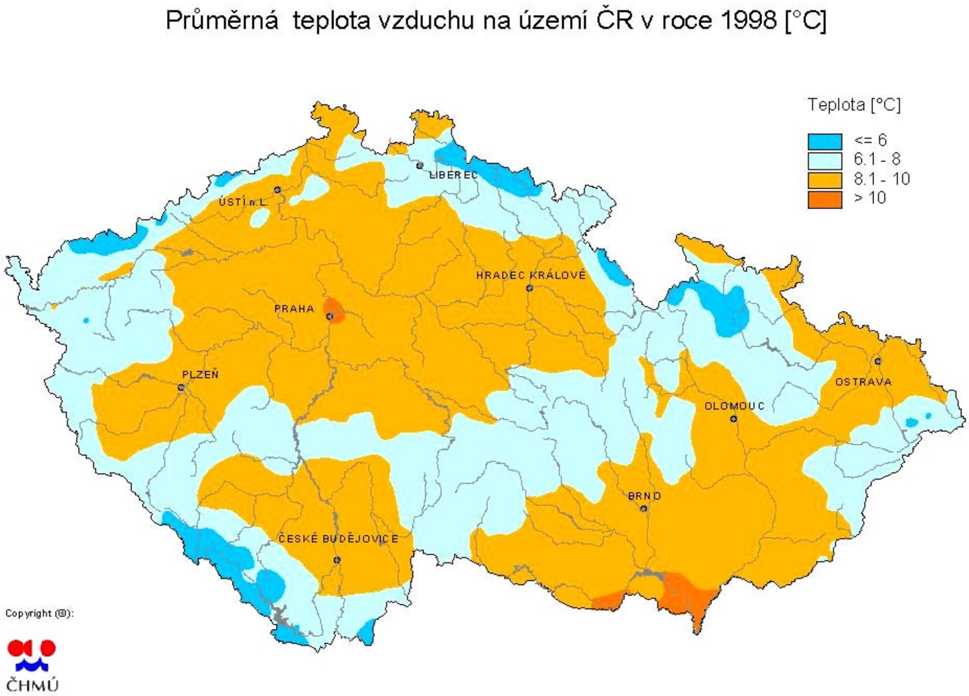

Figure 2: Annual mean temperature in the Czech Republic in 1998 [°C] from the CHMII website.

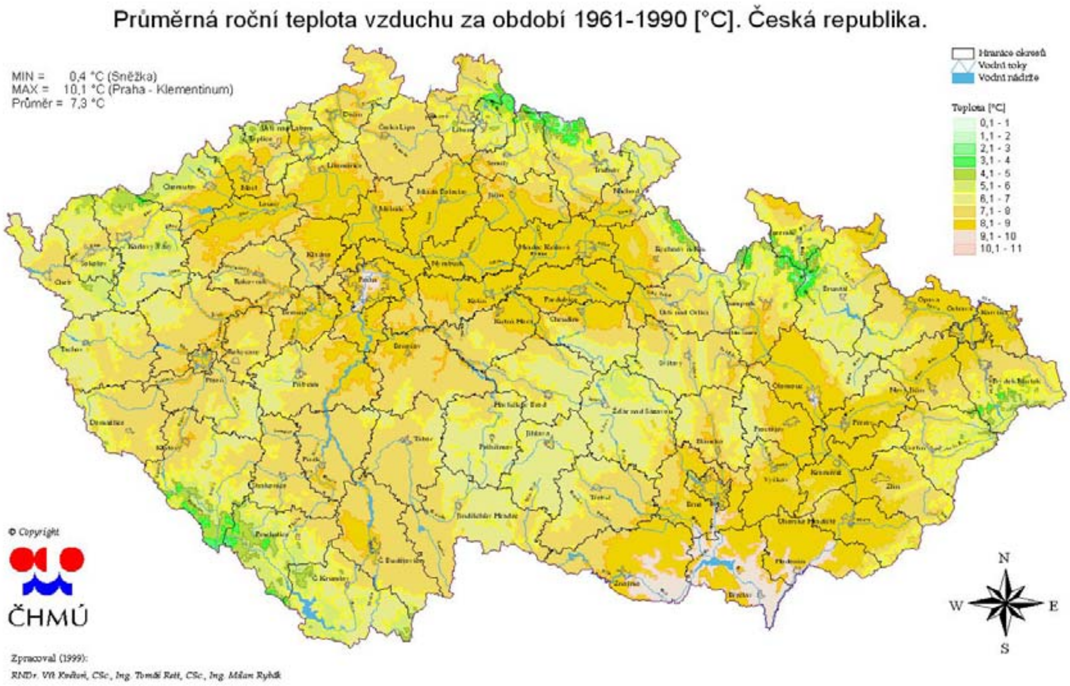

Figure 3: Long-term Mean Air Temperature for the period 1969-1990 [°C] from the CHMI website.

3 Methods

Climate data are measured at meteorological stations, which represent discrete locations. Climate maps covering extensive areas over no-measured locations are produced using several interpolation techniques.

3.1 Interpolation Techniques

There are two main approaches used in GIS. The first group of interpolators includes Inverse Distance Weighting (IDW), Spline, Thiessen polygons and more complex geostatistical techniques called Kriging or co-kriging. These interpolators determine weights for measured sites, generally as a function of distance or patterns of spatial variance. (Goodale, Aber and Ollinger 35-49) The second group consists of alternative methods such as multivariate regression, lapse rate method and Trend surface analysis (TSA). A good description and evaluation of different interpolators for estimating temperature can be found in a conference paper by F. C. Collins.

3.2 Methods Used in Past Works

This section lists different approaches used for interpolating climate variables. Most of them come from journals about climate.

David T. Price et. al. compare two elevation-dependent interpolation techniques of climate data from sparse weather station network in Canada: thin-plate smoothing splines and a statistical method termed Gradient plus Inverse-Distance Squared (GIDS). (Price et al. 81-94)

The method of thin-plate smoothing splines was also studied and compared to inverse distance weighted averaging (IDWA) and co-cringing by A. Dewi Hartkamp et.al. for 200 meteorological stations in the state Jalisco in Mexico (an area of 20 000 km^2). DEM at 1km resolution was used.

David P. Brown and Andrew C. Comrie as mentioned in introduction modeled winter temperature and precipitation in Arizona and New Mexico, USA for the period 1961-1990. They used regression models at 1km resolution for the varying topography of the Southwest of the U.S. Kriging and inverse distance weighting interpolation algorithms were utilized to account for model residuals.

In the case of the Climate Atlas of Czechia, most of the climate variables dependent on elevation were interpolated using local linear regression and digital model of the relief (DEM). ("Climate Atlas of the Czech Republic.")

3.3 Regression Analysis

The regression approach extrapolates climate using climate data, elevation, and empirical or theoretical relationships between climate and elevation or between climate and more variables. This approach is called regression analysis. Regression is based on correlation between dependent climate variables and independent variables such as altitude, latitude, continentality, solar radiation, and the cloudiness factor, some of which can be extracted from a digital elevation model (DEM). (Ninyerola, Pons and Roure 1823-1841)

A critical step in regression analysis is determining which independent variables are significant to the dependent variable. Identifying the significant independent variables can be done by statistical tool testing for significance by classic statistics software. ("ArcGIS Desktop Help 9.2.")

At global scale, temperature decreases by 6.5°C per 1km increase in altitude. (Goodale, Aber and Ollinger 35-49) The relationship between temperature as a climate variable and elevation can be described using simple regression equations. This way the spatial variation of temperature is emphasized and related to grid position based on DEM. According to Ch. L. Goodale at al., “Regression can summarize strong regional climate trends that have physical meaning, such as decreasing temperature or solar radiation with latitude." Regression is not only faster in computing, but also demands less storage space. Consider for example a regional climate model. The model would contain only a DEM layer, while climate datasets could be computed using simple up-to-date equations. (Goodale, Aber and Ollinger 35-49)

In case of the Climate Atlas of the Czech Republic published by the CHMI in 2007, linear regression was used for climate variables which were considered to be dependent on altitude. They applied the least squares method, where regression coefficients for each station based on the nearest stations were calculated and subsequently interpolated to obtain spatial distribution. Using map algebra and straight-line equation, the spatial distribution of the given climate variable was found. This approach was employed most often. They used a 500m horizontal resolution grid resampled to 100m to display maps at scale 1:1 000 000. ("Climate Atlas of the Czech Republic.")

