DOWNSCALING OF CLIMATE VARIABLES USING SUPPORT VECTOR MACHINE (SVM)

A DISSERTATION

Submitted in partial fulfillment of the requirements for the award of the degree
of

MASTER OF TECHNOLOGY
in
WATER RESOURCES DEVELOPMENT (CIVIL)

By

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the dissertation entitled **"DOWNSCALING OF CLIMATE VARIABLES USING SUPPORT VECTOR MACHINE"** in partial fulfillment of the requirement for the award of degree of MASTER OF TECHNOLOGY in Water resource development and submitted in the Department of Water Resources Development and Management of Indian Institute of Technology Roorkee is record of my work carried out during a period from July 2010 to July 2011 under the supervision of **Prof. M.L Kansal** and **Prof. S.K Jain**, Professor at Department of Water Resource Development and Management, Indian Institute of Technology Roorkee, India.

The matter embodied in this dissertation has not been submitted by me for the award of any other degree

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praise to christ jesus, my god and my savior...

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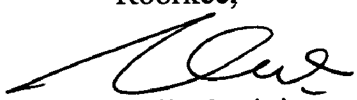
Roorkee,



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ABSTRACT

World's climate which had been observed over the past several decades is consistently associated with changes in a number of components of the hydrological cycle and hydrological systems such as: changing precipitation patterns, intensity and extremes; widespread melting of snow and ice; increasing atmospheric water vapour; increasing evaporation; and changes in soil moisture and runoff.

The Intergovernmental Panel on Climate Change (IPCC), an authoritative international body predicts that global temperatures will rise by 1.1 to 6.4° C by the end of 21 century and this will head to negative influence to the nature in some cases. Thus it is, very important that scientist make prediction of the future climate as the first step of mitigation planning and adaptation.

Global Climate Models (GCM) are considered to be the best tool to predict future climate with resolutions of hundreds of kilometers whilst the spatial resolution of regional climate models (RCM) which can give input data required for hydrological application as finer spatial resolution of the order of tens of kilometers. Further, many impact applications require the equivalent of point scale climate variations that are parameterized in coarse-scale models.

In view of the above, the output from a GCM has to be downscaled to obtain the information relevant to hydrologic studies. Statistical downscaling method is based on the view that the regional climate is conditioned by two factors: the large scale climate state and regional/local physiography.The large-scale output of GCM simulation is fed into this stastical model to estimate the corresponding local and regional climate characteristics. In this study, Multi Linear Regression (MLR) and Support Vector Machine for Regression (SVR) method approach were applied for statistical downscaling for precipitation and temperature variables in Roorkee area.

The 30 years (1981-2010) observed data of precipitation, minimum and maximum temperature were collected and as the predictants. The predictors were extracted from Scenario IS92a data of Coupled Global Climate Model (CGCM2) in Canadian Center for Climate Modeling and Analysis (CCCma) website. The values of the climate variables at pressure levels of 850 mb, 500 mb and 200 mb are found to be representative as the predictor variables.

The best combination of predictors for downscaling precipitation among the available variables are temperature, geopotential height, and specific humidity at 200 mb. V (vertical) or Meridional wind is found influences the computations when downscaling the minimum temperatures whereas U (horizontal) or Zonal wind influences the computation of the maximum temperature.

The result of downscaling shows that SVR are better computation than the MLR as seen by the improvement of error measurements. For precipitation SVR shows a 4.678 % improvement for r, 10.931 % for NSE and 5.447 % for RMSE. For minimum temperature SVR shows a 4.331 % improvement in r, 9.243 % in NSE and 16.504 % in RMSE and for maximum temperature SVR shows a 14.440 % improvement in r, 31.437 % and 19.541 % in NSE and RMSE respectively.

The future projection by SVR model until 2040 for precipitation shows that there will be little increase of precipitation and for temperature shows that there will be not much change of temperature in Roorkee area.

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CHAPTER I
INTRODUCTION

I.1 GENERAL

Warming of the climate system is unequivocal and is already impacting a range of human and natural systems. Scientists have observed changes in the timing of seasons; the range of plant and animal species; regional pattern of precipitation, flooding, and drought. Sea levels are rising and glaciers and Arctic sea ice are forging a steady retreat, as is now evident from observations of increase in global average air and ocean temperatures, widespread melting of snow and ice, rising sea levels. Since 1980, eleven of the last twelve years (1995-2006) rank among the twelve warmest years in the instrumental record of global surface temperature (IPCC Summary, 2007). For instance, the Antarctic peninsula has experienced a major warming over the last 50 years, with temperatures at Faraday/Vernadsky station have increased by 2.5°C since the 1950s (Turner et.al 2005).

The Intergovernmental Panel on Climate Change (IPCC), an authoritative international body has concluded that this warming is primarily the result of human activities (Downie, 2009). Since the time of the Industrial Revolution (1850), activities including deforestation and the burning of fossil fuels have released increasing quantities of greenhouse gases into our atmosphere. These gases, which include carbon dioxide and methane, among others, trap heat that would otherwise escape into space. As such, the gases which have accumulated in the Earth's atmosphere have intensified the natural effect and now are causing climate change.

Looking towards the future, the IPCC Special Report on Emissions Scenarios (SRES) predicts that temperatures will rise by 1.1 to 6.4° C by the end of 21 century, with range largely dependent on future greenhouse gas emissions. The type and severity of impacts that are associated with such temperature increases will vary by region, but on the whole they are expected to be negative and in some cases disastrous.

Furthermore, the greater the temperature increase, the greater the impacts we can expect. Fragile ecosystems, coastal areas and low–lying islands will be destroyed. Species unable to adapt to changing conditions will go extinct. Agricultural pests and vector-borne diseases will spread, and people will suffer as droughts, floods, and storms become may both more frequent and more intense The world's poor will be hit first, and hardest, as changing climatic conditions exacerbate problems of food security, water scarcity, and sanitation. (Downie, 2009).

It is almost certain that the world is experiencing climate change and hence additional risks will arise in the future. Thus it is very important that scientist should make prediction of the future climate. This is necessary so that we can prepare ourselves to face the future climate and make strategies as part of mitigation planning and adaptation.

General Circulation Model or Global Climate Models (GCM) have been developed to simulate the present climate and used to predict future climatic change. These are designed to simulate time series of climate variables globally, accounting for the effects of greenhouse gases in the atmosphere. GCMs perform reasonably well in simulating climatic variables at larger spatial scale, but poorly at the smaller space and time scales relevant to regional impact analyses, especially in the important area of hydrology. GCMs have resolutions of hundreds of kilometer ($>10^4$ km^2). However, many impact applications required the equivalent of point scale climate variations that are parameterized in coarse-scale models. Therefore the output from a GCM has to be downscaled to obtain the information relevant to hydrologic studies (Wilby 2004).

Downscaling climate data is a strategy for generating locally relevant data from GCM. The overarching strategy is to connect global scale predictions and regional dynamics to generate regionally specific forecasts. Basically, downscaling technique is a movement process from large scale to small scale. One way to connect the GCM large scale with a smaller scale (study area) is to use Statistical Downscaling (SD) technique. SD is a statistical process of downscaling where data on large-scale grids in the period and particular time is used as the basis for determining the data on the smaller grid scale.

1.2. OBJECTIVE OF PRESENT STUDY

The objective of this dissertation work is:

To downscale precipitation and temperature data at Roorkee area from GCM output data by using the Support Vector Machine (SVM) and Multiple Linear Regression (MLR) method and compare the results.

1.3 SCOPE OF PRESENT STUDY

Roorkee area is taken as the area for the present study. Mean monthly precipitation, maximum and minimum temperature are the climate variables that are proposed to be downscaled. SVM and MLR are the methods that will be used to downscale the climate variables.

1.4 ORGANIZATION OF DISSERTATION

The dissertation is arranged in six chapters as follows:

1. **Chapter I**: The first chapter provides background for the study and the objectives which are proposed to be achieved in this study.
2. **Chapter II**: Literature review.
3. **Chapter III**: This chapter covers description of downscaling methods.
4. **Chapter IV**: In this chapter the support vector machine method is explained.
5. **Chapter V**: This chapter informs about the study area and the data used in the study.
6. **Chapter VI**: This chapter provide downscaling computation and result analyses.
7. **Chapter VII**: This chapter presents the summary of important conclusions drawn from the study.

CHAPTER II
LITERATURE REVIEW

II.1 GENERAL

Climate (from Ancient Greek klima, meaning inclination) is commonly defined as the weather averaged over a long period of time. The standard averaging period is 30 years, but other periods may be used depending on the purpose. The difference between weather and climate is a matter of time scale. Weather is the day-to-day stuff. The climate cannot be harsh on one particular day, because it is not measured in terms of days, but in terms of many years.

The Intergovernmental Panel on Climate Change (IPCC) glossary definition of climate is: Climate in a narrow sense is usually defined as the "average weather," or more rigorously, as the statistical description in terms of the mean and variability of relevant quantities over a period of time ranging from months to thousands or millions of years. These quantities are most often surface variables such as temperature, precipitation, and wind. The classical period is 30 years, as defined by the World Meteorological Organization (WMO). Consortium for Atlantic Regional Assessment (CARA) glossary defined Climate Variables as "measures of climate such as average, maximum and minimum temperature; precipitation, humidity, cloud type and amount, solar radiation".

Climate in a wider sense is the state, including a statistical description, of the climate system which is an interactive system consisting of five major components: the atmosphere, the hydrosphere, the cryosphere, the land surface, and the biosphere. The climate system continues to evolve over time, influenced by: its own internal dynamics, external forcings such as volcanic eruptions, solar variations, and human-induced forcings such as fossil fuel burning and land use change.

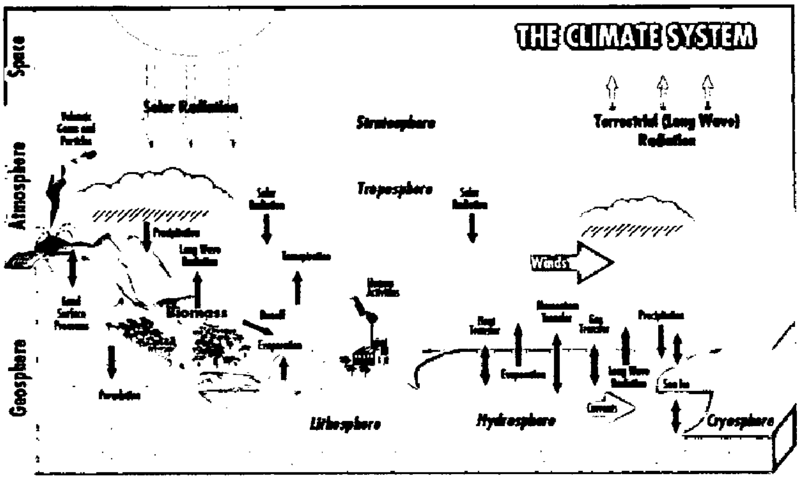


Figure 2.1
Climate System

Figure 2.1 shows the main physical processes that take place within the climate system and thus exert an influence on climate. The components of the global climate system consisting of the atmosphere (including the troposphere and stratosphere), the geosphere [which includes the solid earth (lithosphere), the oceans, rivers and inland water masses (hydrosphere) and the snow, ice and permafrost (cryosphere)] and the biosphere [the transition zone between them within which most plant and animal life exists and most living and dead organic matter (biomass) is to be found].

II.2 CLIMATE CHANGE

Climate change is defined as variation and shifts in weather condition over space and time of different scale and magnitude. In fact, climatic change refers to drastic or secular change in heat balance of the earth-atmosphere system, moisture, cloudiness and precipitation caused by either external or internal factor (Singh, 2005).

Climate change is nothing new or unnatural. Climate has been changing since the world began. It has changed continually on most time scales we can measure, and it has changed catastrophically, far more radically than what is feared to occur in the next 200 years. Most climate change occurs on time scales far longer than a human lifetime: centuries, millennia or millions of years.

During most of its estimated 4.6-billion-year life, the Earth did not have the sort of atmosphere that could support life on land. Earth's early atmosphere probably included large amounts of carbon dioxide (CO_2), and it took billions of years for algae and other small, plantlike organisms in the seas to remove that CO_2 and replace it with enough oxygen that life could be sustained on land.

Not only would animals and plants have suffocated in the early atmosphere, but the lack of protection from ultraviolet sunlight could have killed them. The ultraviolet from the Sun is strong enough to break the bonds of organic molecules like DNA, and is fatal to many forms of life and harmful to others. It was not until about 450 to 350 million years ago, that plants, insects, and finally fish-like animals came ashore. Until that point the "natural" global atmosphere and climate had been largely lethal to living things.

II.2.1 Natural Green House Effect

The greenhouse effect is a process where energy from the sun readily penetrates into the lower atmosphere and onto the surface of Earth and is converted to heat, but then cannot freely leave the planet. This can be sketched as follows:
Sun's Radiation → absorbed by Earth → some re-radiated to space as heat → some trapped by the atmosphere.

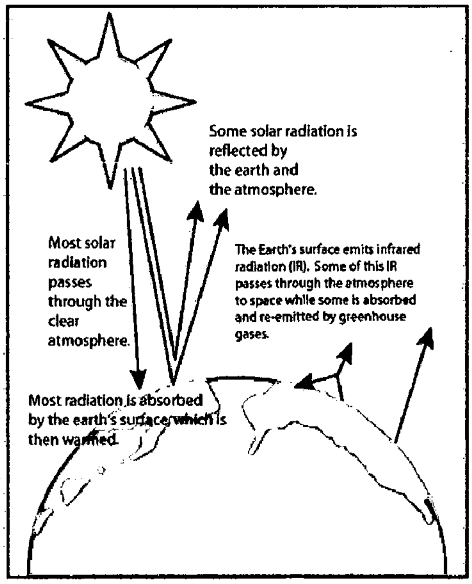


Figure 2.2

Illustration of the Earth's radiative balance. (Adapted from: NOAA)

Due to the presence of certain "greenhouse gases" that trap heat, like carbon dioxide, methane, water vapor, and Chlorofluorocarbon (CFC's), the atmosphere retains the sun's radiation and warms up the planet.

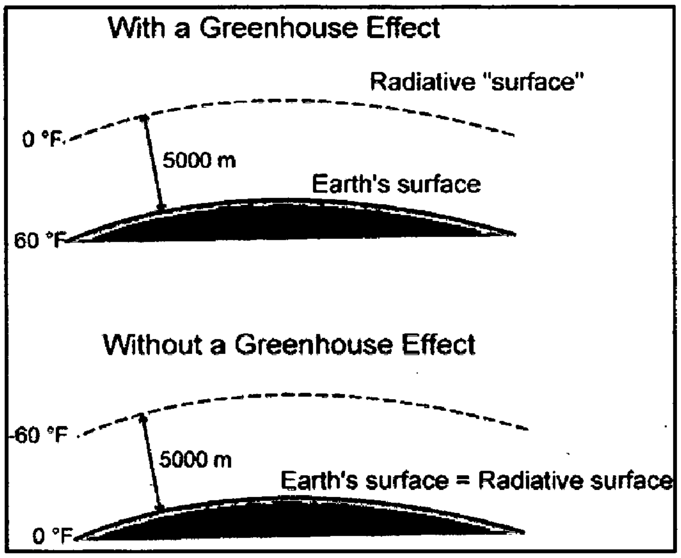


Figure 2.3

The illustration of radiation balance and the role of greenhouse effect.

Figure 2.3 demonstrates the importance of greenhouse gases in regulating the temperature of the lower atmosphere. The top diagram shows a greenhouse Earth where the apparent temperature "surface" lies 5000m up in the atmosphere from the land surface. In the past 100 years this apparent temperature "surface" has been rising. By contrast, without a greenhouse effect, the Earth would look like the lower diagram, with a uniform temperature in the atmosphere of 0°F (18°C).

Basically a "natural" greenhouse effect keeps the Earth's climate warm and habitable, but by increasing the abundance of greenhouse gases in the atmosphere, humankind is increasing the overall warming of the Earth's surface and lower atmosphere, this process is called "global warming."

II.2.2 Causes Of Climate Change

There are some basic components that influence the state of the Earth's climatic system. Changes in the state of this system can occur externally (from extraterrestrial systems) or internally (from ocean, atmosphere and land systems) through any one of the described components. For example, an external change may involve a variation in the Sun's output which would externally vary the amount of solar radiation received by the Earth's atmosphere and surface. Internal variations in the Earth's climatic system may be caused by changes in the concentrations of atmospheric gases, mountain building, volcanic activity, and changes in surface or atmospheric albedo or reflectivity. (Pidwirny & Jones , 1999)

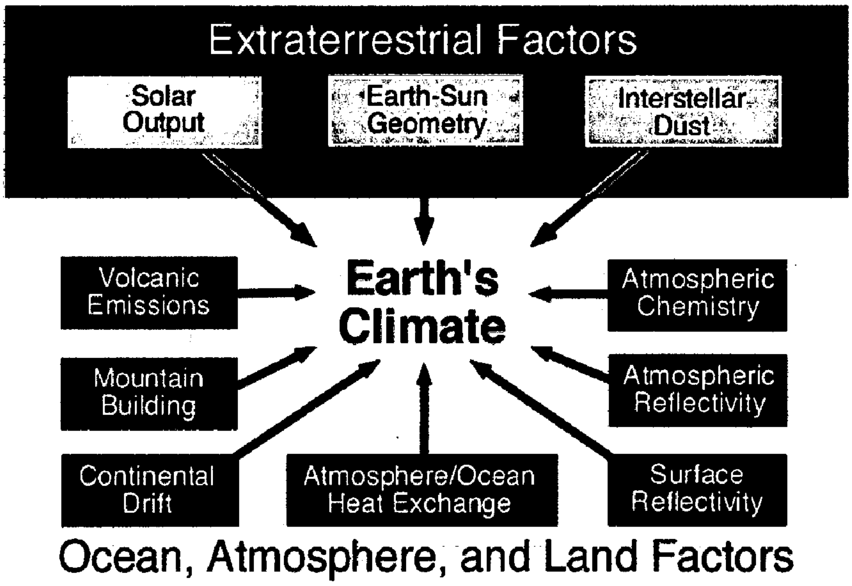


Figure 2.4
Influence Factors of the Earth's climate.

The work of climatologists has found evidence to suggest that only a limited number of factors are primarily responsible for most of the past episodes of climate change on the Earth. These factors include:

- Variations in the Earth's orbital characteristics.
- Atmospheric carbon dioxide variations.
- Volcanic eruptions
- Variations in solar output.

A. Variations in the Earth's Orbital Characteristics

The Milankovitch theory suggests that normal cyclical variations in three of the Earth's orbital characteristics are probably responsible for some past climatic change. The basic idea behind this theory assumes that over time these three cyclic events vary the amount of solar radiation that is received on the Earth's surface. The elliptical path of the Earth around the Sun (eccentricity) brings it closer to or farther from the Sun every 100,000 years (Figure 2.5a).

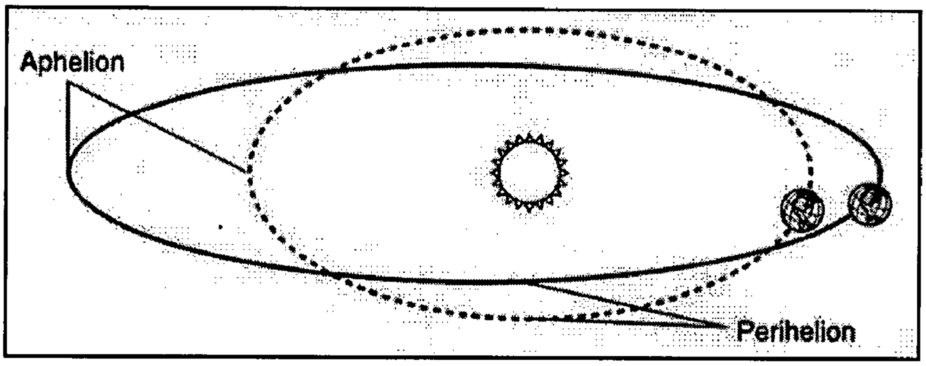


Figure 2.5a

Eccenticity

Also, the Earth like a spinning top wobbles as it rotates on its axis, exposing more or less of each hemisphere to the direct rays of the Sun. It does this, in a process called *precession,* with a periodicity of 22,000 years.(Figure 2.5b).

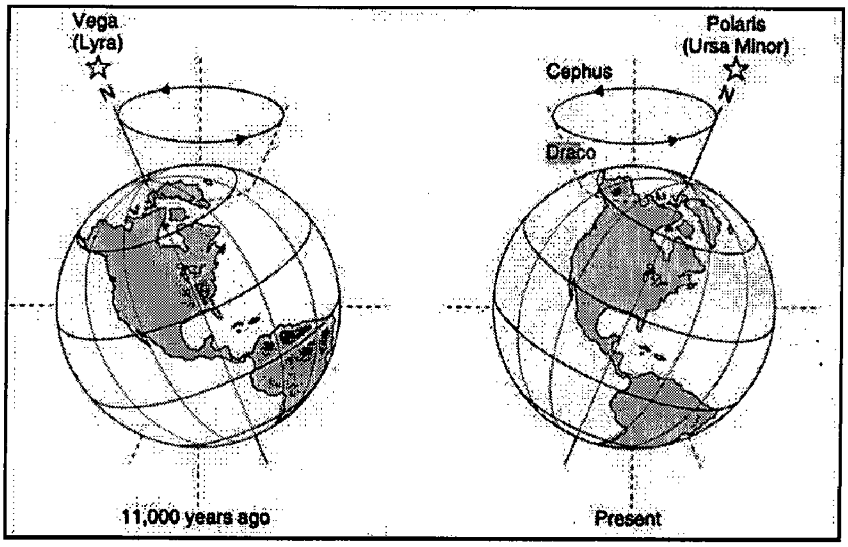


Figure 2.5b

Precession

Finally, the tilt of the Earth's axis with respect to the Sun (obliquity) changes over a period of 40,000 years (Figure 2.5c).

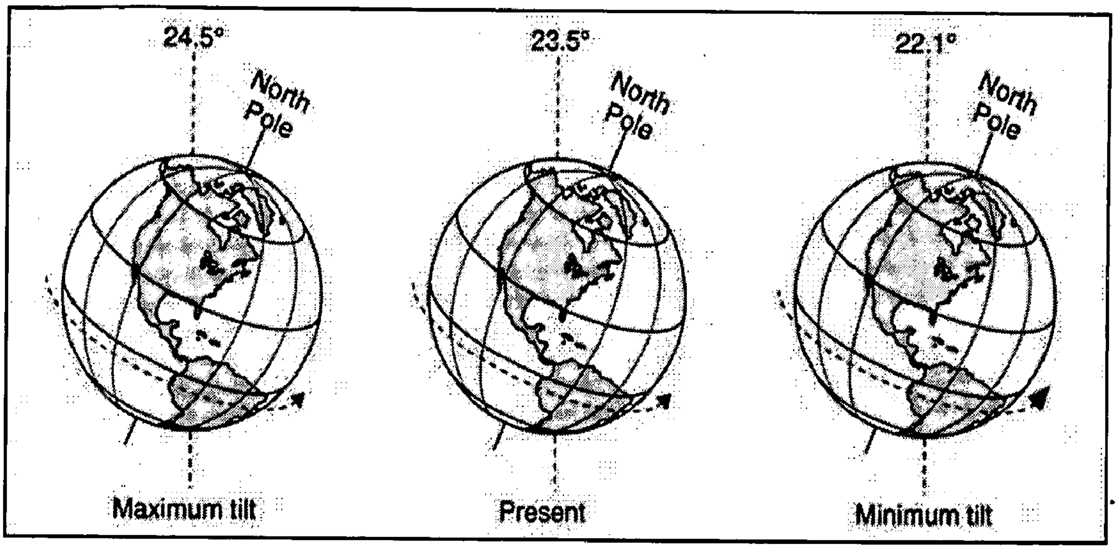


Figure 2.5c
Obliquity

The summation of these three periodicities determines the amount of solar radiation reaching the Earth at a particular time. The resulting cold and warm periods and glacial retreats and advances. The most recent glaciations peaked about 18,000 years ago, and between then and 6,000 years ago the Earth's climate warmed by an average 5°C (Hardy, 2003). Computer models and historical evidence suggest that the Milankovitch cycles exert their greatest cooling and warming influence when the troughs and peaks of all three cycles coincide with each other.

B. Atmospheric Carbon Dioxide Variations

Studies of long term climate change have discovered a connection between the concentration of carbon dioxide in the atmosphere and mean global temperature. Carbon dioxide is one of the more important gases responsible for the greenhouse effect. Certain atmospheric gases, like carbon dioxide, water vapor and methane, are able to alter the energy balance of the Earth by being able to absorb long wave radiation emitted from the Earth's surface. The net result of this process and the re-emission of long wave back to the Earth's surface increase the quantity of heat energy in the Earth's climatic system.

Over the past three centuries, the concentration of carbon dioxide has been increasing in the Earth's atmosphere because of human influences. Human activities like the burning of fossil fuels, conversion of natural prairie to farmland, and deforestation have caused

Over the past three centuries, the concentration of carbon dioxide has been increasing in the Earth's atmosphere because of human influences. Human activities like the burning of fossil fuels, conversion of natural prairie to farmland, and deforestation have caused the release of carbon dioxide into the atmosphere. From the early 1600s, carbon dioxide has increased from 310 ppmv (parts per million by volume) to 380 ppmv in 2010. Climatologists estimate that a level pf 450 ppmv—as projected for 2050—may result in an eventual 1.8-3°C (3.2-5.4° F) increase in temperature (Butler,2010)

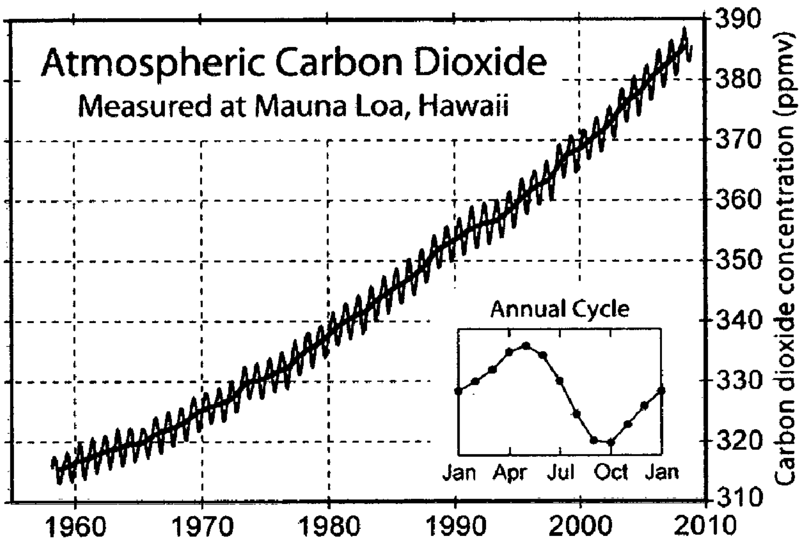


Figure 2.6:
The increasing carbon dioxide concentration in the atmosphere from 1960 to 2010 taken from Mauna Loa-Hawaii Recording.

C. Volcanic Eruptions

For many years, climatologists have noticed a connection between large explosive volcanic eruptions and short term climatic change. For example, one of the coldest years in the last two centuries occurred the year following the Tambora volcanic eruption in 1815. Accounts of very cold weather were documented in the year following this eruption in a number of regions across the planet. Several other major volcanic events also show a pattern of cooler global temperatures lasting 1 to 3 years after their eruption. The satellite data indicated that the sulfur dioxide plume from the volcano eruption caused a several percent increase in the amount of sunlight reflected by the Earth's atmosphere back to space causing the surface of the planet to cool.

D. Variations in Solar Output

Until recently, many scientists thought that the Sun's output of radiation only varied by a fraction of a percent over many years. However, measurements made by satellites equipped with radiometers in the 1980s and 1990s suggested that the Sun's energy output may be more variable than was once thought. Measurements made during the early 1980s showed a decrease of 0.1 percent in the total amount of solar energy reaching the Earth over just an 18 month time period. If this trend were to extend over several decades, it could influence global climate. Numerical climatic models predict that a change in solar output of only 1 percent per century would alter the Earth's average temperature by between 0.5 to 1.0° Celsius.

II.3 THE IMPACTS OF CLIMATE CHANGE ON CRITICAL AREAS

According to Water Aid Paper (Environmental Resources Management London, 2007) the effects of minor levels of climate change are already being felt, with impacts across many economic sectors. While there will clearly be some gains from climate change (for example, agriculture in some northern regions should increase in productivity due to a rise in temperatures), most of the impacts will be negative, and gains and losses will not be evenly distributed. For example:

A. WATER

Rising global temperatures will lead to an intensification of the hydrological cycle, resulting in dryer dry seasons and wetter rainy seasons, and subsequently heightened risks of more extreme and frequent floods and drought. Changing climate will also have significant impacts on the availability of water, as well as the quality and quantity of water that is available and accessible. Melting glaciers will increase flood risk during the rainy season, and strongly reduce dry-season water supplies to one-sixth of the World's population.

B. AGRICULTURE

Declining crop are likely to leave hundreds of millions without the ability to produce or purchase sufficient food supplies, especially in Africa. At mid to high latitudes, crop yields may increase for low levels of change in temperature, but will decline at higher levels of temperature change.

C. ECOSYSTEMS:

Changing temperatures will cause ecosystems to shift – forests, land types and plant species will dieback in some areas as temperatures rise, but increase in other areas. However, in many cases, the pace of change in temperature may be too fast for ecosystems to adjust, resulting in the loss of forests and species.

D. HEALTH:

Higher temperatures expand the range of some dangerous vector-borne diseases, such as malaria, which already kills one million people annually, most of whom are children in the developing world. Further, heat waves associated with climate change, and increases in water borne diseases, will result in increased health problems.

E. COASTLINES:

Melting ice and thermal expansion of oceans are the key factors driving sea level rise. In addition to exposing coastlines, where the majority of the human population live, to greater erosion and flooding pressures, rising sea levels will also lead to salt water contamination of groundwater supplies, threatening the quality and quantity of freshwater access to large percentages of the population.6 For example, according to some estimates a 1 meter rise in sea level will displace 80 percent of the population of Guyana.

Table 2.1

Examples of climate change impacts in Asia

Boreal Asia	• Expanded agricultural growing season • Increased active soil temperatures/ better soil climate • Northward shift of agricultural boundary • Change to timing of snowmelt and therefore altered flow regime • Decrease in dry summer season water flow
Arid & Semi-Arid Asia	• Exacerbation of threats caused by land use/ cover change & population pressures • Significant increase in surface air temperatures • Increased evapotranspiration in plants • Acute water shortages
Temperate Asia	• Significant surface warming & rainfall pattern shifts • Increased plant respiration & saturation deficits, decreased agricultural productivity • Intensification of climatic hazards (e.g. floods, droughts, sea level rise, storm surges)
Tropical Asia	• Changes to hydrological regime • Increased flooding, water logging, salinity caused by higher runoff in some river basins • Decreased surface runoff in some basins due to increased evaporation • Changes in freshwater availability in coastal regions • Sea level rise, leading to inundation of low-lying areas, shoreline retreat, changes to water table, salinisation/ acidification of soil

Source : IPCC Climate Change 2001 : *Impact,Adaptation and Vulnerability*

II.4 OBSERVED CHANGES IN CLIMATE AS RELATE TO WATER

Based on the IPCC Technical Paper VI report , the hydrological cycle is intimately linked with changes in atmospheric temperature and radiation balance. For widespread regions, cold days, cold nights and frost have become less frequent, while hot days, hot nights and heatwaves have become more frequent over the past 50 years.

Climate warming observed over the past several decades is consistently associated with changes in a number of components of the hydrological cycle and hydrological systems such as: changing precipitation patterns, intensity and extremes; widespread melting of snow and ice; increasing atmospheric water vapor; increasing evaporation; and changes in soil moisture and runoff (IPCC, 2008).

II.4.1 Precipitation and Water Vapour

A number of model studies suggest that changes in radiative forcing (from combined anthropogenic, volcanic and solar sources) have played a part in observed trends in mean precipitation. Widespread increases in heavy precipitation events (e.g., above the 95th percentile) have been observed, even in places where total amounts have decreased. These increases are associated with increased atmospheric water vapour and are consistent with observed warming (IPCC, 2008).

Theoretical and climate model studies suggest that, in a climate that is warming due to increasing greenhouse gases, a greater increase is expected in extreme precipitation, as compared to the mean. Hence, anthropogenic influence may be easier to detect in extreme precipitation than in the mean. This is because extreme precipitation is controlled by the availability of water vapor, while mean precipitation is controlled by the ability of the atmosphere to radiate long-wave energy (released as latent heat by condensation) to space, and the latter is restricted by increasing greenhouse gases.

The water vapor content of the troposphere has been observed to increase in recent decades, consistent with observed warming and near-constant relative humidity. Total column water vapor has increased over the global oceans by 1.2 ± 0.3% per decade from 1988 to 2004, in a pattern consistent with changes in sea surface temperature.

Many studies show increases in near surface atmospheric moisture, but there are regional differences and differences between day and night (IPCC, 2008).

II.4.2 Snow and Land Ice

The cryosphere (consisting of snow, ice and frozen ground) on land stores about 75% of the world's freshwater. In the climate system, the cryosphere and its changes are intricately linked to the surface energy budget, the water cycle and sea-level change.

A. Snow cover, frozen ground, lake and river ice

Snow cover has decreased in most regions, especially in spring and summer. Degradation of permafrost and seasonally frozen ground is leading to changes in land surface characteristics and drainage systems. Permafrost warming and degradation of frozen ground appear to be the result of increased summer air temperatures and changes in the depth and duration of snow cover. Freeze-up and break-up dates for river and lake ice exhibit considerable spatial variability. Averaged over available data for the Northern Hemisphere spanning the past 150 years, freeze-up has been delayed at a rate of 5.8 ± 1.6 days per century (IPCC, 2008).

B. Glaciers and Ice Caps

On average, glaciers and ice caps in the Northern Hemisphere and Patagonia show moderate but rather consistent increase in mass turnover over the last half-century, and substantially increased melting. As a result, considerable mass loss occurred on the majority of glaciers and ice caps worldwide. The widespread 20th-century shrinkage appears to imply widespread warming as the primary cause although, in the tropics, changes in atmospheric moisture might be contributing. There is evidence that this melting has very likely contributed to observed sea-level rise (IPCC, 2008).

II.4.3 Sea Level Rise

Global mean sea level has been rising and there is high confidence that the rate of rise has increased between the mid-19th and the mid-20th centuries. The average rate was 1.7 ± 0.5 mm/ yr for the 20th century. Rising sea level potentially affects coastal regions, but attribution is not always clear. Global increases in extreme high water levels since 1975 are related to both mean sea-level rise and large-scale inter-decadal climate variability (Woodworth and Blackman, 2004).

II.4.4 Evapotranspiration

A. Pan Evaporation

Decreasing trends during recent decades are found in sparse records of pan evaporation (measured evaporation from an open water surface in a pan, a proxy for potential evapotranspiration) over the USA, India, Australia, New Zealand and China (IPCC,2008).

B. Actual Evapotranspiration

Using observations of precipitation, temperature, cloudiness-based surface solar radiation and a comprehensive land surface model, (Qian et al., 2006) found that global land evapotranspiration closely follows variations in land precipitation. Global precipitation values peaked in the early 1970s and then decreased somewhat, but reflect mainly tropical values, and precipitation has increased more generally over land at higher latitudes. Changes in evapotranspiration depend not only on moisture supply but also on energy availability and surface wind.

C. Soil Moisture

Among more than 600 stations from a large variety of climates, identified an increasing long-term trend in surface (top 1 m) soil moisture content during summer for the stations with the longest records, mostly located in the former Soviet Union, China, and central USA. The longest records available, from the Ukraine, show overall increases in surface soil moisture, although increases are less marked in recent decades (Robock et al., 2005).

D. Runoff and River Discharge

At the global scale, there is evidence of a broadly coherent pattern of change in annual runoff, with some regions experiencing an increase in runoff (Milly et al., 2005). There is more robust and widespread evidence that the timing of river flows in many regions where winter precipitation falls as snow has been significantly altered. Higher temperatures mean that a greater proportion of the winter precipitation falls as rain rather than snow, and the snowmelt season begins earlier

II.5 EL NIÑO/LA NIÑA

According to Environmental Law Institute – USA, El Niño and La Niña are the two extremes of the El Niño-Southern Oscillation, also known as ENSO. ENSO is generated by interactions between the ocean and the atmosphere in the Tropical Pacific. ENSO is the strongest of all naturally occurring climate cycles on the annual-to-decadal time scale; it creates some of the most pronounced variability in climate events on a year-to-year basis, including the frequency and severity of droughts, floods, hurricanes, and tornadoes, among other events.

During the "normal" phase of the ENSO cycle, trade winds blow from east to west (from an area of higher pressure to an area of lower pressure), pushing the surface layer of the ocean westward. This warmer surface water gets pushed westward by the trade winds and "piles up" in the west Pacific; the eastern Pacific, by contrast, is much colder, since cold water from deeper in the ocean wells up to replace the water that has been blown westward. During these normal years, large rain clouds form over the warm water, bringing rain to countries like Indonesia and Malaysia.

During El Niño years, the pressure difference between east and west is less, and therefore, trade winds do not blow as hard, and the warm surface water remains farther east. Thus, the rain clouds form farther east, and the rain falls farther east, resulting in above average rainfall for places like California and Peru, and droughts for places like Indonesia and Australia. El Niño is known as the "warm phase" of ENSO. By contrast, during La Niña years, the pressure difference between east and west increases, causing more water than normal to be pushed westward, resulting in even colder surface water in the eastern Pacific and even warmer surface water in the western Pacific, delivering more rain than normal to countries like Indonesia and Australia, which can result in flooding in these areas. La Niña is known as the "cold phase" of ENSO.

it is possible that an increase in global temperatures may exacerbate El Niño conditions. Even though the trade winds would still blow the warmest water west, the water in the east would not be as cold, since global temperature increases would increase water temperatures. Thus, "normal" years would resemble El Niño years, since warm water would be present in the east Pacific. As a result, future El Niño events would be magnified: areas which are normally wet during El Niño years would become wetter, and dry areas drier. This could have a profound effect on the growing seasons in these areas, and also upon seasons in these areas, and also upon health conditions arising from extreme wet or dryness.

II.6 MONSOON

The word “monsoon” is used to indicate the winds in the areas where they change their direction twice each year. On this basis, the word monsoon was applied to all those winds of the globe which had directional change from summer season to winter season and vice-versa. According to Singh (2005) monsoon is surface convective system which is originated due to differential heating and cooling of the land and water (oceans) and thermal variations. The monsoons, which help balance global temperatures and sustain life on earth, affect a vast area of the globe - from Africa across Asia to the Pacific; northern China and the Himalayas to north Australia; and even Mexico and parts of Central America - directly influencing the lives of over half the world's population. In India, 50% of the arable land is irrigated solely by monsoon rains.

There are two Indian monsoon seasons. The summer or south-west monsoon comes in from the direction of Africa, and brings heavy rain to the west coast and large areas of northern India between June and August. The winter, or north-east monsoon, sweeps down from the plateaus of Asia and the Himalayas, and brings rain and cooler weather to south-east India between October and December.

The key to understanding the basic monsoon mechanism lies in the fact that land heats up and cools more quickly than the sea; the latter holding its temperature more or less steady. As the sun moves north bringing summer heat, the land steadily gets hotter and hotter, while the temperature of the ocean lags far behind. The effect on a huge land mass like Asia as the hot air rises over the land, leaving below a vast area of low pressure, is to draw in massive amounts of air from over the ocean, where higher pressures are maintained. This is the south-west monsoon pattern (it is the wind, and not the resulting rain, which is defined as the monsoon).

Around September, with the sun fast retreating south, the northern land mass begins to cool rapidly. As it cools, air pressure builds up over the land. Meanwhile the oceans are still holding their warmer summer temperatures. The cooler high pressure air over inland Asia then starts to move down towards the lower pressure areas over the ocean, and India north-east monsoon is formed and make month October-December as period of rains. Meanwhile the air moving out from inland Asia is replaced and balanced by warmer air moving in northwards from the oceans at around 40,000 feet. For most of India, the main monsoon is the south-west monsoon.

II.7 IPCC SPECIAL REPORT ON EMISSIONS SCENARIOS (SRES)

In order to understand how global climate could change over the next hundred years, it is necessary for climate models to represent in some way information on possible changes in greenhouse gas emissions over that time period. Such information, on theoretical paths for growth in greenhouse gas emissions over time, is necessarily based on a wide range of considerations related to the future development of human societies, such as population changes, economic development, technological change, energy supply and demand, and land use change.

In September 1996, the IPCC initiated an 'open process' approach for the development of new emissions scenarios, involving input and feedback from a broad community of experts, culminating in approval of a Special Report on Emissions Scenarios (SRES) by the IPCC Working Group III in March 2000. The scenarios are firmly based on published and peer reviewed literature, and represent the state-of-the-art at the time of preparation of the SRES. The SRES scenarios are characterized on the basis of four 'storylines' (Figure 2.8), which are based on sets of assumptions about possible alternative futures. Each storyline yields a family of scenarios, totaling 40 altogether, with each considered equally sound. The future worlds described by the four storylines are as follows:

A1: a world of very rapid economic growth, global population that peaks in mid-century and declines thereafter, and the rapid introduction of new and more efficient technologies. Three A1 groups are defined with specific technological emphases: fossil intensive (A1FI), non-fossil energy sources (A1T), or a balance across all sources (A1B).

A2: a very heterogeneous world, featuring self-reliance, preservation of local identities, continuously increasing population and economic development which is primarily regionally oriented.

B1: a convergent world with the same global population as in the A1 storyline, but with rapid change in economic structures toward a service and information economy, with reductions in material intensity and the introduction of clean and resource-efficient technologies.

B2: a world which emphasizes local solutions to economic, social and environmental sustainability, with continuously increasing global population, intermediate levels of econ mic development, and less rapid and more diverse technological change than in the B1 and A1 storylines.

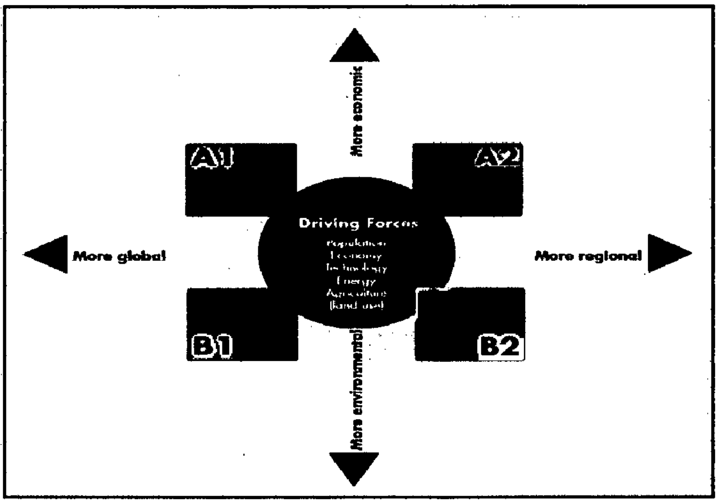


Figure 2.7
Schematic diagram of the SRES scenarios

II.8 CLIMATE CHANGE MITIGATION

Climate change mitigation is action to decrease the intensity of radiative forcing in order to reduce the potential effects of global warming. Mitigation is distinguished from adaptation to global warming, which involves acting to tolerate the effects of global warming. Most often, climate change mitigation scenarios involve reductions in the concentrations of greenhouse gases, either by reducing their sources or by increasing their sinks.

The UN defines mitigation in the context of climate change, as a human intervention to reduce the sources or enhance the sinks of greenhouse gases. Examples include using fossil fuels more efficiently for industrial processes or electricity generation, switching to renewable energy (solar energy or wind power), improving the insulation of buildings, and expanding forests and other "sinks" to remove greater amounts of carbon dioxide from the atmosphere.