3.4 The Choice of Interpolation Method

First of all, the choice of spatial interpolation method is very important in mountainous regions where data collection is sparse and climate variables may change over short spatial scales. (Collins and Bolstad) The relief of the Czech Republic varies from 115m above sea level to 1602m above the sea level. There are a number of mountainous regions. Second, twenty two meteorological stations for the whole area of the Czech Republic can be considered a very sparse distribution. Third, a regionalized variable such as temperature is strongly correlated with elevation. (Collins and Bolstad) Fourth, the regression method was superior to all other methods studied in F.C. Collins paper, which compares seven interpolation methods for temperature estimation. Fifth, regression gives the most visually plausible results. (Collins and Bolstad) Sixth, regression analysis should use the simplest model possible. Seventh, regression was used as the primary method for the Climate Atlas of Czechia. Eighth, the correlation (R-statistics) between temperature and elevation was very significant.

The performance and accuracy of linear regression is further discussed and compared to other interpolation techniques in section 6, Accuracy.

The reasons described above explain why linear regression was chosen as the most appropriate interpolator for estimating mean air temperature.

4 Data Sources

4.1 DEM

The Digital elevation model (DEM) used in regression analysis originates from the NASA/NGA Shuttle Radar Topography Mission (SRTM), launched in year 2000. The SRTM dataset for USA is 1 arc second horizontal resolution (+- 30 meters on the equator).

The global datasets comprise an annulus between 60°N latitude and 56°S latitude. The model is global, because GTOPO30 data were used to fill in latitudes beyond 60°N and 56°S, as well as void areas within the SRTM data. GTOPO30 is another coarser DEM of 30 arc seconds (+- 1 km) horizontal resolution developed by the USGS EROS Data Center in 1996 from a variety of data sources. The horizontal resolution of SRTM global datasets is 3 arc seconds (+- 90 meters along the equator), where pixel values represent elevation in meters. ("ArcGIS Desktop Help 9.2.") For altitudes of central Europe each pixel represents a rectangle of 60 x 90m. ("Digitální model reliéfu ČR.")

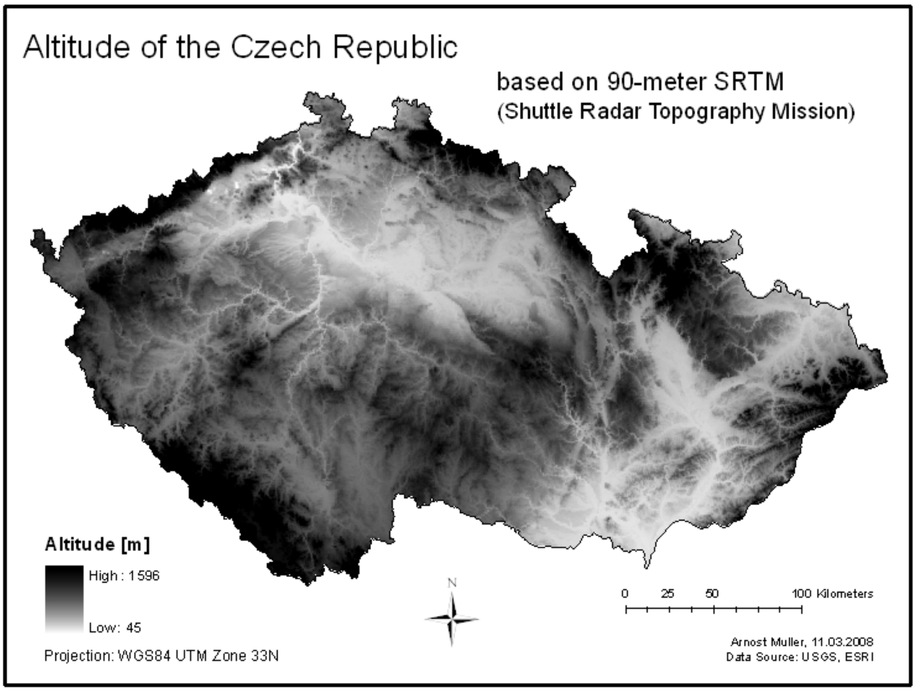

Figure 4: SRTM DEM containing altitude information.

The horizontal datum of SRTM datasets is WGS84. Data are expressed in geographic coordinates (latitude/longitude). SRTM is vertically referenced to the WGS84/EGM96 geoid. The SRTM data meet the absolute vertical accuracy of 16 meters (linear error at 90% confidence), respectively, as it was specified for the mission. ("SRTM.") The vertical accuracy is actually significantly better than 16 meters, closer to +/- 10 meters, according to USGS. The actual vertical accuracy is further discussed in chapter 6.

Because the original data distributed through USGS Seamless Server contained void areas, final DEM was downloaded from ESRI Data and Maps 2006. SRTM Water Body Dataset was also downloaded, but the data were incomplete. It contained only parts of rivers and very few streams.

4.2 Mean Temperatures

Temperatures as well as other climate variables are measured at meteorological stations. Most of the meteorological stations in the Czech Republic are operated by employees of the Czech Hydrometeorological Institute (CHMI) or volunteers, who provide their data to this institute. The CHMI belongs to the Ministry of the Environment of the Czech Republic. CHMI operates 209 climatological stations (including 38 professional synoptic weather stations) and 585 precipitation stations (situation in January 2008). See a map of the climatological stations at http://www.chmi.cz/meteo/ok/images/st_cz.gif, where dark blue squares stand for professional meteorological stations, light blue for automatic, red for basic and khaki green for military operated stations. CHMI doesn't provide its data for free except for 22 meteorological stations. Mean temperatures annual data were accessed at the CHMI web page (http://www.chmi.cz/meteo/ok/infklime.html) and copied to a spreadsheet.

To be able to use the data in ArcGIS, commas as decimal separator needed to be switched for periods. Long-term annual mean temperatures were obtained for 22 meteorological stations from the same website mentioned above. Just 22 stations for an area of almost 79000km^2 and for 1487m variation in altitude can be considered a very sparse coverage. Look up figure1 for location of the 22 stations.

Median of altitude	376*m*
Maximum altitude	1324*m*
Minimum altitude	158*m*
Nr. of stations higher than 500m	5

Table 1: Characteristics of the 22 meteorological stations

4.3 ArcČR 500 v. 2.0a

The dataset ArcČR 500 version 2.0a was obtained from ArcData Praha, s.r.o. free of charge for academic purposes if following license agreement. Shapefiles containing administrative regions of the Czech Republic, rivers and streams, water bodies, and all cities were used to fulfill spatial context of the climate maps. The colored relief image was used for the map of the study area in figure 1. The datasets were requested in WGS84 format.

5 Procedure Description

Input datasets mentioned in data sources in section 4 were downloaded and imported into a new personal geodatabase using ArcCatalog.

5.1 DBF files

A database file with meteorological stations (including coordinates, altitude and mean temperatures) in tabular format was edited in MS Excel. Commas as decimal separators by numbers were switched for periods, and saved as DBF IV file format. Default format of character encoding was widows 1250, which should display special characters with accents of the Czech alphabet correctly. But it did not either in MS Excel or in ArcGIS. Encoding was attempted to change in a free-ware program “Prevod”, but with no results. Finally, encoding ASCII was used, so that all labels in ArcGIS are displayed correctly but without Czech accents.

In ArcGIS, a database file (.DBF) with the meteorological stations and WGS84 geographical coordinates was converted to a point shapefile using “Display XY Data” function (X Field = E_Longitude, Y Field = N_Latitude). Coordinate system of the input data needed to be defined as geographic "WGS 84" (Name: GCS_WGS_1984) using “Define Projection” tool in Data Management toolbox so that further projection changes of the data frame would take effect correctly.

5.2 DEM

SRTM data were clipped to the borders of the Czech Rep. using raster calculator. In options of spatial analyst extension, you have to set the analysis extent as the borders shapefile. Then you run a raster calculator with only one parameter set [DEM]. This way the DEM does not change but will be clipped exactly to the borders. When using the clip tool in Arc Toolbox, the result was a rectangular clip of the extent of the Czech Republic, overreaching the borders.

5.3 Regression Analysis

Generally speaking, there is a strong relationship between mean temperature and altitude in the Czech Republic. Linear regression was chosen as the most appropriate interpolator for point input measurements of mean temperatures, because of the reasons given in chapter 3.4.

Linear regression is an approximation of point measurements by a line, see graph in figure 5. The high correlation between mean temperature and altitude is underlined by a surprisingly high R-squared (R^2) coefficient of determination - R^2 ranging from 0.90 to 0.96. R^2 is the square of correlation coefficient in the case of linear regression. R^2 coefficient is a measure of how well the regression line approximates the real data points. An R^2 of 1.0 indicates a perfect fit of the line throughout data. ("Coefficient of determination.")