Scientific consensus on global warming, together with the precautionary principle and the fear of abrupt climate change is leading to increased effort to develop new technologies and sciences and carefully manage others in an attempt to mitigate global warming. Most means of mitigation appear effective only for preventing further warming, not at reversing existing warming. The Stern Review identifies several ways of mitigating climate change. These include reducing demand for emissions-intensive goods and services, increasing efficiency gains, increasing use and development of low-carbon technologies, and reducing fossil fuel emissions.

The Summary for Policymakers (SPM) of the IPCC concludes that there was a high level of agreement and much evidence that 'there is substantial economic potential for the mitigation of global greenhouse gas emissions over the coming decades, that could offset the projected growth of global emissions or reduce emissions below current levels', taking into account financial and social costs and benefits. The consideration of technologies with the largest economic potential within this timescale is presented in the table 2.2 below.

Tabel 2.2

Key mitigation technologies and practices by sector

Sector	**Key mitigation technologies and practices currently commercially available**	**Key mitigation technologies and practices projected to be commercialized before 2030**
Energy Supply	Improved supply and distribution efficiency; fuel switching from coal to gas; nuclear power; renewable heat and power (hydropower, solar, wind, geothermal and bioenergy); combined heat and power; early applications of CCS (e.g. storage of removed CO2 from natural gas)	Carbon Capture and Storage (CCS) for gas, biomass and coal-fired electricity generating facilities; advanced nuclear power; advanced renewable energy, including tidal and waves energy, concentrating solar, and solar PV.
Transport	More fuel efficient vehicles; electric vehicle; hybrid vehicles; cleaner diesel vehicles; biofuels; modal shifts from road transport to rail and public transport systems; non-motorised transport (cycling, walking); land-use and transport planning	Second generation biofuels; higher efficiency aircraft; advanced electric and hybrid vehicles with more powerful and reliable batteries
Buildings	Efficient lighting and daylighting; more efficient electrical appliances and heating and cooling devices; improved cook stoves, improved insulation; passive and active solar design for heating and cooling; alternative refrigeration fluids, recovery and recycle of fluorinated gases	Integrated design of commercial buildings including technologies, such as intelligent meters that provide feedback and control; solar PV integrated in buildings
Industry	More efficient end-use electrical equipment; heat and power recovery; material recycling and substitution; control of non-CO2 gas emissions; and a wide array of process-specific technologies	Advanced energy efficiency; CCS for cement, ammonia, and iron manufacture; inert electrodes for aluminium manufacture
Agriculture	Improved crop and grazing land management to increase soil carbon storage; restoration of cultivated peaty soils and degraded lands; improved rice cultivation techniques and livestock and manure management to reduce CH4 emissions; improved nitrogen fertilizer application techniques to reduce N2O emissions; dedicated energy crops to replace	Improvements of crop yields

	fossil fuel use; improved energy efficiency	
Forestry/ forests	Afforestation; reforestation; forest management; reduced deforestation; harvested wood product management; use of forestry products for bio-energy to replace fossil fuel use	Tree species improvement to increase biomass productivity and carbon biosequestration. Improved remote sensing technologies for analysis of vegetation/ soil carbon sequestration potential and mapping land use change
Waste	Landfill methane recovery; waste incineration with energy recovery; composting of organic waste; controlled waste water treatment; recycling and waste minimization	Biocovers and biofilters to optimize CH4 oxidation

II.9 GCM

Global Climate Models (GCM) another term for General Circulation Models (also referred to as GCM) is a computer program which simulates the behavior of the real atmosphere and/or ocean by incorporating our understanding of physical climate processes into a set of mathematical equations which are used to calculate the future evolution of the system from some initial conditions.

The key equations are those relating to the conservation of mass, momentum and energy in the atmosphere and ocean (Figure 2.9). The equations are solved at a large number of individual points on a three dimensional grid divide the atmosphere or ocean into a horizontal grid with a horizontal resolution covering the world (Figure 2.9) or by equivalent (e.g. spectral) methods. There are 3 Types of GCM :

- Atmosphere general circulation models (AGCMs)
- Ocean general circulation models (OGCMs)
- Coupled atmosphere-ocean general circulation models (AOGCMs)

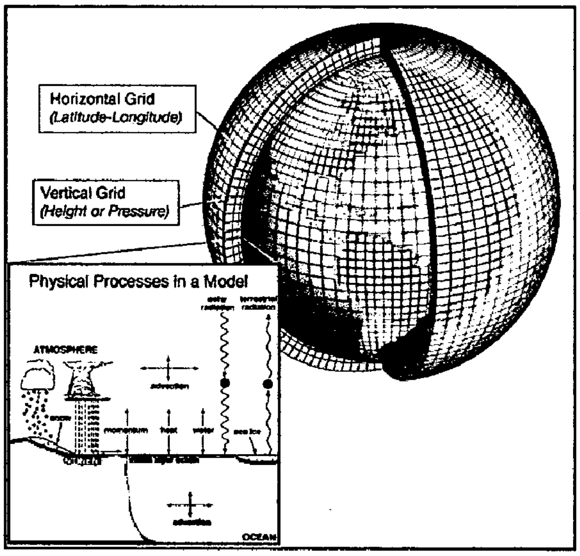


Figure 2.8
GCM Scheme

The closeness of the points on the grid depends largely on the computing power available; in general, the more powerful the processor, the more detailed the achievable resolution of the model and the better the simulation. Typical calculations may have time steps of about half an hour over a global grid with resolution in the atmosphere of about 250 km in the horizontal and 1 km in the vertical.

For the ocean component, spatial resolutions are typically 125-250 km in the horizontal and 200-400 m in the vertical. To make the numerical simulation process possible within the limits of present-day supercomputers, it is necessary to 'parameterize' the effects of short time and small space scale phenomena, such as individual clouds and storms. Given the large thermal inertia of the ocean, the oceanic component of a coupled GCM may be 'spun up' over an extended period of time to allow it to reach a state close to equilibrium before coupling with the atmospheric component. In the real world, the ocean is probably never in equilibrium.

Typically, OGCM is spun up over 1000 model years (maybe 10,000 years for the deep ocean) while the AGCM, together with the land-surface and sea-ice components, is typically run over five model years, prior to full coupling. Once coupled, the model is usually allowed to run for a few model decades to establish a control climate simulation, prior to interpretation of the results or further experimentation, such as altering the radiative forcing through increasing atmospheric carbon dioxide concentrations.

Many GCMs have been developed around the world for studies of seasonal to interannual predictability (El Niño time-scales), greenhouse forcing, nuclear winter and so on. Some of these have been derived directly from the operational global atmospheric models used for weather forecasting but extended for climate studies by coupling to appropriate models of the ocean, sea-ice and land-surface processes. Many have been purpose built for climate. The representation of the various physical processes and feedbacks differs from model to model. The sophistication of the modeling of the ocean ranges from so-called mixed layer models to incorporation of the complex three-dimensional deep-ocean circulation.

There is also a broad spectrum in the treatment of the complexity of the land-surface component. In a few models, land and ocean carbon-cycle components have been included, as well as a sulphur-cycle component, representing the emissions of sulphur and their oxidization to form aerosols. Atmospheric chemistry has largely been modeled outside the main climate model (i.e. off line), but recently it has been included in some models.

To summarize the key features of GCMs are:

- GCMs have a rougher resolution of more than 2° latitude-longitude ($>10^4$ km^2)
- A regional model provides and response to local control, usually the processes within the sub-grid GCMs.
- Many impacts models require information at scales of 50 km or less, so some method is needed to estimate the smaller-scale information.
- A direct result of coarse spatial resolution of GCMs is mismatch in spatial scale between available climate predictions and the required scale by the users of climate prediction.
- Some applications also require the climate predictions with a higher time resolution. Most of plants models require daily weather input.

Due to above reason, downscaling climate data is needed so that the GCM result can be used in smaller scale of hydrological models. Downscaling technique will be explained in chapter III.

Some GCM products from various sources are:

- CSIRO Mark3 (Australia)
- GISS-AOM (USA)
- GISS-ER (USA)
- UKMO HadCM3 (UK)
- UKMO HadGEM (UK)
- INM CM3.0 (Russia)
- IPSL CM4 (France)
- MRI CGCM2.3.2 (Japan)
- NCAR CCSM3 (USA)
- CCCma CGCM (Canada)

CHAPTER III
DOWNSCALING METHODE

III.1 INTRODUCTION

As mentioned before in Chapter II, there are some issues about the use of GCM in the field of water resources which basically deal with the data scale. The GCMs typically performe well on the use of global scale but a GCM is not expected to give results at a smaller scale due to logistic reasons. This is where the downscaling techniques become important.

Downscaling Climate data is a strategy for generating locally relevant data from Global Circulation Models (GCM). The overarching strategy is to connect global scale predictions and regional dynamics to generate regionally specific forecasts. Figure 3.1 shows the concept of downscaling. Many of the processes which control local climate, e.g. topography, vegetation and hydrology, are not included in coarse-resolution GCMs. The development of statistical relationships between the local- and large-scales may include some of these processes implicitly.

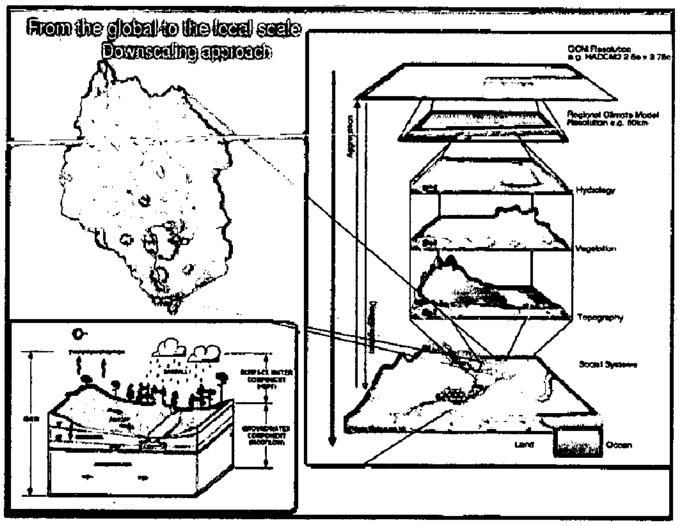


Figure 3.1. A graphical depiction of downscaling.

(Source : David Viner, Climatic Research Unit, University of East Anglia, UK)

Downscaling methodologies fall into two broad categories based on the very different approaches used to resolve climate parameters on regional to local scales, which result in information at substantially finer resolutions (smaller areas) than global-scale GCM provide. The first category is called Dynamic Downscaling and the second is Statistical Downscaling

III.2 DYNAMIC DOWNSCALING

Dynamic downscaling (sometimes it is called mesoscale simulation) basically attempts to nest a finer-scale grid (e.g., 10 km by 10 km) within a GCM over an area of interest (e.g., parts of the Ganga River Basin). Dynamic downscaling imbeds a regional model with a higher resolution within a global model, whereby the results of the global model are only used to set up the initial and boundary conditions of the regional model. The horizontal grid space in regional models usually varies from 15 to 50 km, whereas the grid space of global models is in the range of 100 to 400 km (see Figure 3.2).

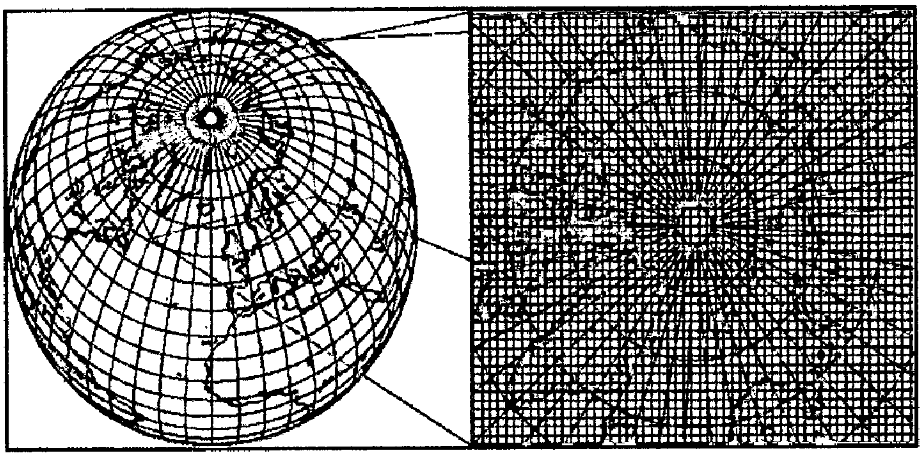


Figure 3.2. Usual grid spaces of a general circulation model (~ 3.75° left) and a regional climate model for the Arctic (~ 0.5° right). At each case only every second grid line is shown.
Source :www.awi.de

There are many advantages to dynamic downscaling particularly around the variety of factors (e.g., temperature, precipitation, soil moisture, wind direction and strength, etc.) generally available in both GCM and the nested finer-scale grid. However, dynamic downscaling requires supercomputer systems and there are too few supercomputer systems available to perform such mesoscale simulations for all the areas around the world to more fully assess the local/regional impacts and consequences of climate change. As supercomputer capabilities and availability increase, dynamic downscaling will become more widely accessible.

III.3 STATISTICAL DOWNSCALING

Statistical or empirical downscaling is a method for obtaining high-resolution climate or climate change information from relatively coarse-resolution global climate models (GCM). Typically, GCM have a resolution of 150-300 km by 150-300 km. Many impacts models require information at scales of 50 km or less, so some method is needed to estimate the smaller-scale information.

Statistical downscaling first derives statistical relationships between observed small-scale (often station level) variables and larger (GCM) scale variables, using either headings weather classification, weather generator and regression models (Figure 3.3). Future values of the large scale variables obtained from GCM projections of future climate are then used to drive the statistical relationships and so estimate the smaller-scale details of future climate is more fully developed and more widely used probably because it can be performed on a PC. This method is dependent on the availability of two important data sets :

(1) A multi-decadal data set (e.g., 25-30 years) of past climate change parameters (e.g., weather station data from a number of stations across the region or locale of interest) .
(2) GCM data sets for the same parameters for the same past time period (these data are generally available at most modeling centers around the world).

With these data a statistical (e.g., using any of a range of statistical techniques) relationship of past climatic changes between the observational data from the set of "local" weather stations and the estimate of past changes contained in the GCM projected for that past time period can be established for that region. Then, to project climatic conditions for some time in the future (e.g., 2025-2050), use the GCM data for that future time period (again, generally available at most modeling centers around the world) and the previously established statistical relationship for each of the weather station locations, and the variables can be downscaled and provide an estimate of the future climatic conditions for that location. The following sections outline the main SD techniques under the broad headings weather classification, weather generator and regression models.

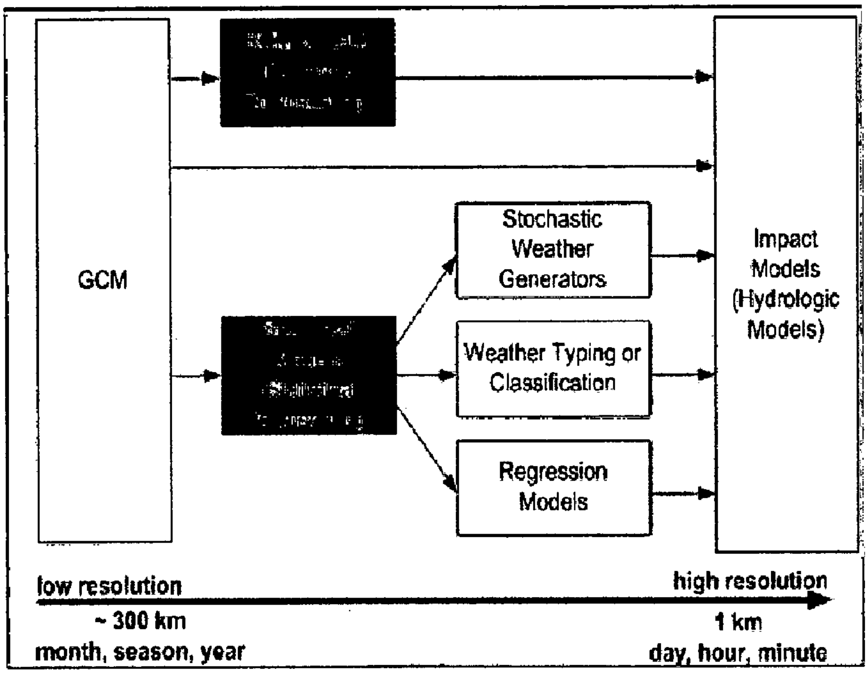


Figure 3.3. Downscaling Scheme

(Source : Fowler, H. et al , *Linking climate change modeling to impact studies : Recent advances in downscaling techniques for hydrological modeling* , 2007)

III.3.1 Weather Classification Schemes

Weather classification methods group days into a finite number of discrete weather types or "states"' according to their synoptic similarity. Typically, weather states are defined by applying cluster analysis to atmospheric fields or using subjective circulation classification schemes.

In both cases, weather patterns are grouped according to their similarity with 'nearest neighbours' or a reference set. The predictand is then assigned to the prevailing weather state, and replicated under changed climate conditions by resampling or regression functions. Classification-based methods can have limited success in reproducing the

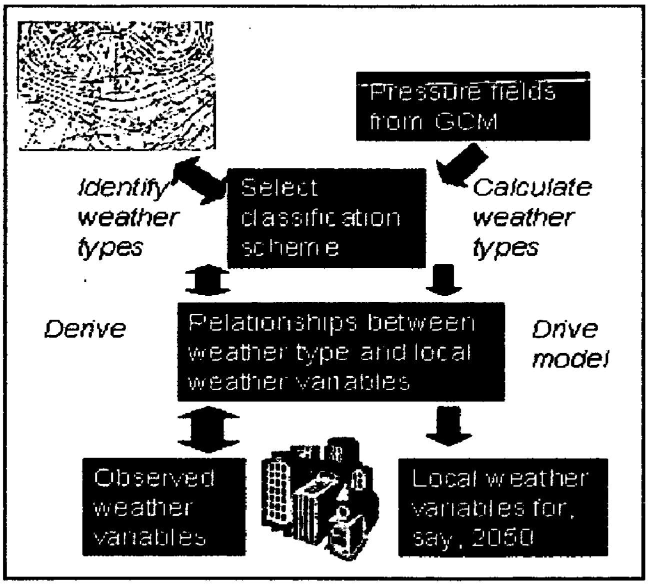


Figure 3.4: The weather typing approach to statistical downscaling. Blue arrows indicate steps based on observed climate data. Red arrows indicate the application of GCM data to determine site values corresponding to a particular future time period.

These models reproduce key characteristics of precipitation such as interannual variability, occurrence and persistence of wet and dry spells at individual sites, and correlations between precipitation series for pairs of sites.

III.3.2 Weather Generator

Weather generators (WG) are models that replicate the statistical attributes of a local climate variable (such as the mean and variance) but not observed sequences of events These models are based on representations of precipitation occurrence via Markov processes for wet-/dry-day or spell transitions. Secondary variables such as wet-day amounts, temperatures and solar radiation are often modeled conditional on precipitation occurrence (e.g.. dry-days in summer may have on average more sunshine than wet-days)..

WG are adapted for statistical downscaling by conditioning their parameters on large-scale atmospheric predictors, weather states or rainfall properties. However, parameter modification for future climate scenarios can lead to unanticipated outcomes). For example, changes to parameters governing wet-dry-spell lengths can affect simulated persistence characteristics of at-site wet and dry spells. Recent approaches include extensions to multi-site and multi—variety series.

Analogue approaches are examples of a weather classification method in which predictands are chosen by matching previous to the current weather-state. The method was originally designed by Lorenz (1969) for weather forecasting applications but was abandoned due to its limited success. It has resurfaced for climate applications since longer series of predictors have emerged following the completion of reanalysis projects. Even so. the analogue method still suffers whenever the pool of training observations is limited and or the number of classifying predictors is large. However, it compares favorably with more complex regression methods and is suitable for providing multi-site and multi-variety series.

Another approach is to classify spatial rainfall occurrence patterns using hidden Markov models, then infer corresponding synoptic weather patterns. A hidden Markov model represents a doubly stochastic process, invoking an underlying (hidden) stochastic process that is translated into another stochastic process that yields the sequence of observations.

The observed process (e.g.. precipitation occurrence at a network of sites) is conditional on the hidden process (the weather states). Weather states evolve according to a first order Markov chain, in which transitions from one state to the next have fixed probabilities and depend only on the current state. Alternatively, non-homogeneous hidden Markov models have transition probabilities that are conditioned by atmospheric predictors and thus vary in time.

temperatures and solar radiation even before modifications are applied to the parameters governing these variables.

Moreover WG based on first-order Markov chains (i.e.. one-state-to-the-next transitions) often underestimate temporal variability and persistence of precipitation .However, conditioned WG methods are useful for temporal downscaling, for instance disaggregating monthly precipitation totals and rain days into daily amounts, or daily totals into sub-daily components).

III.3.3 Regression Models

Regression models are a conceptually simple means of representing linear or nonlinear relationships between predictands and the large scale atmospheric forcing. Commonly applied methods include multiple regressions. Canonical correlation analysis (CCA), artificial neural networks and support vector machine which are akin to nonlinear regression. Some multi-site regression-based methods are also becoming available in which the unexplained variance is represented by stochastic processes.