The R^2 in the work of modeling temperature for the State Sãu Paulo in Brazil varied in the range from 0.924 to 0.953. The significant correlation between the climate dependent variables, with latitude and altitude as independent variables could explain most of the spatial variability. (Rodriguez-Lado et al. 460-467)

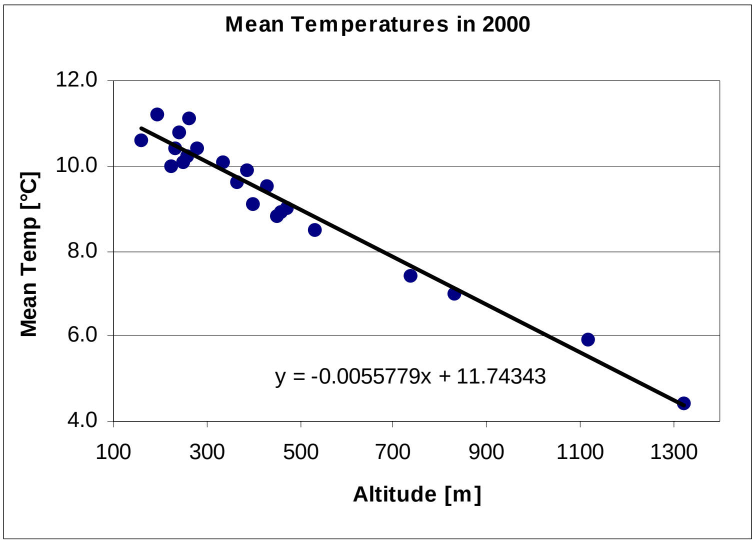

Figure 5: Strong correlation between mean temp. and altitude represented by the fitting line.

Linear regression can be described by the equation: $Ti = a(DEM) + b$, where a and b are regression coefficients, *DEM* (altitude of each pixel) is the independent variable and *Ti* as the dependent variable is the resulting mean temperature for each pixel i. Coefficients were calculated first in MS Excel in charts, second in Geoda software. Both applications gave the same results. Geoda is a free software developed at the University of Illinois. Its default input files are shape files (.SHP) and it is mainly used for exploratory data analysis. Geoda includes a tool called "Regress" for computing multivariate regression. Unlike MS Excel, the results are in a form of a well-arranged protocol and include a variety of statistics. The protocols for each linear regression calculation are attached in appendix B and contain the regress. coefficients ALTITUDE (a) and CONSTANT (b).

Protocols from Geoda software also include R^2 and adjusted R^2. The later one is "a modification of R^2 that adjusts for the number of explanatory terms in a model." Unlike R^2, "the adjusted R^2 increases only if the new term improves the model more than would be expected by chance" according to Wikipedia. This way you can test which and how many variables are significant independent variables for regression. Multivariate regression for estimating mean temperatures was also tested in Geoda. Lets compare the results (parts of protocols below are for the year 1998):

```
Linear REGRESSION (1 independent variable: altitude)
Degrees of Freedom  :    20
R-squared           :    0.942423  F-statistic           :      327.364
Adjusted R-squared  :    0.939545  Prob(F-statistic)     :7.24657e-014
Sum squared residual:    3.54548   Log likelihood        :     -11.1376

Multivariate REGRESSION (2independent variables: altitude, lattitude)
Degrees of Freedom  :    19
R-squared           :    0.953342  F-statistic           :      194.109
Adjusted R-squared  :    0.948431  Prob(F-statistic)     : 2.2636e-013
Sum squared residual:    2.87314   Log likelihood        :     -8.82463

Multivariate REGRESSION (3independent variables: altitude, lattitude,
longitude)
Degrees of Freedom  :    18
R-squared           :    0.963108  F-statistic           :      156.636
Adjusted R-squared  :    0.956959  Prob(F-statistic)     :4.38633e-013
Sum squared residual:    2.27177   Log likelihood        :     -6.24132
```

Coefficient of determination (R^2) for multivariate regression with two variables is about 0.01 higher than linear regression, and about 0.02 higher for multiv. regres. with three variables. Multivariate regression has lower residuals also. But neither latitude nor longitude has a significant influence on temperature in the Czech Rep. compared to altitude.

5.4 Climate Maps

Climate maps showing mean temperatures were interpolated by linear regression method. This was done by plugging equations with calculated coefficients into Raster Calculator in Spatial Analyst extension of ArcGIS, see Figure 6. The output file was a grid (raster) with the same cell size (0.00084°x0.00084°) as the DEM. The raster datasets were saved as "IMAGINE Image" (.IMG) file format, because of less storage space than in ArcGIS grid format.

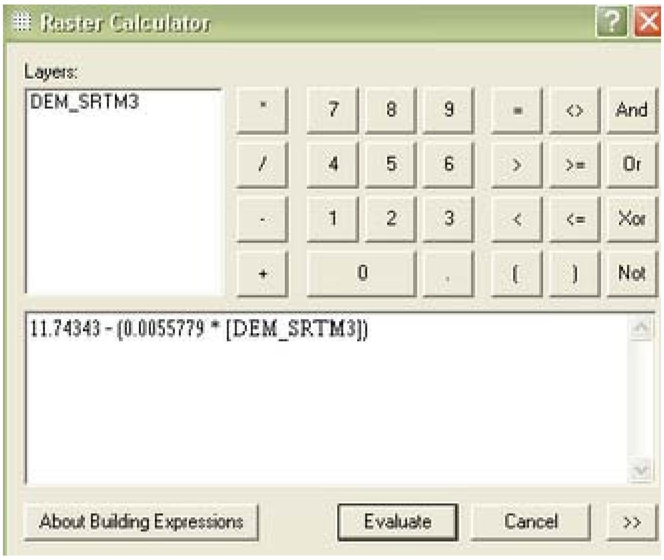

Figure 6: Raster Calculator in ArcMap

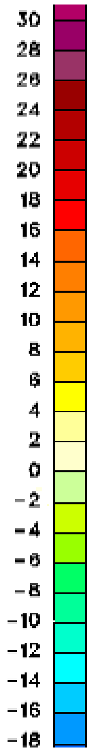

Figure 7 on the right: Color schema of the Aladin model for air temperature

5.5 Color Schema

Climate maps were symbolized using a non ArcGIS color schema partly following the schema of the climate predicting model "Aladin" (http://www.chmi.cz/meteo/ov/aladin/) shown in figure 7. Annual mean temperatures in the Czech Republic range from 1°C to 12°C. In the scale in figure 7 this would be a beige – orange color schema. Orange color for moderate temperatures around 10°C seemed appropriate. Colder temperatures close to 0°C were symbolized blue to reach better contrast. The blue-orange color schema was set in ArcMap manually for each class.

5.6 Classification

Number of classes was considered along with choosing the color schema. In ArcMap, Natural Breaks (Jenks) and Quantile classification techniques were tested. Quantiles made the Czech Republic look too cold. Natural breaks gave similar results to the maps from CHMI in Figures 2. and 3, where the mountainous areas are the cold ones. The number of classes was tested for 4, 5, 7, 8 and 10 classes with regard to the color schema. Four classes displayed in figure 8 didn't show too much variation in temperatures. Ten classes in figure 9 were too many for the blue-orange color schema, when red had to be used to distinguish the warmest temperatures. Eight classes were chosen as a good compromise between variation and color schema.

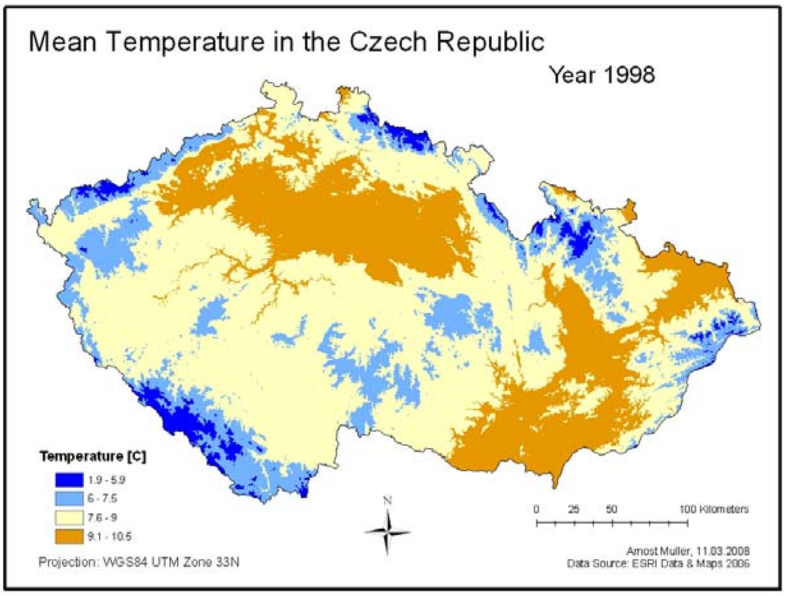

Figure 8: Classifying mean temperatures into 4 classes color schema

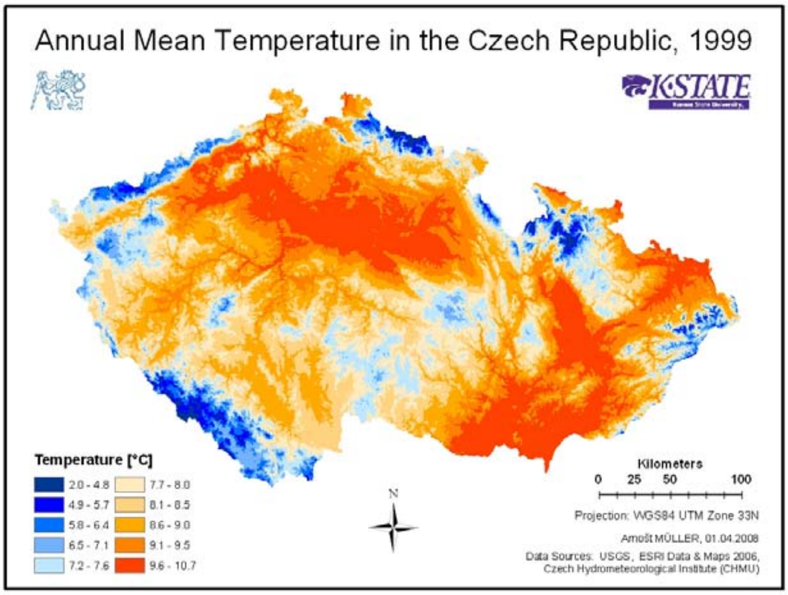

Figure 9: Classifying mean temperatures into ten classes color schema

For the purpose of an animated map, each annual map was classified into five and eight classes using Natural Breaks. The brakes were averaged and averaged (mean) breaks were used to classify all ten annual maps in the same way, so that comparison between different years is possible. This was essential for creating an animated map.

	y98	y99	y00	y01	y02	y03	y04	y05	y06	y07	mean
Natural Breaks (Jenk) 5classes	6.1	6.2	7.0	6.2	6.8	6.4	5.8	5.7	6.5	7.0	**6.4**
	7.3	7.5	8.2	7.5	7.9	7.6	7.1	6.9	7.6	8.2	**7.6**
	8.1	8.3	9.0	8.3	8.7	8.4	7.9	7.7	8.3	9.1	**8.4**
	8.9	9.1	9.9	9.1	9.4	9.2	8.8	8.6	9.1	9.9	**9.2**
	10.5	10.7	11.5	10.7	10.9	10.7	10.5	10.2	10.5	11.6	**10.8**

Table 2: Averaging Natural Breaks for 5 classes

For the purpose of the web application, class breaks of mean temperatures were rounded to .0 or .5 for the lower classes to improve readability. This classification also makes the long-term temperatures for the period 1961-1990 (normal) appear warmer.

	y98	y99	y00	y01	y02	y03	y04	y05	y06	y07	mean	round.
Natural Breaks (Jenk) 8 classes	5.0	5.1	5.9	4.7	5.7	5.3	4.6	4.6	5.6	5.8	**5.2**	**5.0**
	6.1	6.2	7.0	5.7	6.7	6.4	5.8	5.7	6.5	6.9	**6.3**	**6.0**
	6.9	7.0	7.8	6.5	7.5	7.2	6.6	6.5	7.2	7.8	**7.1**	**7.0**
	7.5	7.7	8.5	7.2	8.1	7.8	7.3	7.1	7.8	8.4	**7.7**	**7.7**
	8.0	8.2	9.0	7.7	8.6	8.3	7.9	7.7	8.3	9.0	**8.3**	**8.3**
	8.6	8.8	9.6	8.2	9.1	8.8	8.4	8.2	8.7	9.6	**8.8**	**8.8**
	9.2	9.4	10.2	8.8	9.7	9.4	9.1	8.8	9.3	10.2	**9.4**	**9.4**
	10.5	10.7	11.5	10.1	10.9	10.7	10.5	10.2	10.5	11.6	**10.7**	**11.6**

Table 3: Averaging and rounding Natural Breaks for 8 classes

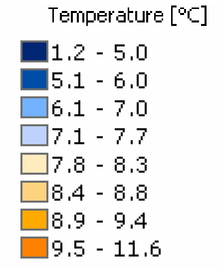

Figure 10: Blue-orange color schema and eight classes used for web application.

5.7 Converting Rasters to Vectors

Raster datasets with mean temperatures were converted to vectors (polygon shapefiles) to save storage space and to enhance display performance of ArcGIS server. Prior to conversion, rasters had to be reclassified from floating to integer pixel value type. However, the polygon shapefiles created with Spatial Analyst tool "Convert Raster to Features" contained not only a tremendous number of polygons, but also many topological errors. Displaying speed was slow. When trying to generalize those polygons with the "Simplify Polygon" tool in Data Management Tools-Generalization, both methods the "POINT_REMOVE" and "BEND_SIMPLIFY" were tested. Simplification tolerance was set for 1km reference baseline and 5km^2 minimum area. The problem was that simplified shapefiles contained void areas. This problem could have been handled by the option "RESOLVE_ERRORS", because running that operation takes more than one night.

Finally, it turned out that resampling rasters to a double less resolution (from 0.000833° x 0.000833° cell size to 0.001666° x 0.001666°) enhanced the displaying speed and saved the same amount of storage space (four times less) as the polygon shapefiles. This was done with the Resample tool with nearest neighbor assignment, which is the fastest of the interpolation methods. It is used primarily for discrete data, and does not change the values of the cells. The maximum spatial error is one-half the cell size. ("ArcGIS Desktop Help 9.2.")

5.8 Spatial Reference

UTM cylindrical projection zone 33N was used instead of the national system S-JTSK Krovak's conic projection. UTM is more universal, known and used outside the Czech Republic in other countries and projects the Czech Republic more horizontal. Besides that, CHMI also used UTM projection based on WGS84 ellipsoid.

5.9 Deviations from Normal

Long-term 1961-1990 temperatures called normal measured at each of 22 meteorological stations were subtracted from the annual mean temperature and thus were deviations for each of 10 years obtained. These point measurements were interpolated using inverse distance weighting (IDW) with the power 2, 5 maximum neighbors and the minimum of 3.

Subtracting temperature values pixel by pixel (pixel containing mean temp. value from pixel containing normal value) using map algebra yielded irrelevant results due to the nature of linear regression data. Basically, this way you are subtracting two lines of almost the same or very similar slope and all what really matters is the absolute member of the regression equation. The result you get is a small range (e.g. in case of normal and year 98, deviations ranged from 0.071 to 0.075, but according to the mean temperatures in appendix A, year 98 was approx. 0.9°C warmer than the normal).

5.10 GIS Structure

Deviation shapefiles were stored in a single feature class. As mentioned in Input Data in chapter 4, other layers mostly provided by ArcData Praha s.r.o. were used to fulfill the spatial context of climate maps for the map reader. Those layers shown in figure 11 are:

- Regions: 14 administrative units were obtained from ArcData ArcČR 500 v. 2.0a
- CZ_Border: was first obtained from ESRI Europe map, second by dissolving Regions, so that regions match the state border.

- Cities: obtained from ArcData ArcČR 500 v. 2.0a, 9 most populated cities were extracted and deleted
- 9cities: 9 most populated cities according to a census in 2001 were extracted from Cities
- Rivers: obtained from ArcData ArcČR 500 v. 2.0a
- Water_bodies: obtained from ArcData ArcČR 500 v. 2.0a
- Shaded_relief: was obtained from ArcData ArcČR 500 v. 2.0a
- The DEM-SRTM3 obtained from ESRI Data and Maps 2006 is not a part of the ArcGIS web application.

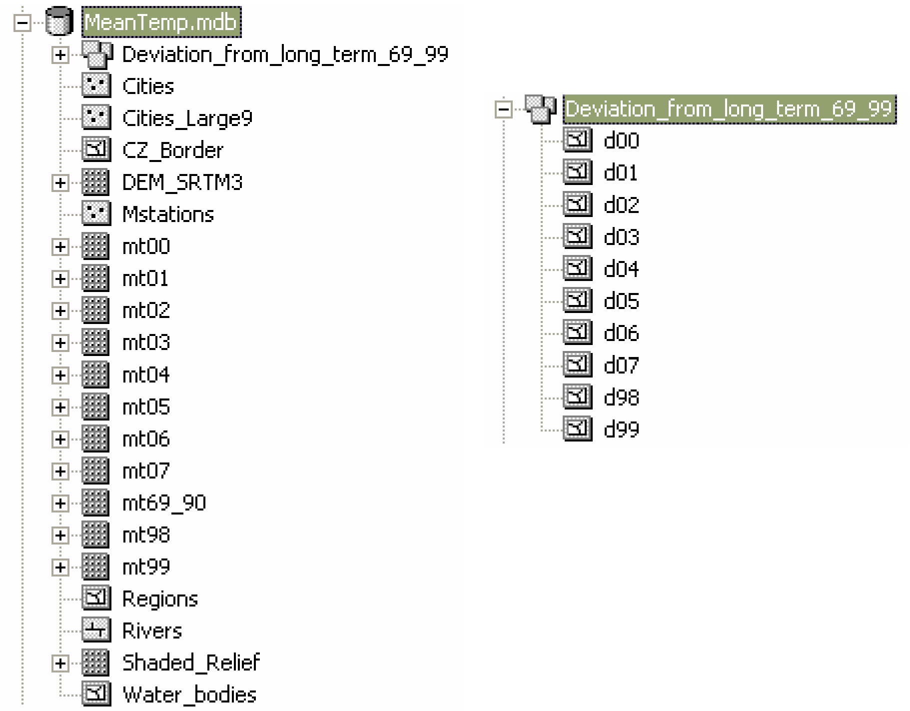

Figure 11: Print Screens from Arc Catalog showing the structure of the geodatabase

6 Accuracy

In case of regression analysis, results depend on the fit of the regression model and the quality and detail of the input data surfaces. Error assessment is possible if input errors are known. (Hartkamp et al.) Input data for regression analysis were mean temperatures obtained from CHMI and DEM.