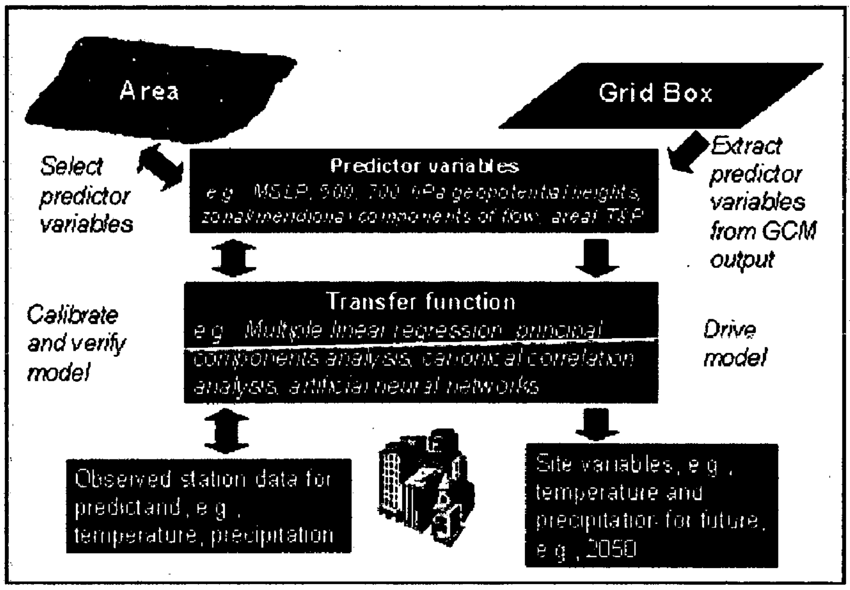


Figure 3.5: The transfer function approach to spatial downscaling. Blue arrows indicate steps based on observed climate data. Red arrows indicate the application of GCM data to determine site values corresponding to a particular future time period.

Table 3.1 provides a summary of their relative strengths and weakness

Table.3.1

A summary of the strengths and weaknesses of the main SD method.

Method	Strength	Weaknesses
Weather typing (e.g. analogue method, hybrid approaches, fuzzy classification, self organizing maps. Monte Carlo methods).	• Yields physically interpretable linkages to surface climate • Versatile (e.g.. can be applied to surface climate, air quality, flooding, erosion, etc.) • Compositing for analysis of extreme events	• Requires additional task of weather classification • Circulation-based schemes can be insensitive to future climate forcing • May not capture intia-type variations in surface climate
Weather generators (e.g. Markov chains, stochastic models, spell length methods, storm arrival times, mixture modelling).	• Production of large ensembles for uncertainty' analysis or long simulations for extremes • Spatial interpolation of model parameters using landscape • Can generate sub-daily information	• Arbitrary adjustment of parameters for future climate • Unanticipated effects to secondary variables of changing precipitation parameters
Regression methods (e.g. linear regression, neural networks, canonical correlation analysis, knging).	• Relatively straightforward to apply • Employs full range of available predictor variables • Off-the-shelf solutions and software avaliable	• Poor representation of observed variance • May assume linearity and'or normality' of data • Poor representation of extreme event

(Source : Wilby et al ,*Guidelines for Use of Climate Scenarios Developed From Statistical Methods,* 2004)

III.4 COMPARISON OF DYNAMIC AND STATISTICAL DOWNSCALING TECHNIQUES

This section provides a comparison between the Dynamic Downscaling and Statistical Downscaling technique.

Table.3.2

A summary of advantages and disadvantages of Dynamic Downscaling and Statistical Downscaling

Scenario type of tool	Description/ Use	Advantage	Disadvantage
Dynamic Downscaling (Regional Model)	Providing high spatial/temporal resolution information	• highly resolved information (spatial and temporal), • information is derived from physically based models, • many variables available, • better representation of the mesocale and weather extremes than in GCM;	• computationally very expensive, particularly for long runs, • lack of two way nesting (feedback with the forcing GCM input), • dependent on usually biased inputs from the forcing GCM • errors in the GCM fields could result in errors in the regional climate scenarios. • fewer scenarios available.
Statistical Downscaling	Providing point/high spatial resolution information	• Can generate information on high resolution grids, or non-uniform regions • Potential for some techniques to address a diverse range of variable • Variables are (probably) internally consistent • Computationally (relatively) inexpensive • Suitable for locations with limited computational resources • Rapid application to multiple GCMs	• Assumes constancy of empirical relationships in the future • Demands access to daily observational surface and/or upper air data that spans range of variability • Not many variables produced for some techniques • Dependent on (usually biased) inputs from driving AOGCM

(Source : Mearns.L.O,et al ,*Guidelines for Use of Climate Scenarios Developed from Regional Climate Model Experiments*, 2003)

CHAPTER IV
SUPPORT VECTOR MACHINE

IV.1 INTRODUCTION

Support vector machine (SVM) is a relatively new technique to make prediction, both in the case of classification and regression, which is becoming very popular lately. The foundations of Support Vector Machines (SVM) has been developed by Vapnik (1995) and is gaining popularity due to many attractive features, and promising empirical performance.

The formulation embodies the Structural Risk Minimization (SRM) principle, which has been shown to be superior, (Gunn et al., 1997), to traditional Empirical Risk Minimization (ERM) principle, employed by conventional neural networks. SRM minimizes an upper bound on the expected risk, as opposed to ERM that minimizes the error on the training data. It is this difference which equips SVM with a greater ability to generalize, which is the goal in statistical learning. SVM was developed to solve the classification problem, but recently they have been extended to the domain of regression problems (Vapnik et al., 1996).

In the literature the terminology for SVM can be slightly confusing. The term SVM is typically used to describe classification with support vector methods and support vector regression is used to describe regression with support vector methods. In this study the term SVM will refer to both classification and regression methods, and the terms Support Vector Classification (SVC) and Support Vector Regression (SVR) will be used for specification.

SVC composed two types, SVC on linear and non linear data. At the beginning when it was introduced by Vapnik, SVC only able to separate the data into two classes, but recently; the SVC has been developed so at is able to separate the multi class data. Some of the methods used in separating the multi-class data are: "one-against-all", "one-against-one", and the "Directed Acyclic Graph Support Vector Machine (DAGSVM)" method.

SVR which is based on the non-linear SVM that implicitly apply kernel functions which map the data to a higher dimensional feature space. A linear solution in the higher dimensional feature space corresponds to a non-linear solution in the original, lower dimensional input space. In this study, only SVR method that will be detail explained.

IV.2 STATISTICAL LEARNING THEORY

This section is a very brief review some of Vapnik's statistical learning theory which based on learning examples. As is the case, learning is a stochastic process, with the training data being drawn from two sets of variables: an Input vector $x_i \in X \subseteq \Re^n$ and the response or Output $y_i \in Y \subseteq \Re$.

The relationship between X and Y is probabilistic: an element X does not map uniquely to an element of Y; rather it defines a probability distribution on X. Alternatively for x_i drawn from every X with probability $P(x_i)$ (called the marginal probability), the output y_i is observed with probability $P(y_i | x_i)$ (called the conditional probability of y_i given x_i). In other word, an unknown probability distribution $p(x,y)$ defined on $X \times Y$ determines the probability of observing a training data point (x_i,y_i). Therefore the training data set $T = \{x_i, y_i\}_{i=1}^{Q}$ which we have been using time and again, is actually generated by sampling the cross space $X \times Y$, Q times in accordance with the distribution $p(x,y)$. This learning problem is searching for appropriate estimator function $f: X \rightarrow Y$ which can then be used in predictive mode to generate a value y in output to an unseen input x.

In order to successfully solve the regression or classification task, a learning machine learns an approximating function $f(x, \alpha)$ (also referred to as a hypothesis) which is a function of both inputs $\boldsymbol{x}$ and the parameter or weights $\boldsymbol{\alpha}$ as the notation emphasizes.

IV.2.1 Empirical Risk Minimization and Structural Risk Minimization.

The risk functional the expected value of the loss due to the classification or estimation error. It employs a loss function L to measure the average error, and then search out the estimator from the space hypotheses, that minimizes this risk. If the desired value is y and the predicted value is $f(x, \alpha)$, then the expected risk is defined as:

$$R(\alpha) = \int L\left(y, f(x,\alpha)\right) dP(x,y) \tag{4.1}$$

As the probability P(x,y) is unknown, the risk $R(\alpha)$ cannot directly be minimized therefore an induction principle for risk minimization is required. This inductive principle is called *Empirical Risk Minimization (ERM)* which compute the empirical risk function as :

$$R_{emp}(\alpha) = \frac{1}{N} \sum_{i=1}^{N} L(y_i - f(x_i, \alpha)) \tag{4.2}$$

However this $R_{emp}(\alpha)$ will not able to guarantee a small actual risk if the number of N training examples is limited. In other words, a smaller error on the training set does not necessary implies higher generalization ability (i.e smaller error on an independent test set). To make the most out of limited amount of data, a statistical technique following called *Structural Risk Minimization (SRM)* has been developed by Vapnik (1995).

The theory of uniform convergence in probability developed in 1974 by Vapnik and Chervonenkis (VC) provides bounds on the deviation of the empirical risk from the expected risk. This theory shows that it is crucial to restrict the class of function that the learning machine can implement to one with a capacity that suitable for the amount of available training data.

For $\alpha \in \Lambda$ and $N > h$, a typical uniform VC bound, which holds with probability $1 - \eta$, has the following inductive principle *SRM* form as :

$$R(\alpha) \leq R_{emp}(\alpha) + \sqrt{\frac{h\,(\log\frac{2N}{h}+1)-\log(\frac{\eta}{4})}{N}} \tag{4.3}$$

Here the second term on the right is called *VC Confidence*. The VC The parameter h is called the *VC dimension* of a set of function and it describes the capacity of a set function to represent the data set. When N/h is small, a small empirical risk does not guarantee a small value of the actual risk. In this case, in order to minimize the actual risk $R(\alpha)$,the inequality in right hand in (4.3) should be minimized simultaneously over both term; the empirical risk and the VC confidence interval.

The VC confidence term in (4.3) depends on the chosen class of the function, whereas the empirical risk depends on one particular function chosen by the training procedure. The objective here is to find that subset of the chosen set of the function, such that the risk bound for that subset is minimized. This is done by simply training a series of machines, one of each subset; where for a given subset the goal of training is simply to minimize the empirical risk. One then takes that trained machines in the series whose sum of empirical risk and VC confidence is minimal.

IV.3 FEATURE SPACE

In the case of non linear separable data (which become the base of SVR), SVM formula should modified by construct a mapping into a high dimensional feature space. The input x is first mapped onto an p-dimensional feature space using some fixed (nonlinear) mapping, and then a linear model is constructed in this feature space.

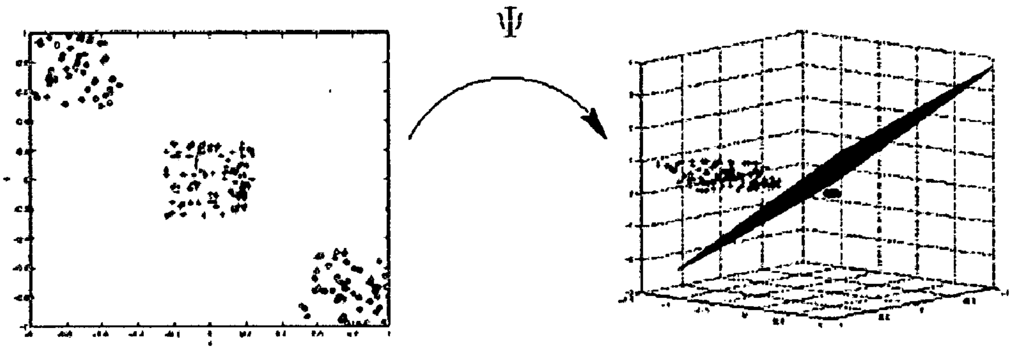


Figure 4.1 Non-linear mapping of input examples into high dimensional feature space. (Classification case, however the same stands for regression as well).

Usually feature space have higher dimension from input vector (input space), this make the computation in feature space probably become bigger, because there are possibility that feature space have infinite number of feature. Besides that it is difficult to know the appropriate transformation function. To solve this problem, SVM used *"kernel trick"*. Kernels Function that commonly used are as follows:

a. Kernel Linier

$$K(x_i,x) = x^t,x \tag{4.14}$$

b. Polynomial Kernel

$$K(x_i,x) = (\gamma\, x_i^T x + r)^p,\ \gamma>0 \tag{4.15}$$

c. Radial Basis Function (RBF)

$$K(x_i,x) = \exp(-\frac{1}{\sigma^2}\,|x_i - x_1|^2),\ \gamma>0 \tag{4.16}$$

d. Sigmoid Kernel

$$K(x_i,x) = \tanh(\gamma x_i^T\, x + r) \tag{4.17}$$

According to Hsu (2004) kernel function that recommended for the first time tested is the RBF, because it has the same performance like liner kernel in certain parameters and has a behavior like kernel sigmoid function with fixed parameter and small range value.

Figure 4.2 provides architecture on the SVM for non linear function estimation, with input vector x and the utilization of kernel function to determine the optimal y values.

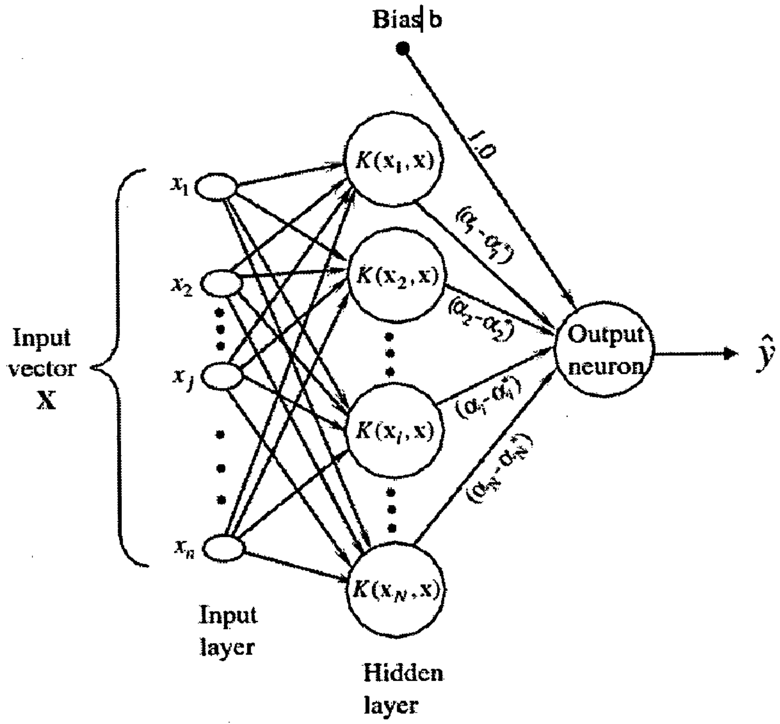
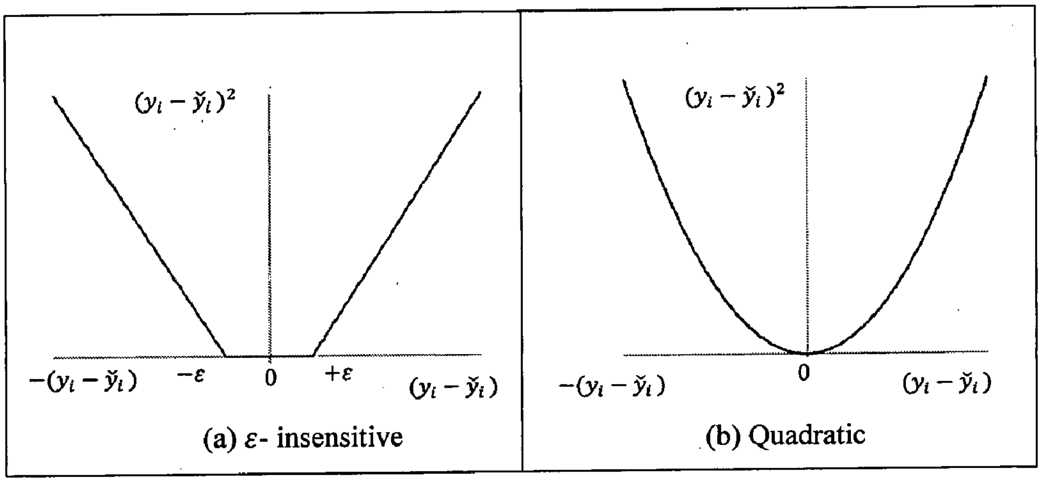


Figure 4.2

Architecture of SVM

IV.4 SUPPORT VECTOR REGRESSION

SVM can be applied to regression problems by the introduction of an alternative loss function, (Smola, 1996). The loss function must be modified to include a distance measure. Figure 4.3 illustrates four possible loss functions.



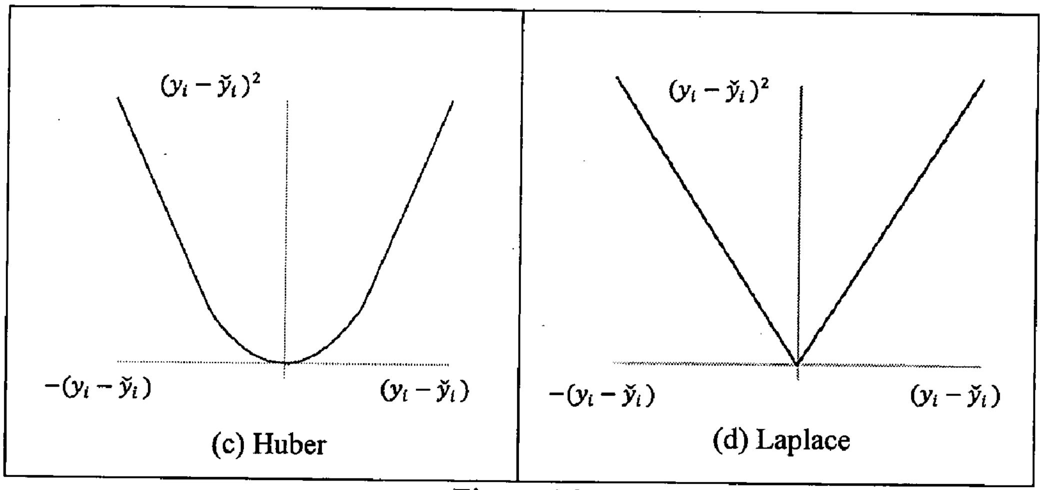


Figure 4.3.
The loss function

Figure 4.3(a) the ϵ insensitive loss function that ensure existence of the global minimum and at the same time optimization of reliable generalization bound, in Figure 4.3(b) quadratic loss function corresponds to the conventional least squares error criterion. Figure 4.3(c) Huber proposed the loss function as a loss function that has optimal properties when the underlying distribution of the data is unknown. Figure 4.3(d) is a Laplacian loss function that is less sensitive to outliers than the quadratic loss function (Figure 4.3b).

Support vector regression is based on the non-linear SVM that implicitly apply kernel functions which map the data to a higher dimensional feature space. A linear solution in the higher dimensional feature space corresponds to a non-linear solution in the original, lower dimensional input space. One approaching method is using the RBF (equation 4.16) and is called Least Square Support Vector Machine (LS-SVM). The main advantage of LS-SVM is that it is computationally more efficient than the standard SVM method, since the training of LS-SVM requires only the solution of a set of linear equations instead of the long and computationally demanding quadratic programming problem involved in the standard SVM (Suykens,1999). In comparison with some other feasible kernel functions, the RBF is a more compact, supported kernel and able to shorten the computational training process and improve the generalization performance of LS-SVM, a feature of great importance in designing a model (Maity, 2010).

In SVR, $\{x_i, y_i\}_{i=1}^{N}$ is considered as a training set, in which $\boldsymbol{x}_i \in \Re^p$ represents a p-dimensional input vector and $y_i \in \Re$ is a scalar measured output, which represents the system output. The goal is to construct a function $y = f(x)$ which represents the dependence of the output y_i on the input x_i. The form of this function is

$$y = w^T \phi(x) + b \tag{4.18}$$

where $\boldsymbol{w}$ is known as the weight vector and $\boldsymbol{b}$ the bias. This regression model can be constructed using a nonlinear mapping function $\phi(x)$. By mapping the original input data into a high – dimensional space, the non-linear separable problem becomes linearly separable becomes linearly separable in space.

The function $(x) : \Re^p \rightarrow \Re^h$ is a mostly non-linear function which maps the data into a higher, possibly infinite, dimensional feature space. The LS-SVM involves equality constraints, and works with a least squares cost function. The optimization problem and the equality constraints are defined by the following equations:

$$\min \psi L\,(w, e) = \frac{1}{2}\, w^T w + \gamma \frac{1}{2} \sum_{i=1}^{N} e_i^2 \tag{4.19}$$

Subjected to equality constrain:

$$y_i - y = e_i, \qquad i = 1, \ldots., N \tag{4.20}$$

Or by substitution to equation (4.18) :

$$y_i = w^T \phi(x_i) + b + e_i, \qquad i = 1, \ldots., N \tag{4.21}$$

Where e_i is the quadratic loss term and $\gamma \in \Re^+$ is a regularization parameter in optimizing the trade-off between minimizing the training errors and minimizing the model's complexity. The objective is now to find the optimal parameters that minimize the prediction error of the regression model. The optimal model will be chosen by minimizing the cost function where the errors e_i are minimized. This formulation corresponds to the regression in the feature space and since the dimension of the feature space is high, possibly infinite, this problem is difficult to solve. Therefore, to solve this optimization problem, the following Lagrange function is given:

$$\min_{w,b} L_p\,(w,b,e;\alpha) = \psi L(w,e) - \sum_{i=1}^{N} \alpha_i \{w^T \phi\,(x_i) + b + e_i - y_i\} \tag{4.22}$$

The solution of equation (4.21) can be obtained by partially differentiating with respect to w, b, e_i and α_i, i.e.

$$\frac{\partial L}{\partial w} = 0 \longrightarrow w = \sum_{i=1}^{N} \alpha_i\, \phi(x_i) \tag{4.23}$$

$$\frac{\partial L}{\partial b} = 0 \longrightarrow b = \sum_{i=1}^{N} \alpha_i = 0 \tag{4.24}$$

$$\frac{\partial L}{\partial e_i} = 0 \longrightarrow \alpha_i = \gamma . e_i, \qquad i = 1, \dots . N \tag{4.25}$$

$$\frac{\partial L}{\partial x_i} = 0 \longrightarrow w^T \phi(x_i) + b + e_i - y_i = 0 \qquad i = 1,\dots,N \tag{4.26}$$

Finally, the estimated values of b and α_i, i.e. $\breve{b}$ And $\breve{\alpha}_i$, can be obtained by solving the linear system and the resulting LS-SVM model can be expressed as:

$$y = f(x) = \sum_{i=1}^{N} \breve{\alpha}_i\, K\,(x, x_i) + \breve{b} \tag{4.27}$$

Where $K(x,x_i)$ is a kernel function in the non-linear RBF (equation 4.16).

The regularization parameter g is also necessary in LS-SVM model and determines the trade-off between the fitting error minimization and smoothness of the estimated function. It is not known beforehand which γ and σ are the best for a particular application problem to achieve the maximum performance with LS-SVM models. Thus, the regularization parameter γ and the value of σ from the kernel function have to be tuned during model calibration.

IV.5 LS-SVMLAB TOOLBOX

The LS-SVMLAB toolbox is program written in C-code mainly intended for use with the commercial Matlab package. It is built around a fast LS-SVM training and simulation algorithm. The Matlab toolbox is compiled and tested for different computer architectures including Linux and Windows. Most functions can handle datasets up to 20000 data points or more. LS-SVMlab's interface for Matlab consists of a basic version for beginners as well as a more advanced version with programs for multi-class encoding techniques and a Bayesian framework.

Figure 4.4 below is briefly sketch how to obtain an LS-SVM model (valid for classification and regression) :

1. Choose between the functional or objected oriented interface (initlssvm)
2. Search for suitable tuning parameters (tunelssvm)
3. Train the model given the previously determined tuning parameters (trainlssvm)
4a. Simulate the model on e.g. test data (simlssvm)
4b. Visualize the results when possible (plotlssvm)

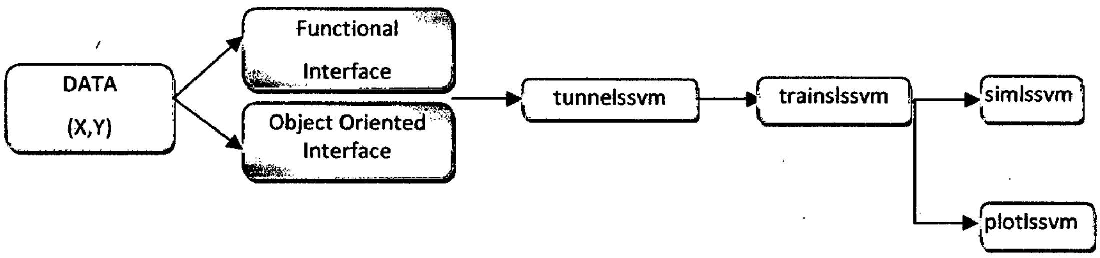


Figure 4.4
List of commands for obtaining an LS-SVM model

A. TUNELSSVM, LINESEARCH & GRIDSEARCH

Purpose

Tune the tuning parameters of the model with respect to the given performance measure.

Description

There are three optimization algorithms: simplex which works for all kernels, gridsearch is used (this one is restricted to 2-dimensional tuning parameter optimization); and the third one is linesearch (used with the linear kernel). The tuning parameters are the regularization parameter gam and the squared kernel parameter (or sig2) in the case of the 'RBF_kernel'

B. TRAINLSSVM

Purpose

Train the support values and the bias term of an LS-SVM for classification or function approximation.

Description

Type can be 'classifier' or 'function estimation' (these strings can be abbreviated into 'c' or 'f', respectively). X and Y are matrices holding the training input and training output. The i-th data point is represented by the i-th row X(i,:) and Y(i,:). gam is the regularization parameter: for gam low minimizing of the complexity of the model is emphasized, for gam high, fitting of the training data points is stressed. Kernel_ par is the parameter of the kernel; in the common case of an RBF kernel, a large sig2 indicates a stronger smoothing. The kernel_ type indicates the function that is called to compute the kernel value (by default RBF_ kernel).

The training can either be proceeded by the preprocessing function ('preprocess') (by default) or not ('original'). The training calls the preprocessing (prelssvm, postlssvm) and the encoder (codelssvm) if appropriate. In the remainder of the text, the content of the cell determining the LS-SVM is given by {X,Y, type, gam, sig2}. However, the additional arguments in this cell can always be added in the calls.

This implementation allows to train a multidimensional output problem. If each output uses the same kernel type, kernel parameters and regularization parameter, this is straightforward. If not so, one can specify the different types and/or parameters as a row vector in the appropriate argument. Each dimension will be trained with the corresponding column in this vector.

C. SIMLSSVM

Purpose

Evaluate the LS-SVM at given points

Description

The matrix Xt represents the points one wants to predict. The first cell contains all arguments needed for defining the LS-SVM (see also trainlssvm, initlssvm). The second cell contains the results of training this LS-SVM model. The cell syntax allows for flexible and consistent default handling.

D. PLOTLSSVM

Purpose

Plot the LS-SVM results in the environment of the training data

Description

The first argument specifies the LS-SVM. The latter specifies the results of the training if already known. Otherwise, the training algorithm is first called. One can specify the precision of the plot by specifying the grain of the grid. By default this value is 50. The dimensions (seldims) of the input data to display can be selected as an optional argument in case of higher dimensional inputs (> 2). A grid will be taken over this dimension, while the other inputs remain constant (0).

CHAPTER V
STUDY AREA AND THE DATA

V.1 ROORKEE AREA

Roorkee is a city and a municipal council in the Indian state of Uttarakhand. It is also known for Roorkee Cantonment (a temporary or semi-permanent military quarters), one of the country's oldest cantonments. It is a part of the district of Haridwar which is merely 30 km distant away. It is about 172 kilometers north of the Indian capital, New Delhi and located between the rivers Ganga and Yamuna on the banks of the upper Ganga Canal, which take off at Haridwar. The town has an administrative status of a Tehsil (sub-division).

Roorkee has a flower-shaped town spread over a flat terrain with the grand spectacle of Himalayan ranges flanking it in the East and the North-east. The dominant feature of the town is the Upper Ganges Canal which flows north-south and bisects the town. The canal has elevated embankments flanked. Roorkee lies at 29 52 'N Latitude and 77 53'E Longitude in Uttarakhand State (see figure 5.1). It has an average elevation level 274 meters above mean sea level.

it is not a heavily industrialized city; therefore the impacts of industrialization do not dominate the city's system. The city is representative of a very large number of similar urban systems. Eventhough it is a major educational and tourist attraction, the city does not have significant floating population.

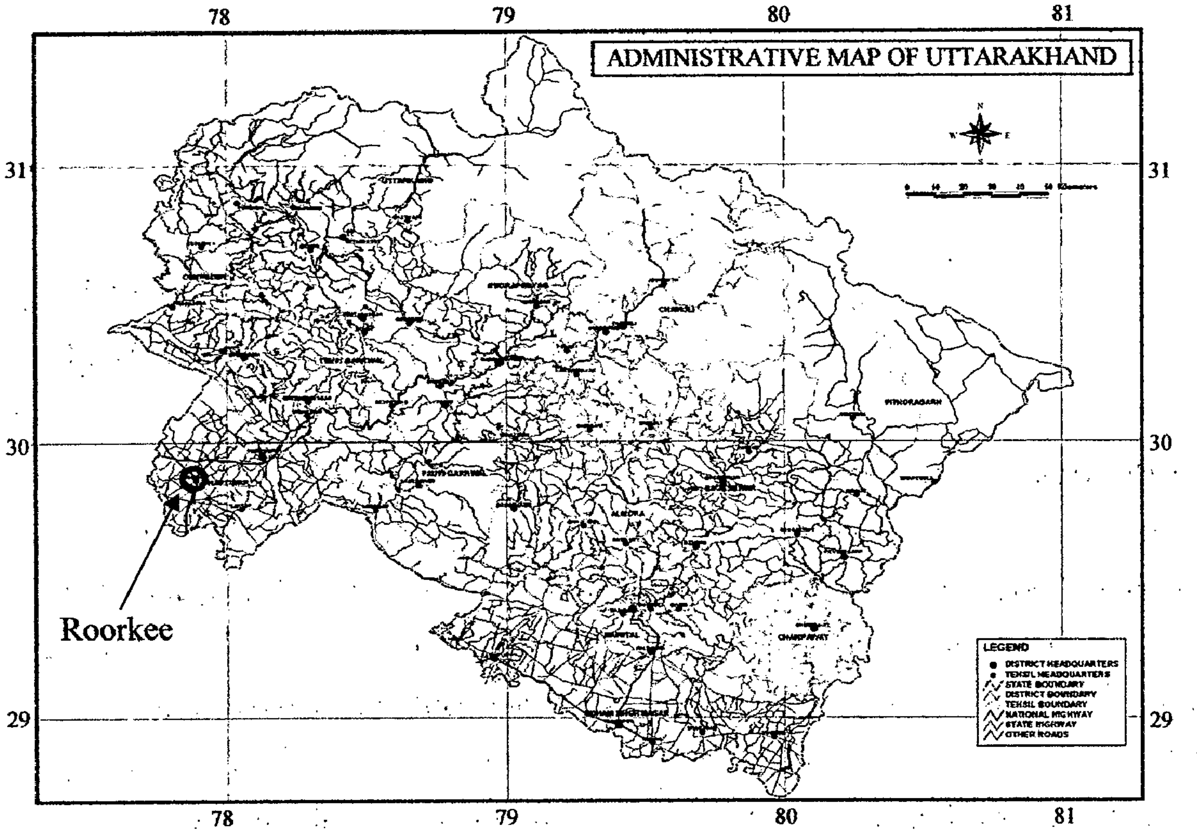


Figure 5.1 Administrative Map of Uttarakhand

V.2 CLIMATE

The climate of Roorkee is typical of Northwestern India. All three predominant season - summer, winter, and monsoon - are witnessed in Roorkee, with very hot summers and very cold winters. Being a submontanic district, with higher latitude than any other portion of the plains, it has longer spells of cold weather then Delhi. Though the heat in May and June is considerable, relief occasionally afforded by the cooling effect of moderate Himalayan storms, the influence of which extends for some distance to the South.

In terms of average annual precipitation (103.2 cm), Roorkee is semi-arid. The South-West monsoon generally breaks in mid-June and the North-East during November-December. Winters begin from late September and continue through February. The coldest months are generally December and January, when the minimum temperature approaches zero. A rise in temperature is experienced from the beginning of March, which heralds the onset of summer The temperature ranges from 0° C to 20° C in Winter (December to March), 25° C to 40° C in Summer (April to June) which warm winds blow frequently and 20° C to 40° C in Rainy season (June to September). Annual variation in mean monthly temperature from 1981-2010 observations is presented in Figure 5.2.

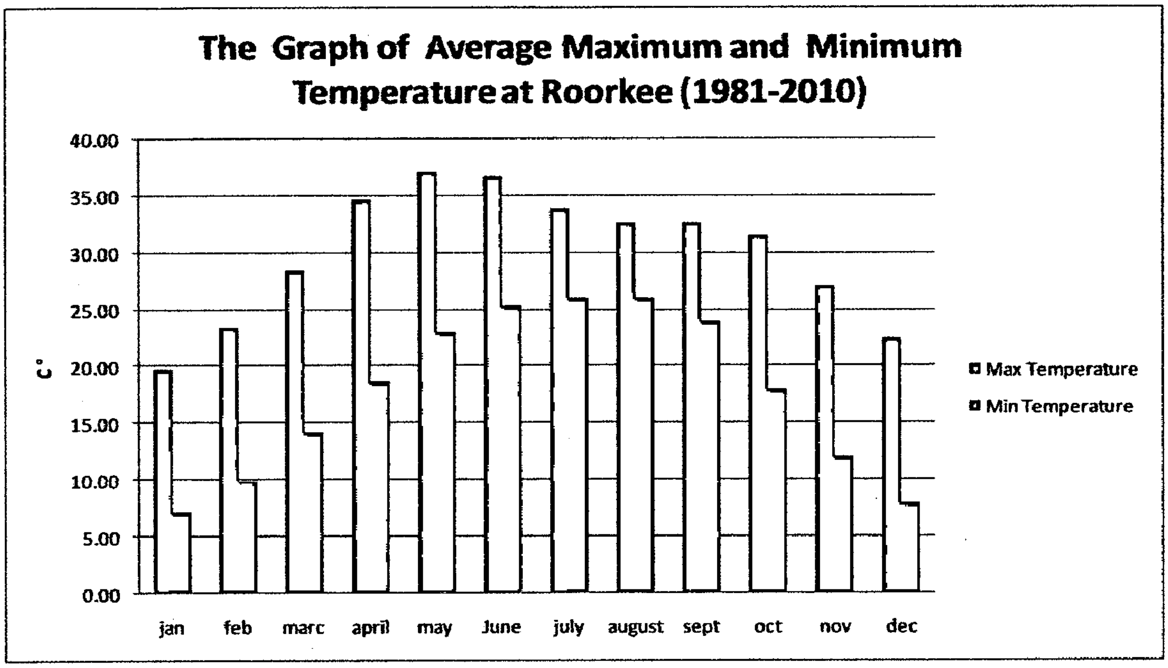


Figure 5.2 Mean monthly minimum and maximum temperature Graph of Roorkee area for the last 30 years (1981-2010)

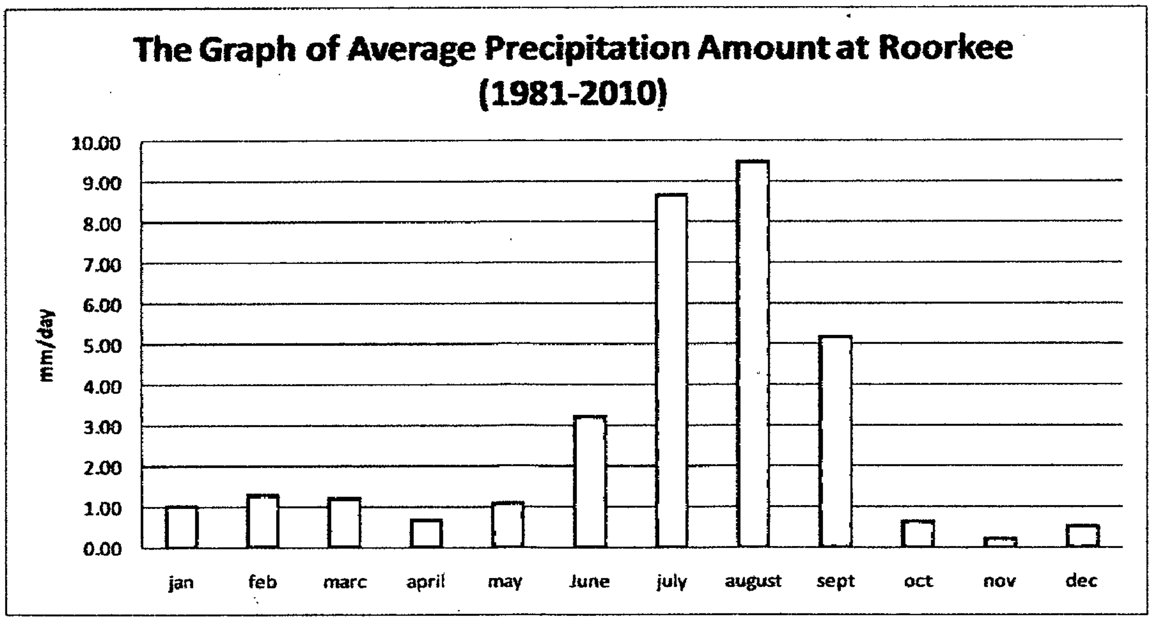


Figure 5.3 Mean monthly precipitation Graph of Roorkee area for the last 30 years (1981-2010)

V.3 IMPORTANT ROORKEE DATA

Some important data recorded by Hydrogy Department of Institute Technology Roorkee are :

Average Annual Rainfall: 1032 mm

Average Temperatures:

January: 13.8° C

June 32.2° C

Annual Temp. difference: 18. 4° C

Highest Temp. Recorded 45. 5° C (on 9th May, 1956)

Lowest Temp. Recorded: -3. 3° C (on 26th January, 1964)

Population 97,064 (according to census 2001)

Literacy rate: 87 % (according to census 2001)

Average max. Humidity 100%

Average min.Humidity 30%

Soil : Alluvial soils of Ganga Plain.

V.4 DATA REQUIRED

To develop the downscaling model, the available data set is partitioned into a training set and a test set. 50% of the available data from 1981-1995 (15 years) is selected for training (calibration) while the remaining 50% from 1996 – 2010 (15 years) is used for testing (validation). The data required is dived into two type, the predictant (Observed data) and the predictors (GCM data). All the data set will be available in appendix.

A. PREDICTANT (OBSERVED DATA)

Observed data is taken from Hydrology Department Station of Institute Technology Roorkee. The observed data that will be used for downscaling calculation are:

1. Mean monthly precipitation
2. Mean monthly minimum temperature
3. Mean monthly maximum temperature

B. PREDICTORS (GCM DATA)

In this study the simulated monthly climate data is taken from of the second generation Coupled General Circulation Model (CGCM2) Canada. The second version of the Canadian Centre for Climate Modelling and Analysis (CCCma) Coupled Global Climate Model (CGCM2), is based on the earlier The First Generation Coupled Global Climate Model , but with some improvements aimed at addressing shortcomings identified in the first version.

In particular, the ocean mixing parameterization has been changed from horizontal/vertical diffusion scheme to the isopycnal/eddy stirring parameterization of Gent and McWilliams (1990), and sea-ice dynamics has been included. In addition, some technical modifications were made in the ocean spinup and flux adjustment procedure.

There are 3 type of data in this CGCMA2 model:

1. GHG+A : Data from an ensemble of three 201-year simulations with CGCM2 using the IPCC "IS92a" forcing scenario in which the change in green house gases (GHG) forcing corresponds to that observed from 1900 to 1990 and increases at a rate 1% per year thereafter until year 2100. The direct effect of sulphate aerosols (A) is also included.

2. A2 : Data from an ensemble of three 111-year simulations using the provisional IPCC SRES "A2" GHG and aerosol forcing scenario. The simulations begin at year 1990 with initial conditions from the corresponding member of the GHG+A runs described above. To obtain data before 1990 please use GHG+A runs above. The A2 results differ only modestly from the IS92a results. Daily data for the time period 1961-2100 from the first member are also available. Daily data for the time period 1961-1989 are obtained from the corresponding GHG+A "IS92a" simulation.

3. B2 : Data from an ensemble of three 111-year simulations using the provisional IPCC SRES "B2" GHG and aerosol forcing scenario. The simulations begin at year 1990 with initial conditions from the corresponding member of the GHG+A runs described above. To obtain data before 1990 please use GHG+A runs above. The B2 scenario produces a more modest warming compared to the "IS92a" and "A2" scenarios. Daily data for the time period 1961-2100 from the first member are also available. Daily data for the time period 1961-1989 are obtained from the corresponding GHG+A "IS92a" simulation.

In this study the scenario IS92a is chosen. The mean monthly data which extends from January 1981 to December 2040 is extracted from CCCma web site http://www.cccma.bc.ec.gc.ca/. The extracted data pertains to 4 grid points whose latitude ranges from 27.83° N to 31.54° N and longitude ranges from 75° E to 78.75° E covering entire Roorkee Area. The CGCM2 grid is uniform along the longitude with grid box size of 3.75° and nearly uniform along the latitude (approximately 3.75°) see figure 5.4 and 5.5.

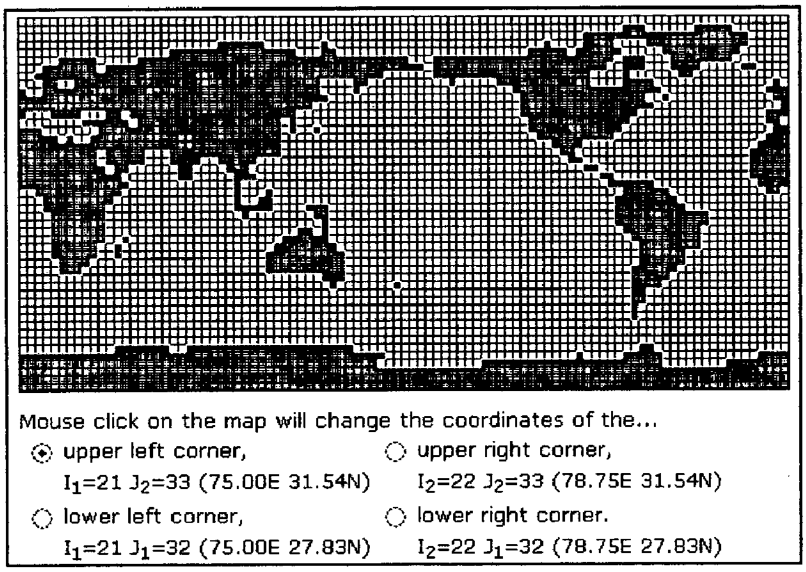


Figure 5.4 Selected Study Area Grid Point at GCMA2 Model

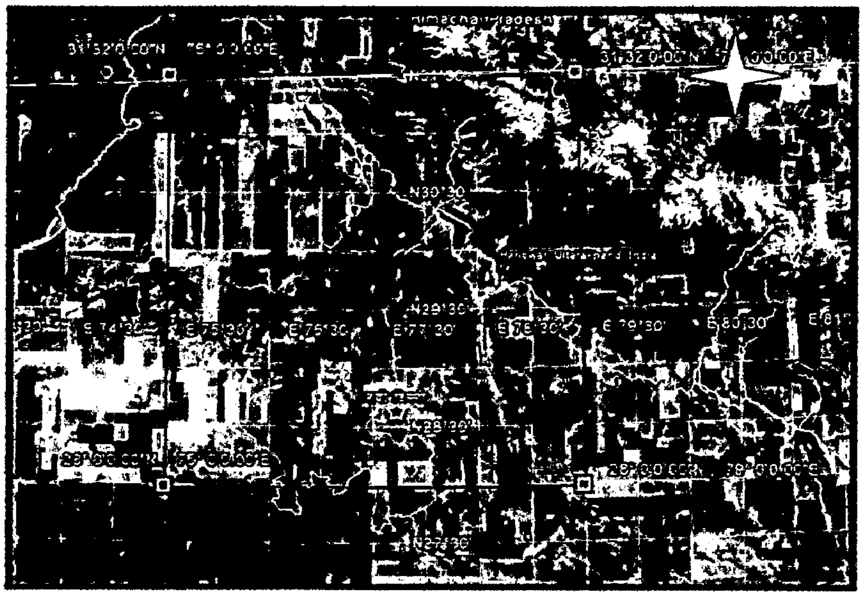


Figure 5.5 3.75 x 3.75 (approx) GRID Map Covered Roorkee Area
Source: Google earth map

According to Tripathi (2006) the choice of predictors could vary from one region to another. Since there are no general guidelines for selection of predictors in different parts of the world, a comprehensive search of predictors is necessary. In general, the values of the climate variables at earth's surface (which corresponds to approximately 1000 mb), 850 mb, 500 mb and 200 mb pressure levels are found to be representative of circulation pattern in the study region (Maini et al., 2004). Some candidate predictors variables provided by CGCM2 are:

1. Air temperature,

   Air temperature is the temperature in the air above area study at the various pressures. The unit is Celsius Degree

2. Specific humidity,

   Specific humidity is a ratio of mass quantities of water vapor to dry air, such as 1:200, for example. The unit is percent (%).