6.1 Vertical Accuracy of DEM

The vertical accuracy of DEM should be significantly better than the 16 meters, closer to +/- 10 meters, according to USGS. But according to William Shaffer, vertical accuracy of SRTM data is 30m.

The vertical accuracy of DEM was studied closely, because of suspiciously low altitudes of 45meters, while the known lowest point of the Czech Republic is 117 m above the sea level. After highlighting altitudes lower than 117m and finding the corresponding areas in Google Earth, it turned out that those areas in the Northwest spreading out not far from Chomutov are coal mining locations.

The difference caused by different vertical coordinate systems (SRTM uses WGS84/EGM96 geoid, while the Czech Republic is referenced to the Baltic Sea level - Bpv system) shouldn't be more than 1m. (Michovský) The vertical accuracy of the SRTM model was tested in the master thesis of Petr Michovský by comparing the real elevation of 24 peaks with elevation from SRTM. The result says SRTM data is in average 8.5m lower, if excluding the peak "Bořeň" with deviation of 78 m! (Michovský) I disagree with that. The peak's highest pixel value in ArcMap was 507m, while its real altitude should be 539m above the sea level. This 32m error was not significant and has not been corrected.

6.2 Accuracy of Mean Temperatures

According to Ing.Luboš Moravčík, the headmaster of Climatological Department of CHMI, temperatures are measured at 1/10°C and mean annual temperatures are calculated with the same precision. This is called an "a priory" error.

The overall accuracy of mean temperatures resulting from regression model is characterized by root mean square (RMS) of residuals. RMS is also called the quadratic mean. It is a measure of the magnitude of a varying quantity and is useful when variates are both positive and negative. ("Coefficient of determination.") Residuals are differences between model predicted and real measured values, see appendix B for residual values of linear regression.

The RMS values for regression models were calculated using formula in figure 12. The sums of squared residuals (x_i^2) given in Geoda protocols in appendix B were used to calculate RMS for each year (x_{rms}), shown in a table below. The overall accuracy of mean temperature is then characterized by RMS = 0.41°C. This value was calculated using the same equation (quadratic mean) shown below.

$$x_{\mathrm{rms}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} = \sqrt{\frac{x_1^2 + x_2^2 + \cdots + x_n^2}{n}}$$

Figure 12: RMS equation

YEAR	sum r^2	x_{rms}
1998	3.545	0.401
1999	2.812	0.358
2000	2.484	0.336
2001	3.049	0.372
2002	3.364	0.391
2003	4.230	0.438
2004	3.498	0.399
2005	4.655	0.460
2006	5.275	0.490
2007	3.089	0.375
	RMS	**0.405**

Table 4: RMS for each year

Comparing our RMS value with RMS values for other interpolation techniques tested with Geospatial Analyst extension of ArcGIS, RMS for inverse distance weighting (IDW) with power of 2 and 5 neighbors was 2.15°C for year 1998. For ordinary kriging, RMS was close to 2°C for the same test year. Linear regression performs more accurately in this case.

Comparing our RMS value to some other works, the final regression models in Arizona and New Mexico by D. P. Brown and A. C. Comrie showed a higher degree of variance for temperature (R^2 = 0.98), but a higher root mean-squared error RMSE = 0.74°C.

Considering the vertical error of DEM (16*m*) and plugging it into one of the regression equation *Ti = 0.0055(DEM_error) + b*, where *b* remains constant, results in 0.09°C error in mean temperature. This error can be left out, because it is less than a priory accuracy of mean temperatures (0.1°C). This is not true for the peak “Bořeň” (a small area of 5x4 pixels in a digital map or 450x360m in real), where the elevation error of 30*m* makes 0.17°C error in temperature. This local error can be left out because it will not be noticed at small and middle scales and because it is such a small area, it does not really matter.

7 Visualization

Visualization of mean temperature maps was enhanced by setting 15% transparency of mean temperature layers and displaying them over a shaded relief. Shaded relief was obtained from ArcČR 500 2.0a data.

The best visualization technique proved to be an animated map. The animated map in GIF picture format was created in Adobe Image Ready. Before that, 10 maps for each year were exported from ArcGIS into images (.PNG) with 200dpi resolution. It was essential for visualization, that all 10 annual maps followed the same template with exactly the same classes of mean temperatures. Only the year and the map itself could have changed. The same classification makes comparison and animation possible. Three animated maps were created: mean temperatures with five classes and eight classes, and one deviation from normal animated map.

The animation of annual mean temperatures shows relative variation in annual change for the last ten years. It provides a good picture of annual variability of air thermal relations in the Czech Republic for the last decade. The animation of deviations from normal underlines the fact that mean temperatures in the last decade were higher than in the last 30 years. Animated maps are included in the electronic appendix and published on the web at http://maps.fsv.cvut.cz/~muller/ . The same web page was incorporated into the web service application http://maps.gis.ksu.edu/cztemp/Animations.htm .

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8 Web Application

. Complete geodatabase including climate maps and deviations from normal maps was published on the server of the Department of Geography at KSU using ArcGIS Server application (http://maps.gis.ksu.edu/cztemp/). Other layers such as administrative boundaries, cities, rivers and streams, were also included to provide better spatial context for the climate maps.

Any user can interactively display layers of his/her interest, find and zoom in to a specific city. The finding city tool was added as a “search by attributes tool”. It does not work for the nine largest cities, which were removed from the cities layer, so they are not labeled twice.

Climate maps are set for 15% transparency, so that they can be displayed over a shaded relief, which connects variations in temperatures to variations in surface (altitude) and gives the user the feel of a real surface. On the other hand, the transparency has a negative side too, when displaying more than one climate layers at the same time!

Users who have not used a GIS before should read at least one page of the ESRI help called Working with layers and map contents at http://maps.gis.ksu.edu/cztemp/Help/LayersAndToc.htm .

Default settings of ArcGIS Server were modified using MS Visual Basic. The identify button tool was removed and the order of items (table of content, navigation arrow and so on) in the left frame was changed.

By the time this thesis was written, a pick tool was to be programmed and incorporated into ArcGIS Server application so that user can only display one climate layer at one time. It would be nice to see the legend with classes for each color by first opening the web application, but then all layers would have to be expanded by default and the table of content would be too long.

Five web links were added to the navigation banner. A link to Geodesy and Cartography study program at CTU, link to the Department of Geography at KSU, and three more web pages were included: animations, data sources and a tutorial how to display a KML service in Google Earth (http://maps.gis.ksu.edu/cztemp/google.htm).

A KML service can be displayed in Google Earth by adding a network link. This works well for simple vector layers such as deviations in case of this project. By selecting "Show contents as options (radio button selection)" on the properties, you can choose which layer to display. This does not work for raster layers, which are displayed all in one. Raster layers were converted to polygons, but the resulting polygons were too large and caused the server to crash! It was attempted to simplify them by dissolving polygons, but it was not enough to make a significant difference in a project with 11 layers. The problem with the KML service is that you have to set all 11 layers visible in the MXD file before creating the service. The first time you add the network link in Google Earth, the server tries to draw all 11 layers and this causes a timeout error.

9 Conclusion

The purpose of this project was to create thematic maps using appropriate interpolation methods for distributing point measurements of annual mean temperatures in the Czech Republic to regularly-spaced grid cells. Linear regression using a 90-meter DEM was chosen as the most appropriate method for a sparse density of meteorological stations. The strong relationship between mean temperature and altitude is described by the R-statistic value between 0.90 and 0.96.

The results are ten annual thematic maps of mean temperatures plus one normal (long-term mean temperature for the period 1961-1990) map and ten maps with deviations from normal. An interactive web-based environment was set up with ArcGIS Server and is hosted at the server of Geography Department at Kansas State University (http://maps.gis.ksu.edu/cztemp/).