3. Precipitation

   Precipitation is any product of the condensation of atmospheric water vapor that falls under gravity. The main forms of precipitation include drizzle, rain, sleet, snow, graupel and hail. The unit is mm/day.

Geopotential height is a vertical coordinate referenced to Earth's mean sea level — an adjustment to geometric height (elevation above mean sea level) using the variation of gravity with latitude and elevation. Thus it can be considered a "gravity-adjusted height." One usually speaks of the geopotential height of a certain pressure level, which would correspond to the geopotential height necessary to reach the given pressure. The unit is meter (m). The Approximate Temperature and Pressure of Various Geopotential Height is shown in table 5.1.

5. Zonal and Meridional Wind Velocities

   Positive u winds (Zonal) are from the west and called Westerlies while positive v winds (Meridional) are from the south and call Southerlies. The unit in m/sec.

6. Sea level pressure.

   Atmospheric pressure at sea level is the result of the force of gravity on the matter above sea level (the atmospheric gases). The unit in hPa (hectoPascal)

Table 5.1

The Approximate Temperature and Geopotential Height from various Pressure.

Pressure	Approximate Height		Approximate Temp	
Sea level	0 m	0 ft	15 C	59 F
1000 mb	100 m	300 ft	15 C	59 F
850 mb	1500 m	5000 ft	5 C	41 F
700 mb	3000 m	10000 ft	-5 C	23 F
500 mb	5000 m	18000 ft	-20 C	-4 F
300 mb	9000 m	30000 ft	-45 C	-49 F
200 mb	12000 m	40000 ft	-55 C	-67 F
100 mb	16000 m	53000 ft	-56 C	-69 F

Source : www.atmos.uiuc.edu

CHAPTER VI
RESULT AND ANALYSIS

VI.1 PREPARATION

VI.1.1 Observed Data

Daily minimum and maximum temperature and precipitation records from Hydrology Department Station, Indian Institute Technology Roorkee were summed and divided by the number of records (day) for that month to obtain mean monthly data for each variable.

The statistic for mean monthly temperature and precipitation are given in table 6.1, which shows that the mean monthly precipitation ranges from 0 - 21.1 mm/day, the mean monthly temperature ranges from 5.1 - 31.7 °C and mean maximum temperature range from 15.8 – 39.6 °C.

Table 6.1

Statistical Description of Temperature and Precipitation data of study period (1981-2010)

Statistical Descriptive	*Observed Mean Mothly precipitation (mm/day)*	*Observed Mean Monthly Minimum Temperature (°C)*	*Observed Mean Monthly Maximum Temperature (° C)*
Mean	2.785	17.664	29.988
Standard Error	0.214	0.374	0.300
Median	1.031	18.185	31.945
Standard Deviation	4.066	7.087	5.684
Kurtosis	3.066	-1.434	-0.885
Skewness	1.902	-0.190	-0.467
Minimum	0.000	5.177	15.816
Maximum	21.137	31.723	39.680

VI.1.2 Selecting The Predictors

In this study, the candidate of predictors was selected by computing the correlation between the observed and GCM data. Pearson product-moment correlation coefficient (PMCC, denoted by *r*) method is chosen as the method for calculate the value. The *r* value can range between +1 and −1. This calculation is simply using Microsoft Excel facility *correlation* in data *analysis*. The interpretation of *r* value according to Wang (2006) is provided in this table 6.2.

Table 6.2

The Interpretation of *r* value

Correlation coefficient value	Interpretation
0 Larger than 0 but smaller than 0.500 From 0.500 to 0.699 From 0.700 to 0.999 1.000	No relationship Weak positive relationship Moderate positive relationship Strong positive relationship Perfect positive relationship
-1.000 From -0.700 to -0.999 From -0.500 to -0.699 Smaller than 0 but larger than -0.500	Perfect negative relationship Strong negative relationship Moderate negative relationship Weak negative relationship

Table 6.3 shows that for precipitation, the predictors at 200Mb pressure level have *weak* to *moderate* correlation with the observed data. 850Mb GPH give *strong* relationship even though in negative values (-0.714). Rainfall and evaporation have *weak negative* correlation with observed precipitation.

For minimum temperature, *strong* positive correlation are given by 500Mb Temp, 200Mb GPH and 850 SpecHum. However, 850Mb GPH give stronger relationship than 200Mb even though in negative values (-0.840).

The predictor candidates for maximum temperatures mostly have *weak* to *moderate* relationship both in negative and positive values. Only 500Mb GPH give slightly better correlation (0.714) with the observed maximum temperature data.

Table 6.3

The Correlation Coeficient (r) value between Observed and GCM data

GCM DATA	Correlation With		
	Observed Mean Monthly Precipitation	Observed Mean monthly MIN Temp	Observed Mean Monthly MAX Temp
200 Mb Temp	0.728	0.698	0.393
500 Mb Temp	0.580	0.853	0.689
850 Mb Temp	-0.125	-0.481	-0.517
200 Mb GPH	0.643	0.834	0.610
500 Mb GPH	0.425	0.807	0.714
850 Mb GPH	-0.714	-0.840	-0.608
200 Mb SpecHum	0.706	0.651	0.380
500 Mb SpecHum	0.651	0.766	0.564
850 Mb SpecHum	0.616	0.822	0.645
200 Mb U wind	-0.554	-0.569	-0.406
500 Mb U wind	-0.333	-0.437	-0.311
850 Mb U wind	0.376	0.273	0.131
200 Mb V wind	0.169	0.058	-0.075
500 Mb V wind	-0.333	-0.437	-0.311
850 Mb V wind	0.235	0.058	0.026
Rainfall	-0.116	-	-
Evaporation	-0.092	-	-

VI.1.3 Performancee Indices

Beside r value others methods that used to measure the error are Nash-Sutcliffe Efficiency (NSE) and Root Mean Square Error (RMSE) measurement.

NSE is defined as:

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - O_{Avg})^2} \qquad 6.1$$

RMSE is defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2} \qquad 6.2$$

Where O_i is the observed value, P_i is predicted output, O_{avg} is the average of measured value and i equals the number of values and n is the number of data. For NSE, the closer the model efficiency is to 1, the more accurate the model is. For RMSE, lower values of RMSE indicate better fit.

For MLR downscaling only in validation part NSE and RMSE are measured, but for SVR the error in calibration and validation both are measured by NSE and RMSE.

V1.2. DOWNSCALING USING MULTIPLE LINEAR REGRESSION (MLR)

Multiple linear regression is a form of regression analysis in which the regression function establishes the relationship between one dependent variable y and more than one independent variables ($x_1, x_2 \ldots x_n$). A linear regression equation is in the following form :

$$y = a + b_1x_1 + b_2x_2 + \ldots + b_nX_n \quad (6.3)$$

Parameters a (intercept) and $b_1, b_2 \ldots b_n$ (coefficient of x_n) are estimated using the least squares method.

In MLR method, the choosing of predictor's variable for downscaling is based on the statistic analysis. The highest *r* (including negative value) for each type of predictors is chosen as the candidate of predictors. The best statistic result from the combination predictors in calibration part is taken as the predictors in validation model

VI.2.1. Precipitation

1. **Calibration (1981-1995)**

The predictor candidates for downscaling precipitation are presented in table 6.4.

Table 6.4

The Candidate Predictors for downscaling precipitation

GCM DATA	Correlation with Observed Mean Monthly Precipitation
200Mb Temp	0.728
200Mb GPH	0.643
850Mb GPH	-0.714
200Mb SpecHum	0.706
200Mb U wind	-0.554
500Mb V wind	-0.393
Rainfall	-0.116
Evaporation	-0.092

Because GPH variable have two potential predictors, at 200 Mb GPH and 850 Mb GPH thus the combination to gain the best model is done separately for each value of GPH. The result of the combinations is in table 6.5

Table 6.5

Summary output of statistic analysis for MLR precipitation in calibration model

Predictors Combination	*Regression Statistics for 7 candidates predictors*	
200 Mb Temp 200 Mb GPH 200 Mb SpecHum 200 U wind 500 V Wind Precipitation Evaporation	Multiple R	0.767
	R Square	0.589
	Adjusted R Square	0.572
	Standard Error	**2.558**

Predictors Combination	*Regression Statistics for 7 candidates predictors*	
200 Mb Temp 850 Mb GPH 200 Mb SpecHum 200 U wind 500 V Wind Precipitation Evaporation	Multiple R	0.757
	R Square	0.573
	Adjusted R Square	0.556
	Standard Error	**2.607**

Predictors Combination	*Regression Statistics for 6 candidates predictors*	
200 Mb Temp	Multiple R	0.767
200 Mb GPH	R Square	0.589
200 Mb SpecHum	Adjusted R Square	0.574
200 U wind	Standard Error	**2.551**
500 V Wind		
Precipitation		

Predictors Combination	*Regression Statistics for 6 candidates predictors*	
200 Mb Temp	Multiple R	0.757
850 Mb GPH	R Square	0.573
200 Mb SpecHum	Adjusted R Square	0.558
200 U wind	Standard Error	**2.599**
500 V Wind		
Precipitation		

Predictors Combination	*Regression Statistics for 5 candidates predictors*	
200 Mb Temp	Multiple R	0.767
200 Mb GPH	R Square	0.589
200 Mb SpecHum	Adjusted R Square	0.577
200 U wind	Standard Error	**2.544**
500 V Wind		

Combination Predictors	*Regression Statistics for 5 candidates predictors*	
200 Mb Temp	Multiple R	0.756
850 Mb GPH	R Square	0.572
200 Mb SpecHum	Adjusted R Square	0.560
200 U wind	Standard Error	**2.595**
500 V Wind		

Predictors Combination	*Regression Statistics for 4 candidates predictors*	
200 Mb Temp	Multiple R	0.764
200 Mb GPH	R Square	0.584
200 Mb SpecHum	Adjusted R Square	0.575
200 U wind	Standard Error	**2.550**

Predictors Combination	*Regression Statistics for 4 candidates predictors*	
200 Mb Temp	Multiple R	0.755
850 Mb GPH	R Square	0.570
200 Mb SpecHum	Adjusted R Square	0.560
200 U wind	Standard Error	**2.594**

Predictors Combination	*Regression Statistics for 3 candidates predictors*	
200 Mb Temp	Multiple R	0.764
200 Mb GPH	R Square	0.584
200 Mb SpecHum	Adjusted R Square	0.577
	Standard Error	**2.542**

Predictors Combination	*Regression Statistics for 3 candidates predictors*	
200 Mb Temp	Multiple R	0.749
850 Mb GPH	R Square	0.561
200 Mb SpecHum	Adjusted R Square	0.553
	Standard Error	**2.613**

From the result of various combination models, the bigger predictor number the bigger is the *r* but also the bigger is the standard error. The combination model which is using 850Mb have bigger standard error and smaller *r* than the model which using 200Mb data. Thus, 200Mb GCM Temp, 200Mb GPH and 200Mb SpecHum are chosen as the predictors for downscaling precipitation variable and become the input data to get the formula for validation model.

A. Input

y : Observed Precipitation

x_1 : 200Mb GCM Temperature

x_2 : 200Mb GPH

x_3 : 200Mb SpecHum

B. Output

The *regression* facility in Microsoft excel produce the value of intercept coefficient and b_1,b_2,b_3 coefficient that next will used as the data input for calculation of MLR precipitation in validation model (see table 6.6).

Table 6.6

Coefficient Variables for Precipitation Validation of MLR Model

	Coefficient
Intercept	104.501
200Mb Temp GCM (x_1)	0.613
200Mb GPH GCM (x_2)	-0.006
200Mb SpecHum GCM (x_3)	45.053

2. Validation (1996-2010)

A. Input

Using the result from calibration output, the equation 6.3 can be rewritten into:

$$y_{ppt} = 104.500 + 0.613.x_1 - 0.006.x_2 + 45.053.\ x_3$$

y_{ppt} : Computed Precipitation

x_1 : 200Mb GCM Temperature

x_2 : 200Mb GPH

x_3 : 200Mb SpecHum

B. Output

MLR analysis result the correlation coefficient between the observed and computed precipitation is 0.714. NSE and RMSE also measured in validation part and the result are 0.492 and 3.002 respectively. From the graph in figure 6.1 it is clearly seen that MLR cannot mimic the lower part of observed precipitation and also for the extreme precipitation. The complete result of calculation for MLR precipitation (MLR PPTn) is given in appendix.

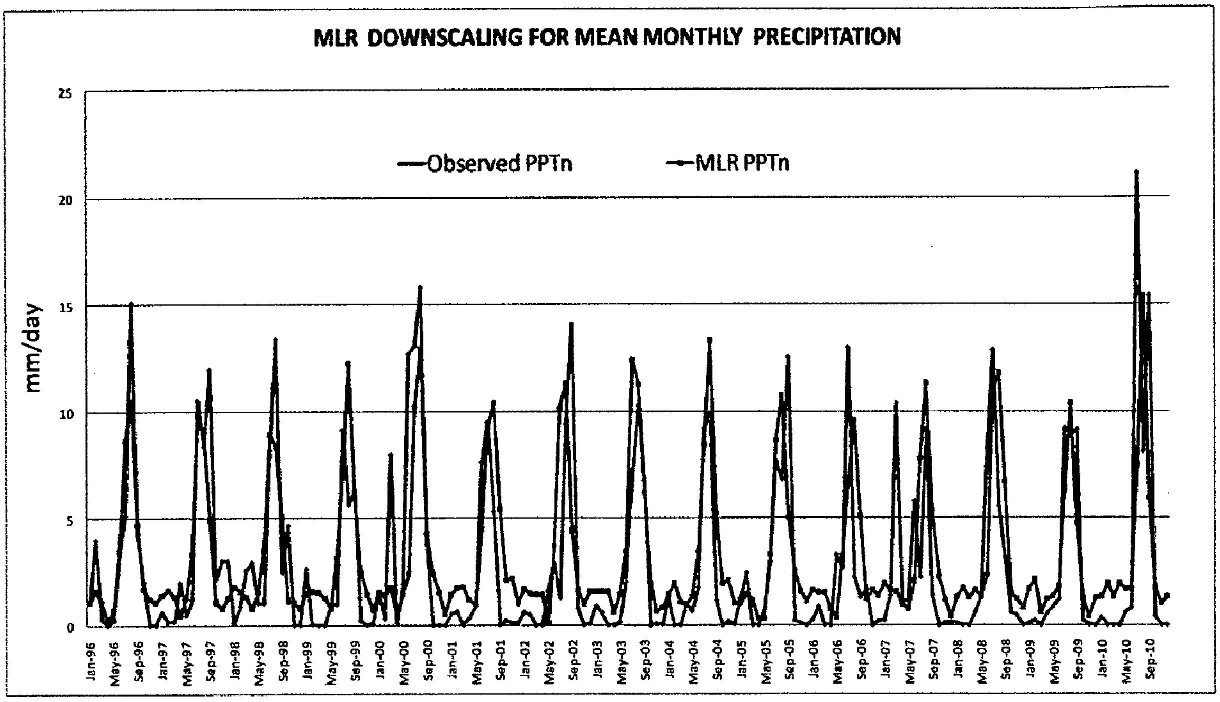


Figure 6.1
Downscaling result of mean monthly precipitation during the validation period using MLR method.

VI.2.2 Minimum Temperature

1. <u>Calibration (1981-1995)</u>

The predictor candidates to develop minimum temperature downscaling are in this table 6.7

Table 6.7
Predictor candidates for MLR downscaling of minimum temperature.

GCM DATA	Correlation with observed mean minimum Temperature
500Mb Temp	0.853
200Mb GPH	0.834
850Mb GPH	-0.840
850Mb SpecHum	0.822
200Mb U wind	-0.569
500Mb V wind	-0.437

Again GPH variable have two potential predictors, which are 200Mb GPH and 850Mb GPH thus the combination will do separately for each value. The result of the combinations is in table 6.8

that result, V (vertical or meridional) wind has an influence in predict the :emperature. This probably happens due to the Indian monsoon which is the · south-west monsoon brings heavy rain between July and september. The north-east monsoon, sweeps down from the plateaus of Asia and the , and brings rain and cooler weather to south-east India between October and Thus, the chosen predictors for minimum temperatures downscaling are the n of four predictors which are 500Mb Temp, 850Mb GPH, 850Mb SpecHum › V wind.

ɔserved minimum temperature
0Mb GCM Temperature
0Mb GPH
0Mb SpecHum
0Mb V wind

ɔrovide the intercept coefficient (a) and b_1, b_2, b_3, b_4 coefficient that next will :he data input for calculation in validation model.

Table 6.9

ɔefficient Variables for Minimum Temperature Validation of MLR Model

	Coefficients
Intercept	61.152
500 Mb Temp GCM (x_1)	0.645
850 Mb GPH GCM (x_2)	-0.027
850 Mb SpecHum GCM (x_3)	567.551
500 Mb V wind (x_4)	-0.077

ɔn (1996-2010)

ɘsult from calibration output, the equation 6.3 can be rewritten into:

$$y_{min} = 61.152 + 0.645.x_1 - 0.027.x_2 + 567.551.x_3 - 0.077.x_4$$

: computed minimum temperature
: 500Mb GCM Temperature
: 850Mb GPH

Tabl

Summary output of statistic analysis for MLF

Predictors Combination	*Regression Statistics for 5 candidates predictors*	
500Mb Temp	Multiple R	0.903
200Mb GPH	R Square	0.815
850Mb SpecHum	Adjusted R Square	0.810
200Mb U wind	Standard Error	**3.072**
500Mb V wind		

Predictors Combination	*Regression Statistics for 4 candidates predictors*	
500 Mb Temp	Multiple R	0.903
200 Mb GPH	R Square	0.815
850 Mb SpecHum	Adjusted R Square	0.811
500 Mb V wind	Standard Error	**3.063**

Predictors Combination	*Regression Statistics for 4 candidates predictors*	
500 Mb Temp	Multiple R	0.901
200 Mb GPH	R Square	0.812
850 Mb SpecHum	Adjusted R Square	0.808
200 Mb U wind	Standard Error	**3.086**

5
8
8
2(

Predictors Combination	*Regression Statistics for 3 candidates predictors*	
500 Mb Temp	Multiple R	0.901
200 Mb GPH	R Square	0.812
200 Mb SpecHum	Adjusted R Square	0.809
	Standard Error	**3.082**

50(
20(
850

The result of combination using 200Mb GPH shov occur in combination of four predictors which incl error (3.086) occur in combination with four pred value in combination three and four with U w combination five and four with V wind also the sam

The combination which using 850 Mb GPH shov (2.980) occurs in combination of four predictors with and four with U wind predictors result the smaller v of five and four with U wind.

Table 6.8

Summary output of statistic analysis for MLR minimum temperature in calibration model

Predictors Combination	*Regression Statistics for 5 candidates predictors*	
500Mb Temp	Multiple R	0.903
200Mb GPH	R Square	0.815
850Mb SpecHum	Adjusted R Square	0.810
200Mb U wind	Standard Error	**3.072**
500Mb V wind		

Predictors Combination	*Regression Statistics for 5 candidates predictors*	
500Mb Temp	Multiple R	0.908
850Mb GPH	R Square	0.825
850Mb SpecHum	Adjusted R Square	0.820
200Mb U wind	Standard Error	**2.988**
500Mb V wind		

Predictors Combination	*Regression Statistics for 4 candidates predictors*	
500 Mb Temp	Multiple R	0.903
200 Mb GPH	R Square	0.815
850 Mb SpecHum	Adjusted R Square	0.811
500 Mb V wind	Standard Error	**3.063**

Predictors Combination	*Regression Statistics for 4 candidates predictors*	
500Mb Temp	Multiple R	0.908
850Mb GPH	R Square	0.825
850Mb SpecHum	Adjusted R Square	0.821
500Mb V wind	Standard Error	**2.980**

Predictors Combination	*Regression Statistics for 4 candidates predictors*	
500 Mb Temp	Multiple R	0.901
200 Mb GPH	R Square	0.812
850 Mb SpecHum	Adjusted R Square	0.808
200 Mb U wind	Standard Error	**3.086**

Predictors Combination	*Regression Statistics for 4 candidates predictors*	
500 Mb Temp	Multiple R	0.907
850 Mb GPH	R Square	0.823
850 Mb SpecHum	Adjusted R Square	0.819
200 Mb U wind	Standard Error	**2.996**

Predictors Combination	*Regression Statistics for 3 candidates predictors*	
500 Mb Temp	Multiple R	0.901
200 Mb GPH	R Square	0.812
200 Mb SpecHum	Adjusted R Square	0.809
	Standard Error	**3.082**

Predictors Combination	*Regression Statistics for 3 candidates predictors*	
500 Mb Temp	Multiple R	0.907
200 Mb GPH	R Square	0.823
850 Mb SpecHum	Adjusted R Square	0.820
	Standard Error	**2.988**

The result of combination using 200Mb GPH shows that smallest standard error (3.063) occur in combination of four predictors which include V wind and the biggest standard error (3.086) occur in combination with four predictors which include U wind. The *r* value in combination three and four with U wind the same (0.901) likewise the combination five and four with V wind also the same (0.903).

The combination which using 850 Mb GPH shows that the smallest standard error (2.980) occurs in combination of four predictors with V wind. The combination of three and four with U wind predictors result the smaller value of *r* (2.988) than combination of five and four with U wind.

Based on that result, V (vertical or meridional) wind has an influence in predict the minimum temperature. This probably happens due to the Indian monsoon which is the summer or south-west monsoon brings heavy rain between July and september. The winter, or north-east monsoon, sweeps down from the plateaus of Asia and the Himalayas, and brings rain and cooler weather to south-east India between October and December. Thus, the chosen predictors for minimum temperatures downscaling are the combination of four predictors which are 500Mb Temp, 850Mb GPH, 850Mb SpecHum and 500Mb V wind.

A. Input

y : Observed minimum temperature

x_1 : 500Mb GCM Temperature

x_2 : 850Mb GPH

x_3 : 850Mb SpecHum

x_4 : 500Mb V wind

B. Output

Table 6.9 provide the intercept coefficient (a) and b_1,b_2,b_3,b_4 coefficient that next will be used as the data input for calculation in validation model.

Table 6.9

Coefficient Variables for Minimum Temperature Validation of MLR Model

	Coefficients
Intercept	61.152
500 Mb Temp GCM (x_1)	0.645
850 Mb GPH GCM (x_2)	-0.027
850 Mb SpecHum GCM (x_3)	567.551
500 Mb V wind (x_4)	-0.077

2. <u>Validation (1996-2010)</u>

A. Input

Using the result from calibration output, the equation 6.3 can be rewritten into:

$$y_{min} = 61.152 + 0.645.x_1 - 0.027.x_2 + 567.551.x_3 - 0.077.x_4$$

y_{min} : computed minimum temperature

x_1 : 500Mb GCM Temperature

x_2 : 850Mb GPH

x_3 : 850Mb SpecHum

x_4 : 500Mb V wind

B. Output

The result of regression minimum temperature model result $r = 0.882$, the measurement of NSE = 0.766 and RMSE = 3.450. From the graph in figure 6.2 we can see that MLR overestimated almost all the upper part of observed temperature and underestimates lower part or small values.

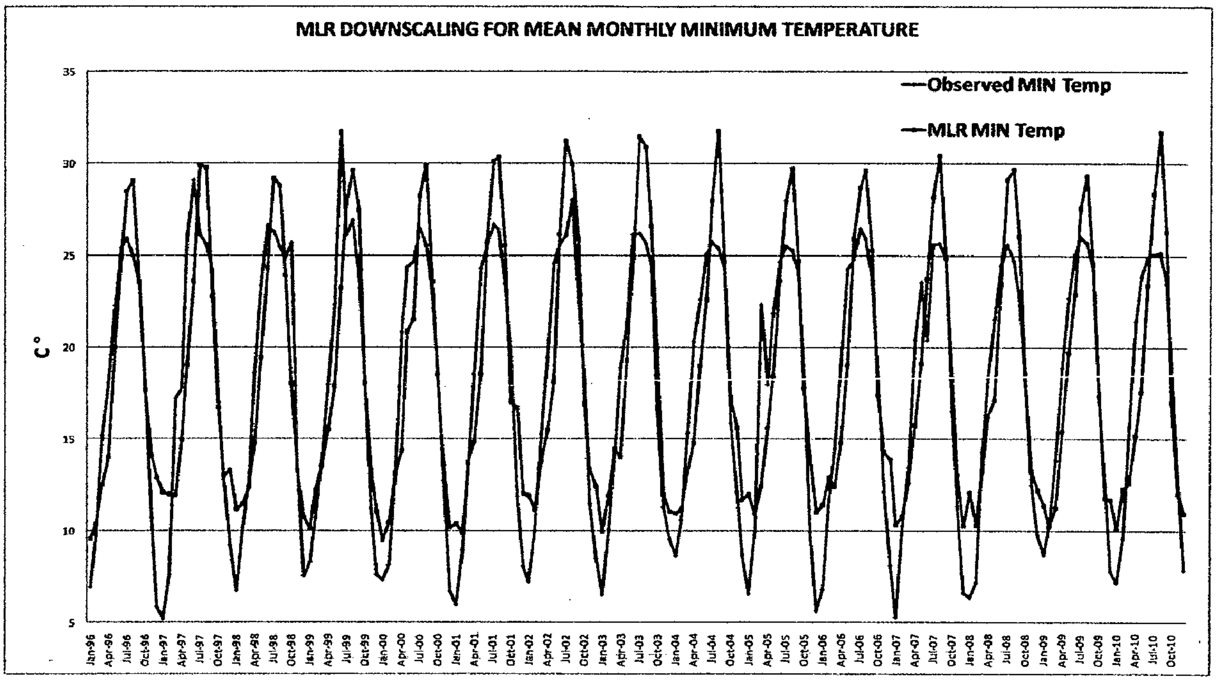


Figure 6.2
Downscaling result of mean monthly minimum temperature during the validation period using MLR method.

VI.2.3 Maximum Temperature

1. <u>Calibration (1981-1995)</u>

The predictor candidates to develop maximum temperature downscaling are in this table 6.10

Table 6.10
Predictor candidates for MLR downscaling of maximum temperature.

GCM DATA	Correlation with observed mean minimum Temperature
500 Mb Temp GCM	0.689
500 Mb GPH GCM	0.714
850 Mb SpecHum GCM	0.645
200 Mb U wind	-0.406
500 Mb V wind	-0.311

Table 6.11
Summary output of statistic analysis for MLR maximum temperature in calibration model

Predictors Combination	*Regression Statistics for 5 candidates predictors*	
500 Mb Temp GCM	Multiple R	0.793
500 Mb GPH GCM	R Square	0.629
850Mb SpecHum GCM	Adjusted R Square	0.618
200 Mb U wind	Standard Error	**3.469**
500 Mb V wind		

Predictors Combination	*Regression Statistics for 4 candidates predictors*	
500 Mb Temp GCM	Multiple R	0.792
500 Mb GPH GCM	R Square	0.628
850Mb SpecHum GCM	Adjusted R Square	0.619
200 Mb U wind	Standard Error	**3.464**

Predictors Combination	*Regression Statistics for 4 candidates predictors*	
500 Mb Temp GCM 500 Mb GPH GCM 850Mb SpecHum GCM 500 Mb V wind	Multiple R	0.791
	R Square	0.626
	Adjusted R Square	0.617
	Standard Error	**3.475**

Predictors Combination	*Regression Statistics for 3 candidates predictors*	
500 Mb Temp GCM 500 Mb GPH GCM 850Mb SpecHum GCM	Multiple R	0.790
	R Square	0.624
	Adjusted R Square	0.618
	Standard Error	**3.470**

Based on the statistic analysis, the biggest *r* value (0.793) is achieved by combination with five predictors and the smallest value of standard error (3.464) is achieved by combination of four predictors which include U (zonal) Wind. Regarding the value of standard error, the combination of four combination include U wind is chosen as the predictors for develop downscaling for maximum temperature. This probably happens because zonal wind which has west–east direction bring strong, hot and dry summer "loo" (wind) from the large desert regions of the northwestern Indian subcontinent (Rana,2007).

A. Input

y : Observed maximum temperature

x_1 : 500 Mb GCM Temperature

x_2 : 500 Mb GPH

x_3 : 850 Mb SpecHum

x_4 : 200 Mb U Wind

B. Output

Same as previous process the value of intercept coefficient (a) and b_1,b_2,b_3 coefficient from MLR process will used as the data input for calculation of MLR temperature in validation part (see table 6.12).

Table 6.12

Coefficient Variables for Minimum Temperature Validation of MLR Model

	Coefficients
Intercept (a)	-403.778
500 Mb Temp GCM (x_1)	-0.451
500 Mb GPH GCM (x_2)	0.073
850 Mb SpecHum GCM (x_3)	1061.202
200 Mb U Wind (x_4)	0.093

2.Validation (1996-2010)

A. Input

Using the result from calibration output, the equation 6.3 can be rewritten into:

$$y_{max} = -403.778 - 0.451.x_1 + 0.073.x_2 + 1061.2020.x_3 + 0.093.x_4$$

y_{max} : computed max temperature

x_1 : 500 Mb GCM Temperature

x_2 : 500 Mb GPH

x_3 : 850 Mb SpecHum

x_4 : 200 Mb U Wind

B. Output

The MLR for maximum temperature validation result r = 0.732, the measurement of NSE = 0.529 and, RMSE = 3.941. From the graph in figure 6.3 we can see that MLR cannot mimic the lower part of observed temperature but better replicate the upper parts of maximum temperature.

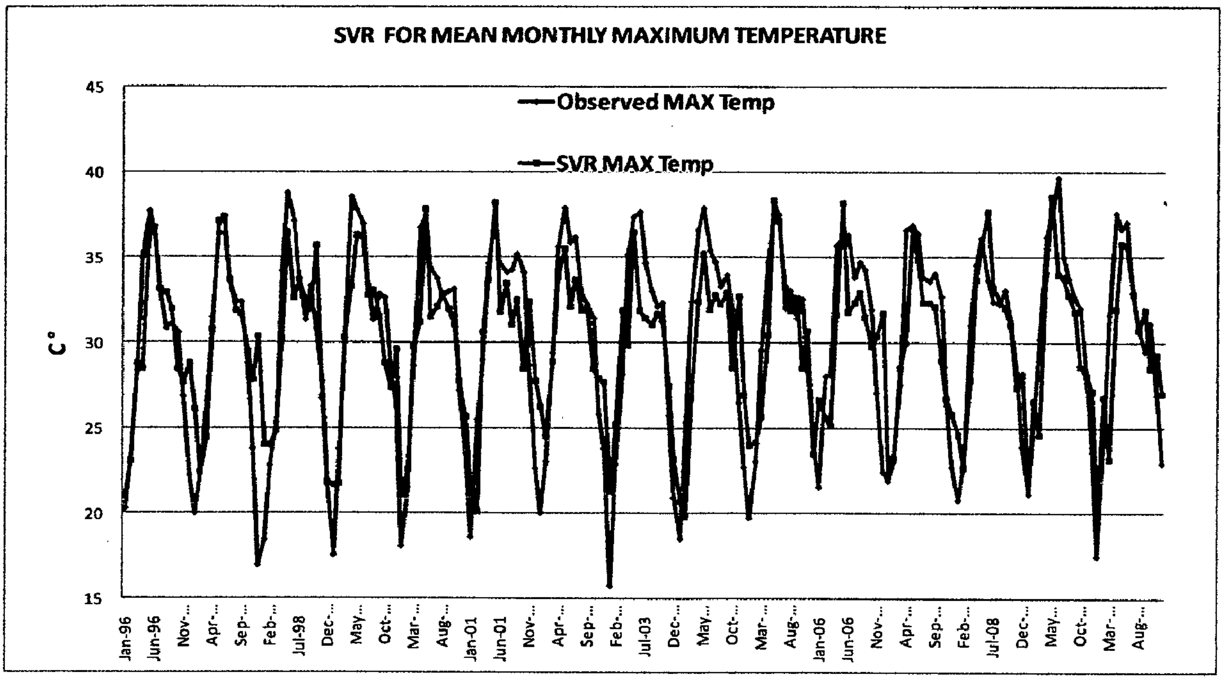


Figure 6.3
Downscaling result of mean monthly maximum temperature during the validation period using MLR method.

V1.3 DOWNSCALING USING SUPORT VECTOR MACHINE

As mentioned in chapter IV, the downscaling by SVM Regression (SVR) was carried out by using MATLAB LS-SVMLab toolbox Version 1.7. The data was divided into two periods and the steps of using the model in this study are given below:

Calibration period

1. Upload the data
2. Downscale calibration data
3. Determined the trial value of gam (gamma) and sig2 (sigma square).
4. Do the train of the model get the value of alpha and b (bias) values.
5. Using the values of alpha and b get the simulated precipitation.
6. Check the errors and correlation.
7. Back to step 3 again until the value of gam and sig2 get the best model (smallest error and biggest correlation).

Validation period

1. downscale validation data
2. Simulate the train result from calibration result using validation data.
3. Rescaling the simulated precipitation.
4. Check the errors and correlation

In this study,the length of data series used for the calibration and validation is the same, 15 years. For the calibration the data is from 1981 – 1995 and for the validation is from 1996 -2010. This is done because from the calibration model will produce the value of α (alpha) for each variable that will be used also in validation part.

This SVR from LS-SVMLab toolbox model has two parameters γ(gam) and σ^2(sig2) to be determined. These parameters are independent, and their near optimal values can be obtained by command *tunelssvm* but in this study by a trial-and-error method was employed. These analysis and calculations of γ and σ^2 parameters is used to perform computed climate variables (precipitation, minimum and maximum temperature). For both period the computed variables is compared to the observed variables and the error parameters is measured by using correlation coefficient (r), RMSE and NSE. The best combination of γ and σ^2 is chosen for further training and validation. The complete model syntax and the calculations in matlab program are shown in appendix. The steps of doing the downscaling using the LS-SVMLab Version 1.7 toolbox are shown figure 6.4.

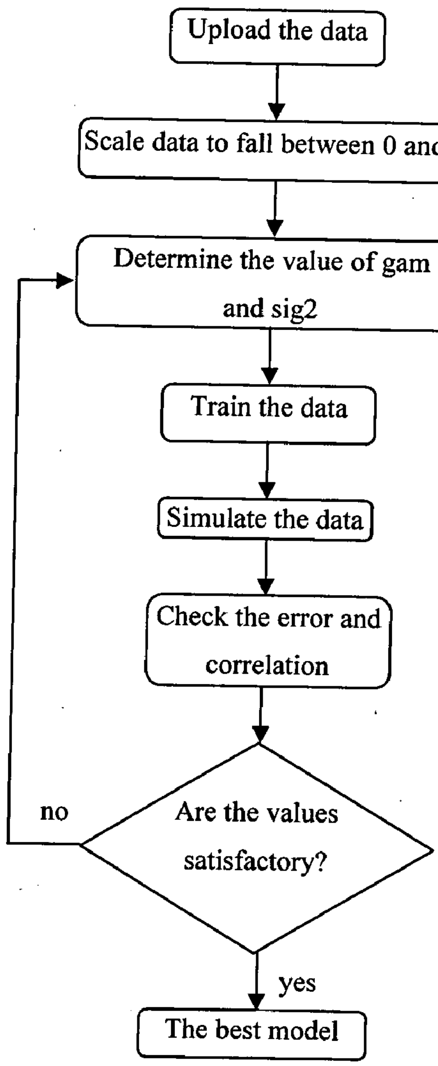


Figure 6.4

Flow chart the SVR downscaling method using LS-SVMLab Version 1.7 toolbox

V1.3.1 SVR Downscaling for Precipitation

As it was mentioned before that for downscaling precipitation variable, the chosen predictors are 200 Mb Temp (x_1), 200 Mb GPH (x_2), 200 Mb SpecHum (x_3). The predictant is observed precipitation data (y). The result of combination γ and σ^2 for precipitation downscaling are shown in table 6.13 from top to bottom in each cell of table 6.13 the statistics are (1) *r* (2) RMSE and (3) NSE.

Table 6.13

Performance statistic of precipitation downscaling for different combination of kernel parameters γ and σ^2 for validation period.

sig2	gamma							
	0.01	0.1	0.3	0.32	0.33	0.34	0.5	1
0.01	0.5991	0.5985	0.5944	0.5939	0.5936	0.5933	0.5535	0.5727
	4.1927	4.0285	3.7769	3.7582	3.7491	3.7404	3.5591	3.4933
	0.0099	0.0859	0.1965	0.2045	0.2083	0.212	0.2865	0.3127
0.1	0.6807	0.6971	0.696	0.695	0.6945	0.694	0.5687	0.6386
	4.1035	3.541	3.1938	3.1842	3.1804	3.1772	4.3969	3.5722
	0.0516	0.2938	0.4255	0.4289	0.4303	0.4314	-0.0889	0.2813
1.5	0.7429	0.7487	0.7477	0.7475	0.7473	0.7472	0.7443	0.7027
	3.9204	3.0741	2.8436	2.8419	2.8416	2.8415	2.872	3.3183
	0.1343	0.4677	0.5446	0.5451	0.5452	0.5452	0.5354	0.3798
1.7	0.7473	0.7499	0.7478	0.7476	0.7475	0.7474	0.7454	0.7346
	3.8903	3.0304	2.8411	2.8393	2.8389	2.8388	2.8639	3.1415
	0.1476	0.4828	0.5454	0.5459	0.5461	0.5461	0.538	0.4441
1.8	0.7473	0.7499	0.7477	0.7475	**0.7474**	0.7473	0.7455	0.7348
	3.89	3.0301	2.8404	2.8387	**2.8383**	2.8381	2.8621	3.14
	0.1477	0.4829	0.5456	0.5461	**0.5463**	0.5463	0.5386	0.4447
2	0.7474	0.7499	0.7475	0.7473	0.7472	0.7471	0.7454	0.735
	3.8898	3.0298	2.8402	2.8385	2.838	2.8379	2.8604	3.1386
	0.1478	0.483	0.5457	0.5462	0.5463	0.5464	0.5392	0.4452

On sequence (1) *r* (2) RMSE (3) NSE

The best combination for the predicted precipitation is $\gamma = 0.33$ and $\sigma^2 = 1.8$ with the value of $r = 0.7474$, RMSE = 2.8383 and NSE = 0.5463. Even though SVR can make 4.678 % improvement in correlation (r) and able to reach lower part in some point, but the upper part or high values still cannot be well replicated by the model particularly the extreme precipitation. Figure 6.5 shows the graph between of observed precipitation and computed precipitation by SVR (SVR PPTn).

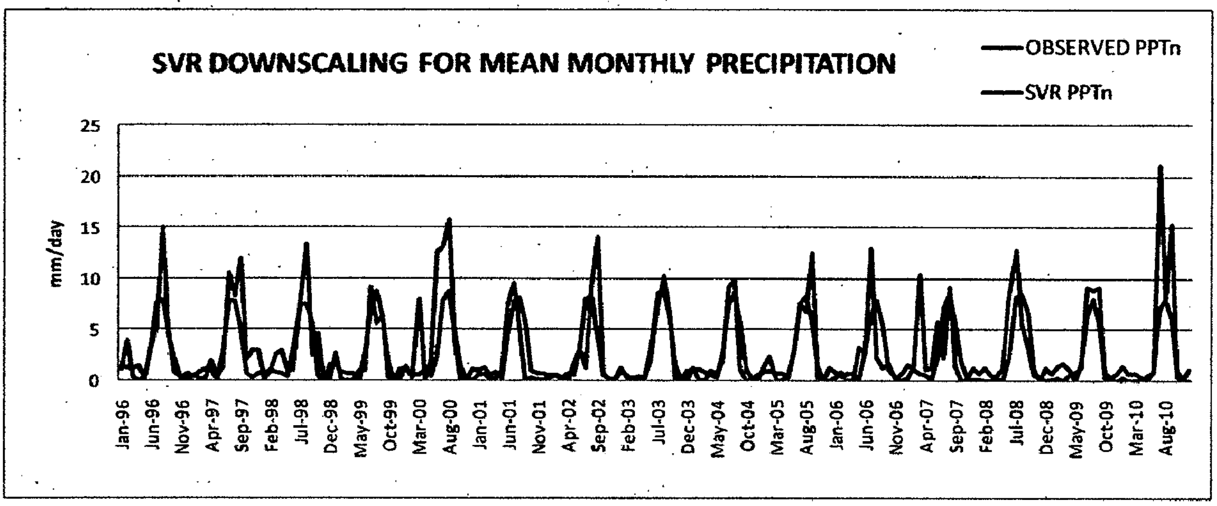


Figure 6.5

Downscaling result of mean monthly precipitation during the validation period using SVR method

V1.3.2 SVR Downscaling for Minimum Temperature

The best combination for the predicted minimum temperature is $\gamma = 0.45$ and $\sigma^2 = 2$ with the value is $r = 0.920$, RMSE = 2.881 and NSE = 0.837. Again if we compare the r value, then SVR make slightly improvement (4.331 %) better than MLR. SVR model can reach the upper part of observed value however in some point still difficult to predict the higher values (green circle). Figure 6.6 shown the graph between of observed minimum temperature and computed minimum temperature by SVR (SVR MIN Temp).