Considering residuals of regression, the overall accuracy of mean temperature is characterized by RMS = 0.4°C. The mean temperature maps are not as strong in showing absolute mean temperatures in degree Celsius as they are in showing relative variation in annual change for the last ten years.

The animation of annual mean temperatures (added to the web service as a single web page http://maps.gis.ksu.edu/cztemp/Animations.htm) provides a good picture of annual variability of air thermal relations in the Czech Republic for the last decade. The results obtained point to the main features of the country's thermal diversity (warm river valleys and central region around Prague in contrast to the cold mountainous regions along the borders). Digital climate maps allow various types of calculations and can serve for further climatological or other analysis.

9.1 Future Work

This work could be primarily extended by including monthly, maximum, and minimum average temperatures. The second basic climate variable – precipitation should be also studied and its annual change visualized.

The use of a thermal band in satellite data or other remotely sensed information may be useful in temperature estimation, according to Fred C. Collins.

The biggest limitation of this work was to have only a subset of 22 meteorological stations. If data from all meteorological stations had been accessed, final maps would have had better accuracy and would have underlined local anomalies such as metropolis reflecting and emitting more heat than surrounding areas.

In terms of the interpolation method, slope, aspect, or solar radiation should also be tested first and then used to improve the performance of regression analysis.

References

"About PRISM Group." PRISM Group, Oregon State University. May 4 2007. <http://www.prism.oregonstate.edu/>.

"ArcGIS Desktop Help 9.2." ESRI. May 2, 2007 <http://webhelp.esri.com/arcgisdesktop/9.2>.

Brown, D. P., and A. C. Comrie. "Spatial Modeling of Winter Temperature and Precipitation in Arizona and New Mexico, USA." Climate Research 22.2 (2002): 115-28.

"Česká republika." Portal of the Public Administration, The Ministry of Interior of the Czech Republic. <http://portal.gov.cz/wps/portal/_s.155/713/_s.155/7205?docid=3>.

"Climate Atlas of the Czech Republic." Czech Hydrometeorological Institute. October 20, 2005 <http://www.chmi.cz/meteo/ok/atlas/ ; http://www.esri.com/news/arcnews/summer07articles/gis-in-climatology.html>.

"Coefficient of determination." Wikipedia. 11 April 2008 2008. <http://en.wikipedia.org/wiki/Coefficient_of_determination>.

Collins, F. C., and P. Bolstad. "A Comparison of Spatial Interpolation Techniques in Temperature Estimation." Santa Fe, April 5, 2008.

Daly, Christopher, Ronald P. Neilson, and Donald L. Phillips. "A Statistical-Topographic Model for Mapping Climatological Precipitation Over Mountainous Terrain." Journal of Applied Meteorology 33 (Feb 1994): 140-157.

"Digitální model reliéfu ČR." ARCDATA PRAHA. <http://www.arcdata.cz/produkty-a-sluzby/geograficka-data/digitalni-model-reliefu-cr/>.

Goodale, C. L., J. D. Aber, and S. V. Ollinger. "Mapping Monthly Precipitation, Temperature, and Solar Radiation for Ireland with Polynomial Regression and a Digital Elevation Model." Climate Research 10.1 (1998): 35-49.

Hartkamp, A. Dewi, et al. Interpolation Techniques for Climate Variables. NRG-GIS 99-01, 1999.

Michovský, Petr. Vyhodnocení Území Podezřelých z Poklesů Určených Metodou Interferometrie. Masters Degree Czech Technical University, 2005 Prague.

Ninyerola, M., X. Pons, and J. M. Roure. "A Methodological Approach of Climatological Modelling of Air Temperature and Precipitation through GIS Techniques." International Journal of Climatology 20.14 (2000): 1823-41.

Price, D. T., et al. "A Comparison of Two Statistical Methods for Spatial Interpolation of Canadian Monthly Mean Climate Data." Agricultural and Forest Meteorology 101.2-3 (2000): 81-94.

Rodriguez-Lado, L., et al. "Modelling Air Temperature for the State of Sao Paulo, Brazil." Scientia Agricola 64.5 (2007): 460-7.

Shaffer, William. "Validation of SRTM digital elevation models and their application to the Holocene deformation of Mono Basin, California." October 12, 1999 <http://www.volcano.buffalo.edu:9090/VolcanoGroup/1129143604/index_html>.

"SRTM." USGS. <http://seamless.usgs.gov/website/seamless/products/srtm3arc.asp>.

Willmott, C. J., and K. Matsuura. "Smart Interpolation of Annually Averaged Air-Temperature in the United-States." Journal of Applied Meteorology 34.12 (1995): 2577-86.

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APPENDIX A: Input Data Table

MStation	Alti.	N_Lat	E Long	98	99	00	01	02	03	04	05	06	07	61-90
Brno, Turany	241	49.159722	16.695556	9.6	9.9	10.8	9.2	10.0	9.9	9.4	8.9	9.1	10.6	8.7
Ceske Budejovice	388	48.961667	14.468056	9.1	9.3	9.9	8.9	9.8	9.4	8.9	8.8	9.1	10.2	8.2
Doksany	158	50.458611	14.170556	9.7	9.9	10.6	9.1	9.9	9.7	9.7	9.4	9.7	10.5	8.5
Holesov	224	49.318611	17.573333	9.2	9.7	10.0	8.8	9.8	9.5	9.1	8.8	9.4	10.2	8.5
Hradec Kralove	278	50.176111	15.838611	9.3	9.5	10.4	8.8	9.8	9.4	9.0	9.1	9.6	10.4	8.5
Cheb	471	50.069722	12.393056	8.1	8.3	9.0	7.8	8.6	8.1	7.8	7.9	8.3	8.9	7.2
Churanov	1118	49.068333	13.613056	5.0	5.1	5.9	4.8	5.7	5.5	4.7	4.5	5.7	5.6	4.2
Klatovy	430	49.393333	13.303611	8.6	8.6	9.5	8.4	9.1	8.8	8.4	8.1	8.9	9.7	8.0
Kucharovice	334	48.883333	16.083333	9.2	9.2	10.1	8.7	9.8	9.9	9.5	9.3	9.6	10.5	8.5
Liberec	398	50.769167	15.025000	7.8	8.1	9.1	7.7	8.3	8.0	8.0	8.0	8.6	8.8	7.2
Lysa hora	1324	49.546111	18.447778	3.4	3.5	4.4	3.1	4.4	3.5	2.7	3.0	3.9	4.0	2.6
Milesovka	833	50.554722	13.931389	5.7	6.3	7.0	5.7	6.4	6.5	5.9	5.8	6.7	7.1	5.2
Mosnov	251	49.694167	18.120000	9.0	9.3	10.1	8.6	9.4	9.1	9.0	8.4	9.1	9.9	8.2
Olomouc	259	49.569444	17.216944	8.6	9.0	10.2	8.7	9.7	9.4	8.9	8.7	9.0	10.5	8.7
Praha, Karlov	261	50.067500	14.418611	10.3	10.5	11.1	9.8	10.7	10.6	10.3	10.2	10.7	11.0	9.4
Praha, Ruzyne	364	50.100833	14.257778	8.7	8.9	9.6	8.3	9.3	9.0	8.6	8.5	9.1	9.9	7.9
Pribyslav	530	49.582778	15.762500	7.4	7.6	8.5	7.1	8.0	8.0	7.8	6.5	6.8	8.3	6.6
Semcice	234	50.367222	15.004444	9.3	9.6	10.4	9.0	10.1	9.6	9.2	9.1	9.4	10.3	8.7
Svratouch	737	49.735000	16.033611	6.6	6.8	7.4	5.9	7.1	7.1	6.3	6.3	7.1	7.4	5.7
Tabor	461	49.435278	14.661667	8.1	8.2	8.9	7.6	8.5	8.1	7.5	7.4	8.2	9.1	7.6
Velke Mezirici	452	49.353889	16.008611	8.1	8.2	8.8	7.6	8.5	8.1	7.5	7.4	7.9	8.9	7.2
Velke Pavlovice	196	48.908611	16.824444	10.1	10.4	11.2	9.7	10.5	10.3	9.7	9.5	9.9	11.0	9.3

APPENDIX B: Linear Regression Protocols

One complete Geoda regression protocol for year 1998 includes all statistics, while shortened protocols for the other years include just the mean and standard deviation of the dependent variable, R-squared, Adjusted R-squared, and sum of squared residuals, which was used to compute the root mean square (RMS) values in section 6.2 Accuracy.

```
Year 98
SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION
Data set             :  Mstations
Dependent Variable   :        Y98  Number of Observations:   22
Mean dependent var   :    8.22273  Number of Variables   :    2
S.D. dependent var   :    1.67303  Degrees of Freedom    :   20

R-squared            :   0.942423  F-statistic           :     327.364
Adjusted R-squared   :   0.939545  Prob(F-statistic)     :7.24657e-014
Sum squared residual:     3.54548  Log likelihood        :    -11.1376
Sigma-square         :   0.177274  Akaike info criterion :     26.2752
S.E. of regression   :   0.421039  Schwarz criterion     :     28.4573
Sigma-square ML      :   0.161158
S.E of regression ML:    0.401445
-----------------------------------------------------------------------
    Variable    Coefficient     Std.Error    t-Statistic   Probability
-----------------------------------------------------------------------
    CONSTANT     10.71606       0.164463       65.15786    0.0000000
    ALTITUDE  -0.005517322  0.0003049391      -18.09319    0.0000000
-----------------------------------------------------------------------

REGRESSION DIAGNOSTICS
MULTICOLLINEARITY CONDITION NUMBER   3.367288
                                        (Extreme Multicollinearity)
TEST ON NORMALITY OF ERRORS
TEST                  DF          VALUE            PROB
Jarque-Bera            2          0.5261663        0.7686780

DIAGNOSTICS FOR HETEROSKEDASTICITY
RANDOM COEFFICIENTS
TEST                  DF          VALUE            PROB
Breusch-Pagan test     1          0.5337792        0.4650223
Koenker-Bassett test   1           0.477977        0.4893401
SPECIFICATION ROBUST TEST
TEST                  DF          VALUE            PROB
White                  2           0.608735        0.7375898

  OBS          Y98        PREDICTED        RESIDUAL
    1        9.60000        9.38638         0.21362
    2        9.10000        8.57533         0.52467
    3        9.70000        9.84432        -0.14432
    4        9.20000        9.48018        -0.28018
    5        9.30000        9.18224         0.11776
    6        8.10000        8.11740        -0.01740
    7        5.00000        4.54769         0.45231
    8        8.60000        8.34361         0.25639
    9        9.20000        8.87327         0.32673
   10        7.80000        8.52016        -0.72016
   11        3.40000        3.41112        -0.01112
   12        5.70000        6.12013        -0.42013
   13        9.00000        9.33121        -0.33121
   14        8.60000        9.28707        -0.68707
   15       10.30000        9.27603         1.02397
   16        8.70000        8.70775        -0.00775
   17        7.40000        7.79187        -0.39187
   18        9.30000        9.42500        -0.12500
   19        6.60000        6.64979        -0.04979
   20        8.10000        8.17257        -0.07257
   21        8.10000        8.22223        -0.12223
   22       10.10000        9.63466         0.46534
========================= END OF REPORT ==============================
```

Year 99

SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION

```
Data set             :  Mstations
Dependent Variable   :        Y99
Mean dependent var   :       8.45
S.D. dependent var   :    1.68947

R-squared            :   0.955220
Adjusted R-squared   :   0.952981
Sum squared residual:     2.81197
```

Variable	Coefficient	Std.Error	t-Statistic
CONSTANT	10.98487	0.1464656	74.99968
ALTITUDE	-0.005609246	0.0002715692	-20.65494

OBS	Y99	PREDICTED	RESIDUAL
1	9.90000	9.63304	0.26696
2	9.30000	8.80848	0.49152
3	9.90000	10.09861	-0.19861
4	9.70000	9.72840	-0.02840
5	9.50000	9.42550	0.07450
6	8.30000	8.34291	-0.04291
7	5.10000	4.71373	0.38627
8	8.60000	8.57289	0.02711
9	9.20000	9.11138	0.08862
10	8.10000	8.75239	-0.65239
11	3.50000	3.55823	-0.05823
12	6.30000	6.31237	-0.01237
13	9.30000	9.57695	-0.27695
14	9.00000	9.53207	-0.53207
15	10.50000	9.52086	0.97914
16	8.90000	8.94310	-0.04310
17	7.60000	8.01197	-0.41197
18	9.60000	9.67231	-0.07231
19	6.80000	6.85085	-0.05085
20	8.20000	8.39901	-0.19901
21	8.20000	8.44949	-0.24949
22	10.40000	9.88546	0.51454

====================== END OF REPORT ==================

Year 00

SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION

```
Data set             :  Mstations
Dependent Variable   :        Y00
Mean dependent var   :    9.22273
S.D. dependent var   :    1.67602

R-squared            :   0.959805
Adjusted R-squared   :   0.957795
Sum squared residual:     2.48399
```

Variable	Coefficient	Std.Error	t-Statistic
CONSTANT	11.74343	0.1376591	85.3081
ALTITUDE	-0.005577907	0.0002552406	-21.85352

OBS	Y00	PREDICTED	RESIDUAL
1	10.80000	10.39916	0.40084
2	9.90000	9.57921	0.32079
3	10.60000	10.86212	-0.26212
4	10.00000	10.49398	-0.49398
5	10.40000	10.19278	0.20722
6	9.00000	9.11624	-0.11624
7	5.90000	5.50733	0.39267
8	9.50000	9.34493	0.15507
9	10.10000	9.88041	0.21959
10	9.10000	9.52343	-0.42343
11	4.40000	4.35829	0.04171
12	7.00000	7.09704	-0.09704
13	10.10000	10.34338	-0.24338
14	10.20000	10.29876	-0.09876
15	11.10000	10.28760	0.81240
16	9.60000	9.71308	-0.11308
17	8.50000	8.78714	-0.28714
18	10.40000	10.43820	-0.03820
19	7.40000	7.63252	-0.23252
20	8.90000	9.17202	-0.27202
21	8.80000	9.22222	-0.42222
22	11.20000	10.65016	0.54984

====================== END OF REPORT ==================

Year 01

SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION

```
Data set             :  Mstations
Dependent Variable   :        Y01
Mean dependent var   :    7.87727
```

S.D. dependent var : 1.62842

R-squared : 0.947741
Adjusted R-squared : 0.945128
Sum squared residual: 3.04869

Variable	**Coefficient**	**Std.Error**	**t-Statistic**
CONSTANT	10.31096	0.1525061	67.61013
ALTITUDE	-0.005385343	0.0002827693	-19.04501

OBS	Y01	PREDICTED	RESIDUAL
1	9.20000	9.01309	0.18691
2	8.90000	8.22145	0.67855
3	9.10000	9.46007	-0.36007
4	8.80000	9.10464	-0.30464
5	8.80000	8.81383	-0.01383
6	7.80000	7.77446	0.02554
7	4.80000	4.29014	0.50986
8	8.40000	7.99526	0.40474
9	8.70000	8.51225	0.18775
10	7.70000	8.16759	-0.46759
11	3.10000	3.18076	-0.08076
12	5.70000	5.82497	-0.12497
13	8.60000	8.95924	-0.35924
14	8.70000	8.91615	-0.21615
15	9.80000	8.90538	0.89462
16	8.30000	8.35069	-0.05069
17	7.10000	7.45673	-0.35673
18	9.00000	9.05079	-0.05079
19	5.90000	6.34196	-0.44196
20	7.60000	7.82832	-0.22832
21	7.60000	7.87678	-0.27678
22	9.70000	9.25543	0.44457

====================== END OF REPORT ==================

Year 02

SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION

Data set : **Mstations**
Dependent Variable : **Y02**
Mean dependent var : 8.79091
S.D. dependent var : 1.58226

R-squared : 0.938925
Adjusted R-squared : 0.935872
Sum squared residual: 3.36388

Variable	**Coefficient**	**Std.Error**	**t-Statistic**
CONSTANT	11.14459	0.1601956	69.5686
ALTITUDE	-0.005208295	0.0002970268	-17.53477

OBS	Y01	PREDICTED	RESIDUAL
1	10.00000	9.88939	0.11061
2	9.80000	9.12377	0.67623
3	9.90000	10.32167	-0.42167
4	9.80000	9.97793	-0.17793
5	9.80000	9.69668	0.10332
6	8.60000	8.69148	-0.09148
7	5.70000	5.32171	0.37829
8	9.10000	8.90502	0.19498
9	9.80000	9.40501	0.39499
10	8.30000	9.07168	-0.77168
11	4.40000	4.24880	0.15120
12	6.40000	6.80608	-0.40608
13	9.40000	9.83730	-0.43730
14	9.70000	9.79564	-0.09564
15	10.70000	9.78522	0.91478
16	9.30000	9.24877	0.05123
17	8.00000	8.38419	-0.38419
18	10.10000	9.92584	0.17416
19	7.10000	7.30607	-0.20607
20	8.50000	8.74356	-0.24356
21	8.50000	8.79044	-0.29044
22	10.50000	10.12376	0.37624

====================== END OF REPORT ==================

Year 03

SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION

Data set : **Mstations**
Dependent Variable : **Y03**
Mean dependent var : 8.52273
S.D. dependent var : 1.64149

R-squared : 0.928649
Adjusted R-squared : 0.925081
Sum squared residual: 4.2296

Variable	Coefficient	Std.Error	t-Statistic
CONSTANT	10.9511	0.1796304	60.96466
ALTITUDE	-0.005373598	0.0003330618	-16.13394

OBS	Y03	PREDICTED	RESIDUAL
1	9.90000	9.65607	0.24393
2	9.40000	8.86615	0.53385
3	9.70000	10.10208	-0.40208
4	9.50000	9.74742	-0.24742
5	9.40000	9.45724	-0.05724
6	8.10000	8.42014	-0.32014
7	5.50000	4.94342	0.55658
8	8.80000	8.64046	0.15954
9	9.90000	9.15632	0.74368
10	8.00000	8.81241	-0.81241
11	3.50000	3.83646	-0.33646
12	6.50000	6.47490	0.02510
13	9.10000	9.60233	-0.50233
14	9.40000	9.55934	-0.15934
15	10.60000	9.54860	1.05140
16	9.00000	8.99512	0.00488
17	8.00000	8.10310	-0.10310
18	9.60000	9.69368	-0.09368
19	7.10000	6.99076	0.10924
20	8.10000	8.47388	-0.37388
21	8.10000	8.52224	-0.42224
22	10.30000	9.89788	0.40212

===================== END OF REPORT ===================

Year 04

SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION

```
Data set            :  Mstations
Dependent Variable  :        Y04
Mean dependent var  :    8.08636
S.D. dependent var  :    1.76797

R-squared           :   0.949129
Adjusted R-squared  :   0.946586
Sum squared residual:    3.49819
```

Variable	Coefficient	Std.Error	t-Statistic
CONSTANT	10.73054	0.1633623	65.68555
ALTITUDE	-0.005851127	0.0003028983	-19.31714

OBS	Y04	PREDICTED	RESIDUAL
1	9.40000	9.32042	0.07958
2	8.90000	8.46030	0.43970
3	9.70000	9.80606	-0.10606
4	9.10000	9.41989	-0.31989
5	9.00000	9.10393	-0.10393
6	7.80000	7.97466	-0.17466
7	4.70000	4.18898	0.51102
8	8.40000	8.21456	0.18544
9	9.50000	8.77626	0.72374
10	8.00000	8.40179	-0.40179
11	2.70000	2.98365	-0.28365
12	5.90000	5.85655	0.04345
13	9.00000	9.26191	-0.26191
14	8.90000	9.21510	-0.31510
15	10.30000	9.20340	1.09660
16	8.60000	8.60073	-0.00073
17	7.80000	7.62944	0.17056
18	9.20000	9.36138	-0.16138
19	6.30000	6.41826	-0.11826
20	7.50000	8.03317	-0.53317
21	7.50000	8.08583	-0.58583
22	9.70000	9.58372	0.11628

===================== END OF REPORT ==================

Year 05

SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION

```
Data set            :  Mstations
Dependent Variable  :        Y05
Mean dependent var  :    7.89091
S.D. dependent var  :    1.70371

R-squared           :   0.927097
Adjusted R-squared  :   0.923452
Sum squared residual:    4.65544
```

Variable	Coefficient	Std.Error	t-Statistic
CONSTANT	10.40924	0.1884564	55.23421
ALTITUDE	-0.005572642	0.0003494264	-15.94797

OBS	Y05	PREDICTED	RESIDUAL
1	8.90000	9.06623	-0.16623
2	8.80000	8.24705	0.55295
3	9.40000	9.52876	-0.12876
4	8.80000	9.16096	-0.36096
5	9.10000	8.86004	0.23996
6	7.90000	7.78452	0.11548
7	4.50000	4.17902	0.32098
8	8.10000	8.01300	0.08700
9	9.30000	8.54797	0.75203
10	8.00000	8.19133	-0.19133
11	3.00000	3.03106	-0.03106
12	5.80000	5.76723	0.03277
13	8.40000	9.01050	-0.61050
14	8.70000	8.96592	-0.26592
15	10.20000	8.95478	1.24522
16	8.50000	8.38080	0.11920
17	6.50000	7.45574	-0.95574
18	9.10000	9.10524	-0.00524
19	6.30000	6.30220	-0.00220
20	7.40000	7.84025	-0.44025
21	7.40000	7.89040	-0.49040
22	9.50000	9.31700	0.18300

====================== END OF REPORT ==================

Year 06

SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION

Data set : **Mstations**
Dependent Variable : **Y06**
Mean dependent var : 8.44545
S.D. dependent var : 1.5323

R-squared : 0.897873
Adjusted R-squared : 0.892767
Sum squared residual: 5.27532

Variable	Coefficient	Std.Error	t-Statistic
CONSTANT	10.67442	0.200611	53.20954
ALTITUDE	-0.004932329	0.0003719629	-13.26027

OBS	Y06	PREDICTED	RESIDUAL
1	9.10000	9.48573	-0.38573
2	9.10000	8.76068	0.33932
3	9.70000	9.89511	-0.19511
4	9.40000	9.56958	-0.16958
5	9.60000	9.30323	0.29677
6	8.30000	8.35129	-0.05129
7	5.70000	5.16008	0.53992
8	8.90000	8.55352	0.34648
9	9.60000	9.02702	0.57298
10	8.60000	8.71135	-0.11135
11	3.90000	4.14402	-0.24402
12	6.70000	6.56579	0.13421
13	9.10000	9.43640	-0.33640
14	9.00000	9.39695	-0.39695
15	10.70000	9.38708	1.31292
16	9.10000	8.87905	0.22095
17	6.80000	8.06028	-1.26028
18	9.40000	9.52025	-0.12025
19	7.10000	7.03929	0.06071
20	8.20000	8.40062	-0.20062
21	7.90000	8.44501	-0.54501
22	9.90000	9.70768	0.19232

======================== END OF REPORT ============================

Year 07

SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION

Data set : **Mstations**
Dependent Variable : **Y07**
Mean dependent var : 9.21818
S.D. dependent var : 1.76059

R-squared : 0.954695
Adjusted R-squared : 0.952430
Sum squared residual: 3.08948

Variable	Coefficient	Std.Error	t-Statistic
CONSTANT	11.85903	0.1535228	77.24603
ALTITUDE	-0.00584375	0.0002846543	-20.52928

OBS	Y07	PREDICTED	RESIDUAL
1	10.60000	10.45068	0.14932
2	10.20000	9.59165	0.60835
3	10.50000	10.93571	-0.43571

4	10.20000	10.55003	-0.35003
5	10.40000	10.23446	0.16554
6	8.90000	9.10662	-0.20662
7	5.60000	5.32571	0.27429
8	9.70000	9.34621	0.35379
9	10.50000	9.90721	0.59279
10	8.80000	9.53321	-0.73321
11	4.00000	4.12190	-0.12190
12	7.10000	6.99118	0.10882
13	9.90000	10.39224	-0.49224
14	10.50000	10.34549	0.15451
15	11.00000	10.33381	0.66619
16	9.90000	9.73190	0.16810
17	8.30000	8.76184	-0.46184
18	10.30000	10.49159	-0.19159
19	7.40000	7.55218	-0.15218
20	9.10000	9.16506	-0.06506
21	8.90000	9.21765	-0.31765
22	11.00000	10.71365	0.28635

====================== END OF REPORT ==================

Long-term 69-90

SUMMARY OF OUTPUT: ORDINARY LEAST SQUARES ESTIMATION

Data set : **Mstations**
Dependent Variable : **Y61_90**
Mean dependent var : 7.48182
S.D. dependent var : 1.66614

R-squared : 0.953156
Adjusted R-squared : 0.950814
Sum squared residual: 2.86088

Variable	Coefficient	Std.Error	t-Statistic
CONSTANT	9.978982	0.1477338	67.54703
ALTITUDE	-0.00552581	0.0002739207	-20.17303

OBS	Y61_90	PREDICTED	RESIDUAL
1	8.70000	8.64726	0.05274
2	8.20000	7.83497	0.36503
3	8.50000	9.10590	-0.60590
4	8.50000	8.74120	-0.24120
5	8.50000	8.44281	0.05719
6	7.20000	7.37633	-0.17633
7	4.20000	3.80113	0.39887
8	8.00000	7.60288	0.39712
9	8.50000	8.13336	0.36664
10	7.20000	7.77971	-0.57971
11	2.60000	2.66281	-0.06281
12	5.20000	5.37598	-0.17598
13	8.20000	8.59200	-0.39200
14	8.70000	8.54780	0.15220
15	9.40000	8.53675	0.86325
16	7.90000	7.96759	-0.06759
17	6.60000	7.05030	-0.45030
18	8.70000	8.68594	0.01406
19	5.70000	5.90646	-0.20646
20	7.60000	7.43158	0.16842
21	7.20000	7.48132	-0.28132
22	9.30000	8.89592	0.40408

======================== END OF REPORT ============================