Table 6.14

Performance statistic of minimum temperature downscaling for different combination of kernel parameters γ and σ^2 for validation period.

sig2	gamma					
	0.01	0.1	0.3	0.4	0.45	0.5
0.1	0.8741	0.8769	0.8739	0.8711	0.8697	0.8682
	7.0096	6.1781	5.1297	4.805	4.6728	4.5568
	0.0333	0.2491	0.4823	0.5458	0.5704	0.5915
1	0.8813	0.899	0.9113	0.9132	0.9137	0.9139
	6.4934	4.1135	3.0251	2.9297	2.9259	2.9418
	0.1704	0.6671	0.82	0.8311	0.8316	0.8297
2	0.8791	0.8982	0.9147	0.9187	**0.9202**	0.9214
	6.3409	3.7911	2.9125	2.8688	**2.8806**	2.9069
	0.209	0.7172	0.8331	0.8381	**0.8368**	0.8338
3	0.8796	0.8971	0.9131	0.9171	0.9187	0.92
	6.3041	3.6975	2.9326	2.926	2.9512	2.9883
	0.2181	0.731	0.8308	0.8316	0.8287	0.8243
5	0.88	0.8946	0.9103	0.9145	0.9161	0.9175
	6.3357	3.6924	2.9701	2.9855	3.0198	3.0651
	0.2103	0.7318	0.8264	0.8246	0.8206	0.8152

On sequence (1) r (2) RMSE (3) NSE

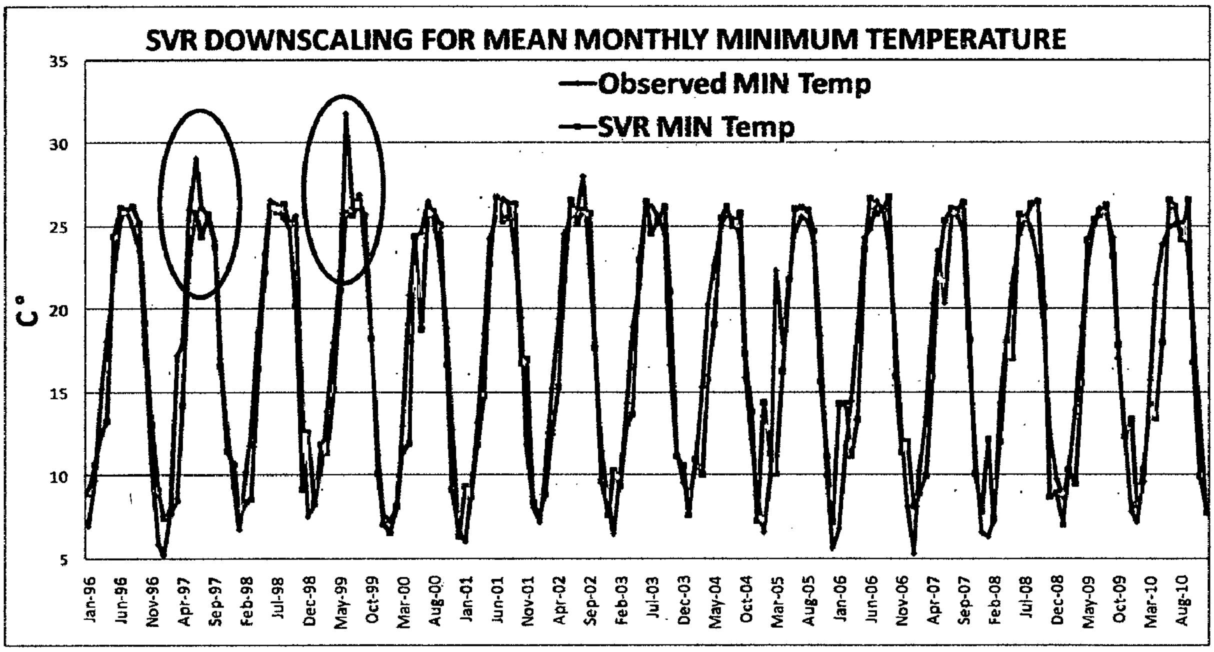


Figure 6.6

Downscaling result of mean monthly minimum temperature during the validation period using SVR method

V1.3.3 SVR Downscaling for Maximum Temperature

The best combination for the computed maximum temperature is γ = 0.9 and σ^2 = 0.2 with the value is r = 0.853, RMSE = 3.179 and NSE = 0.695. From the comparison of r value, the SVR make a better prediction than MLR which is 14.440 %. Figure 6.7 shows the graphic between of observed maximum temperature and computed maximum temperature by SVR (SVR MAX Temp). The model cannot well replicate almost all lower and upper part.

Table 6.15

Performance statistic of maximum temperature downscaling for different combination of kernel parameters $\boldsymbol{\gamma}$ and $\boldsymbol{\sigma^2}$ for validation period.

sig2	gamma					
	0.1	0.5	**0.9**	0.92	1	1.5
0.1	0.8109 4.7385 0.3196	0.8479 3.6476 0.5968	0.8493 3.3239 0.6652	0.8489 3.3157 0.6668	0.8466 3.2892 0.6721	0.82 3.3177 0.6664
0.19	0.8136 4.4272 0.406	0.8442 3.3456 0.6608	0.8387 3.1718 0.6951	0.838 3.1727 0.695	0.8349 3.1834 0.6929	0.8068 3.4628 0.6366
0.2	0.8137 4.4039 0.4123	0.8435 3.3283 0.6643	**0.8377** **3.1709** **0.6953**	0.8370 3.1726 0.6950	0.8339 3.1868 0.6922	0.8339 3.1868 0.6922
0.21	0.8137 4.382 0.4181	0.8429 3.313 0.6674	0.8368 3.1721 0.6951	0.8287 3.2585 0.6782	0.833 3.1923 0.6912	0.8063 3.509 0.6269
0.3	0.8133 4.2331 0.457	0.8373 3.2389 0.6821	0.8294 3.2483 0.6803	0.8287 3.2585 0.6782	0.826 3.3057 0.6688	0.8049 3.7729 0.5686
0.5	0.8098 4.0592 0.5007	0.8284 3.2485 0.6802	0.8193 3.553 0.6174	0.8187 3.5776 0.6121	0.8165 3.6811 0.5894	0.8021 4.4352 0.4039

On sequence (1) r,(2) RMSE, (3) NSE

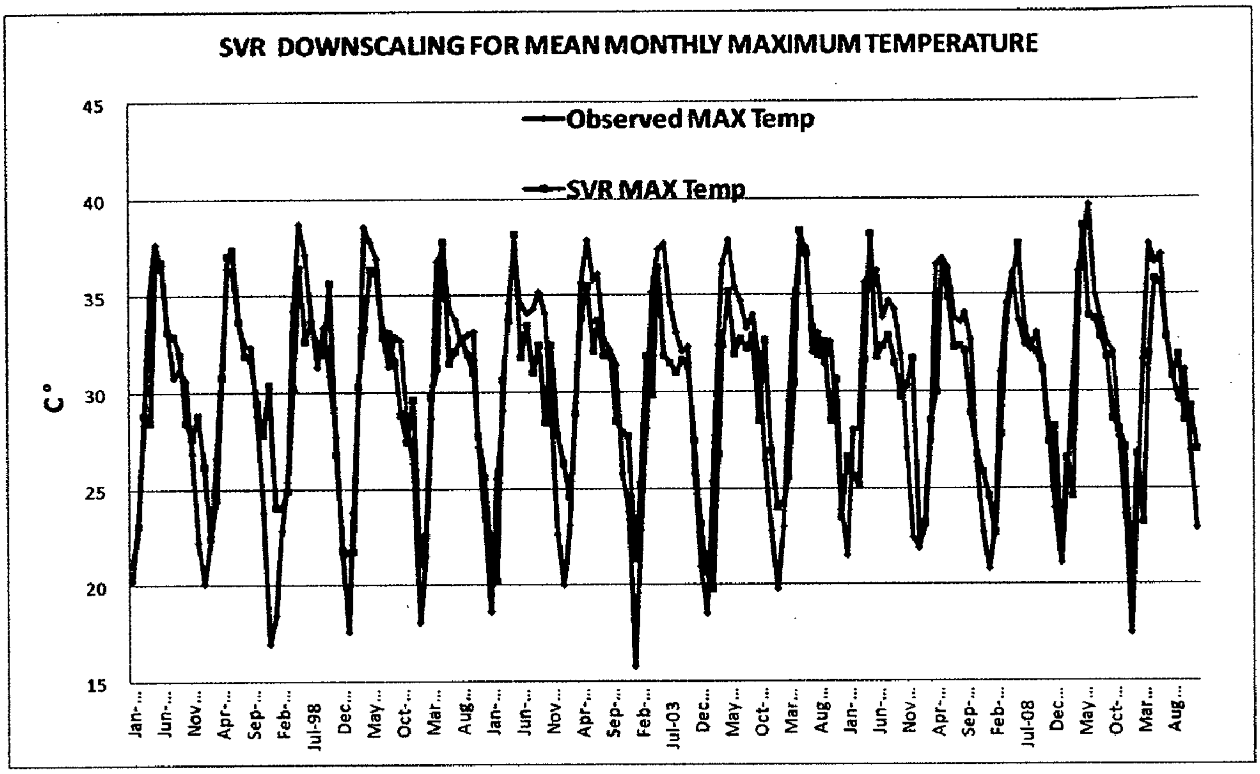


Figure 6.7

Downscaling result of mean monthly maximum temperature during the validation period using SVR method.

V1.4 COMPARISON RESULT

Table 6.16 provides the percentage of improvement result from regression model compare to SVM model in validation part. SVR model give better error measurements. Even in maximum temperature, SVR make 31.4 % improvement from MLR model. The smallest improvement is in *r* value of minimum temperature which is 4.3 %.

Table 6.16

Comparison of error measurement in validation part between MLR and SVR model

Variables	r value			NSE			RMSE		
	MLR	SVR	% of improvement	MLR	SVR	% of improvement	MLR	SVR	% of improvement
Precipitation	0.714	0.747	4.678	0.492	0.546	10.931	3.002	2.838	5.447
Minimum Temperature	0.882	0.920	4.331	0.766	0.837	9.243	3.450	2.881	16.504
Maximum Temperature	0.732	0.838	14.440	0.529	0.695	31.437	3.941	3.171	19.541

The summarize result of error measurement for SVR model is provide in table 6.17. SVR give smaller precision in validation part. The *r* and NSE value are getting smaller whereas RMSE value is getting bigger.

Table 6.17

Error measurements value of SVR model

Variables Name	Errors Measurements					
	Calibration			Validation		
	r	RMSE	NSE	r	RMSE	NSE
Precipitation	0.772	2.537	0.577	0.747	2.838	0.546
Minimum Temperature	0.939	2.632	0.860	0.920	2.881	0.837
Maximum Temperature	0.914	2.408	0.815	0.838	3.171	0.695

V1.5 FUTURE PROJECTIONS

To develop future projection, GCM data are divided into two groups with 15 years span for each group. The first group is from 2011-2025, second group from 2026-2040. For SVR model the data are computed by SVR validated model with the same value of gamma and sigma for each variable. For MLR model the data are computed by MLR validated model with the same formula for each variable.

VI.5.1 Precipitation Projection

Descriptive statistic in table 6.18 shows that mean value of SVR projection for precipitation is between 2.5 - 2.9 mm/day and 2.4 -3.2 mm/day for MLR model. From total amount of precipitation per year, one can see that for SVR model there will be increase of precipitation approximately by 0.5 – 2%. This is in accordance with Tritpathi (2006) which predicted that will precipitation increase in North India (Punjab,Haryana in the north-west,east Uttar Pradesh, west Uttar Pradesh), while MLR predict mixed trend in precipitation.

Table 6.18

Descriptive Statistic of Precipitation Projection

Descriptive statistic of precipitation (mm/day)	Observed 1996-2010	1996-2010		2011-2025		2026-2040	
		MLR	SVR	MLR	SVR	MLR	SVR
Mean	2.778	3.25	2.52	2.41	2.88	2.96	2.92
Standard Error	0.210	0.25	0.21	0.26	0.19	0.26	0.22
Median	1.015	1.61	1.09	0.82	1.39	1.30	1.35
Standard Deviation	4.049	3.39	2.83	3.54	2.60	3.54	2.94
Range	21.137	15.26	8.71	15.57	7.87	14.81	8.84
Minimum	0.000	0.11	0.12	-0.94	0.82	-0.32	0.60
Maximum	21.137	15.36	8.83	14.63	8.69	14.49	9.44
Sum (mm/year)	1048.319	1191.85	922.63	888.18	1054.52	1084.98	1070.174

Figure 6.8a it shows that MLR is reaching negative values in future projection part also it have more variation in the range value. The maximum value can be reach by 14 mm/day and the trend line is flat. The MLR seems underestimates the lower part. Figure 6.8b shows less variation in SVR. The maximum value is always below 10 mm/day. Even though in projection part, there is no negative values but still SVR cannot well compute the lowest amount of precipitation (zero value).The trend line make small positive slope.

Those results possibly happen because regression based statistical downscaling model often cannot explain entire variance of the downscaled variable (Wilby et al, 2004). The Other reason could be that by nature precipitation is much more erratic and dependant on very local factors than for the other predictand (Berastegi, 2011). Also, for precipitation the spatial variation is very large and it has very poor temporal correlation.

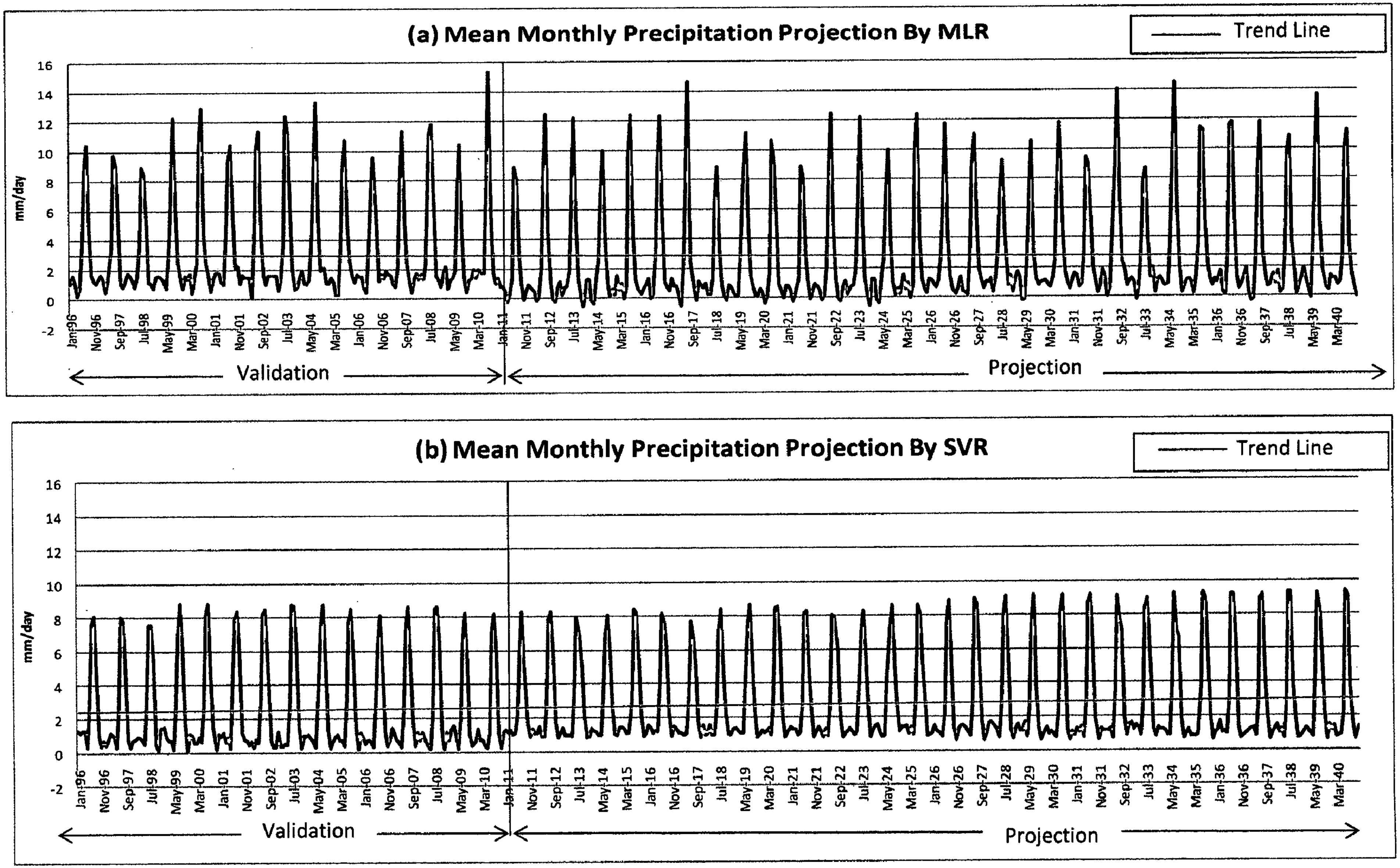


Figure 6.8 Graphical depiction of projected Precipitation. a) Using MLR, b) Using SVR

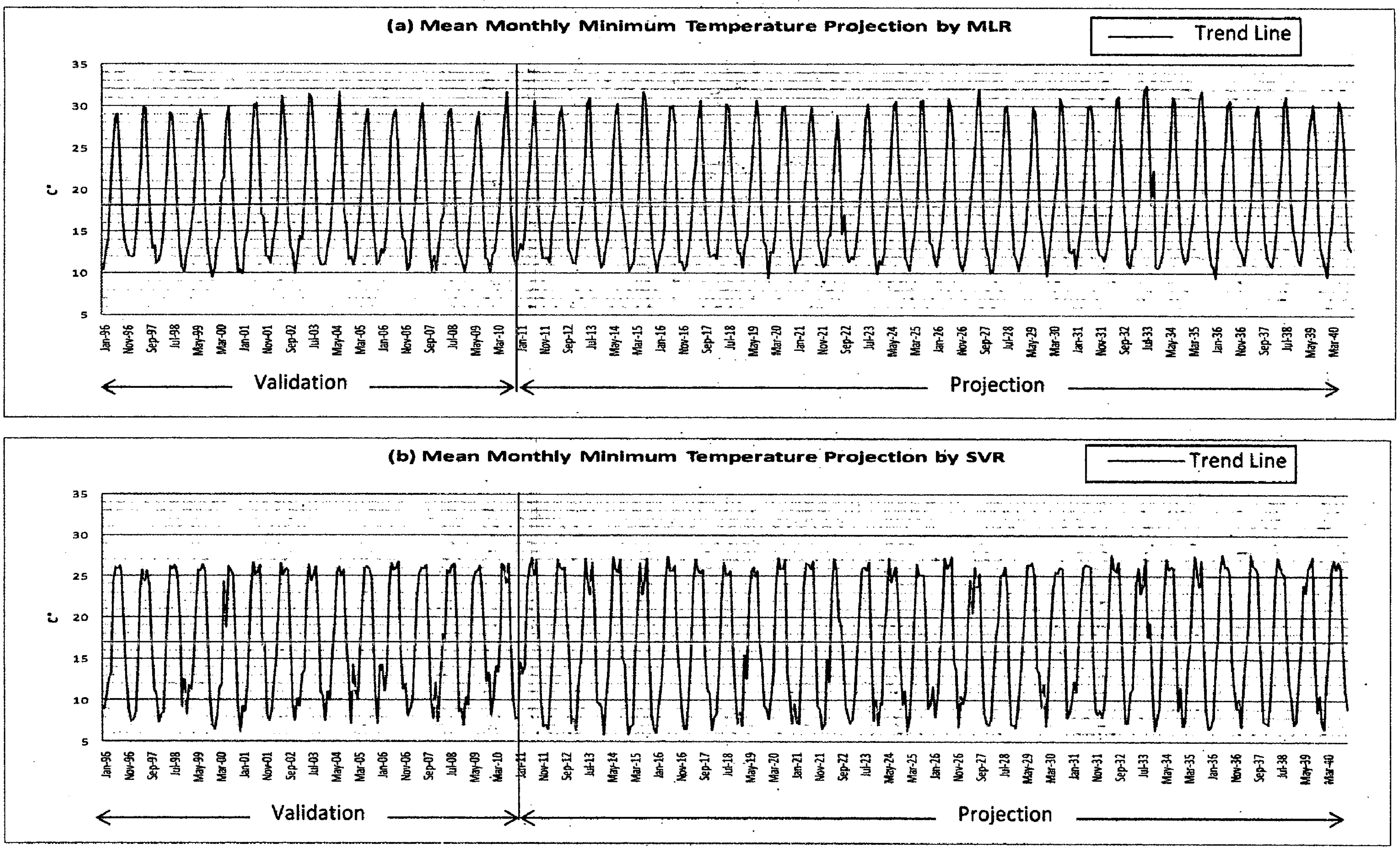


Figure 6.9 Graphical depiction of projected minimum temperature. a) Using MLR, b) Using SVR

VI.5.2 Minimum Temperature Projection

From the projection of mean monthly minimum temperature, by the SVR model one can see that there will be not much change in temperature. The mean value of SVR in table 6.19 is between 16.9- 17.2 °C and MLR the mean value increase from 18.3°C to 18.8 °C. The maximum value of MLR is approximately in 31°C same with the observed value but the minimum value is 9°C, 4°C higher than observed value. SVR have the minimum value 5-6°C, same with observed. For the maximum value, the highest prediction from SVR only 27.68°C, 4°C lower than observed.

Table 6.19

Descriptive Statistic of Minimum Temperature Projection

Descriptive Statistic of minimum temperature C°	Observed 1996-2010	1996-2010		2011-2025		2026-2040	
		MLR	SVR	MLR	SVR	MLR	SVR
Mean	17.75	18.31	17.29	18.50	16.92	18.89	17.32
Standard Error	0.53	0.51	0.53	0.51	0.57	0.53	0.56
Median	18.49	16.70	16.48	16.52	15.81	16.78	16.45
Standard Deviation	7.15	6.81	7.12	6.82	7.63	7.06	7.49
Range	26.55	22.24	20.46	22.31	21.56	23.01	21.24
Minimum	5.18	9.51	6.29	9.41	5.87	9.47	6.44
Maximum	31.72	31.75	26.74	31.71	27.43	32.47	27.68

Figure 6.9a shows the projections for minimum temperature by MLR. The highest value in projection part reach 32° and the lowest is around 7°C. The trend line increase 1°C until 2040. Figure 6.9b shows that SVR have more variation in the upper part. After validation SVR shows not much change and the trend line is flat.

VI.5.3 Maximum Temperature Projection

From the projection of mean monthly maximum temperature by SVR model one can see that there will be not much change. The mean value of the maximum temperature in table 6.20 is between 29.8 – 29.9 °C while the MLR model the mean value is between 28 – 31°C. The SVR predict the highest value of mean monthly maximum temperature until 2040 is 39.25°C, while MLR predict it will reach 42.44°C.

Table 6.20

Descriptive Statistic of Maximum Temperature Projection

Descriptive statistic of mean monthly maximum temperature °C	observed 1996-2010	1996-2010		2011-2025		2026-2040	
		MLR	SVR	MLR	SVR	MLR	SVR
Mean	30.20	28.24	29.95	31.22	29.81	32.01	29.96
Standard Error	0.43	0.50	0.33	0.34	0.40	0.36	0.42
Median	32.00	29.00	31.05	31.58	31.60	32.42	31.35
Standard Deviation	5.76	6.75	4.44	4.59	5.30	4.84	5.61
Range	23.86	23.67	18.74	20.64	19.59	20.10	20.14
Minimum	15.82	15.58	19.84	21.09	19.43	22.35	19.12
Maximum	39.68	39.25	38.58	41.72	39.02	42.44	39.25

Figure 6.10a show the projection maximum temperature by MLR model. It can be seen that the range is getting bigger the trend line increase 2°C until 2040. The highest value of SVR model is around 39°C and the lowest value reach 19°C. After validation part, there is not much change. The trend line is flat.

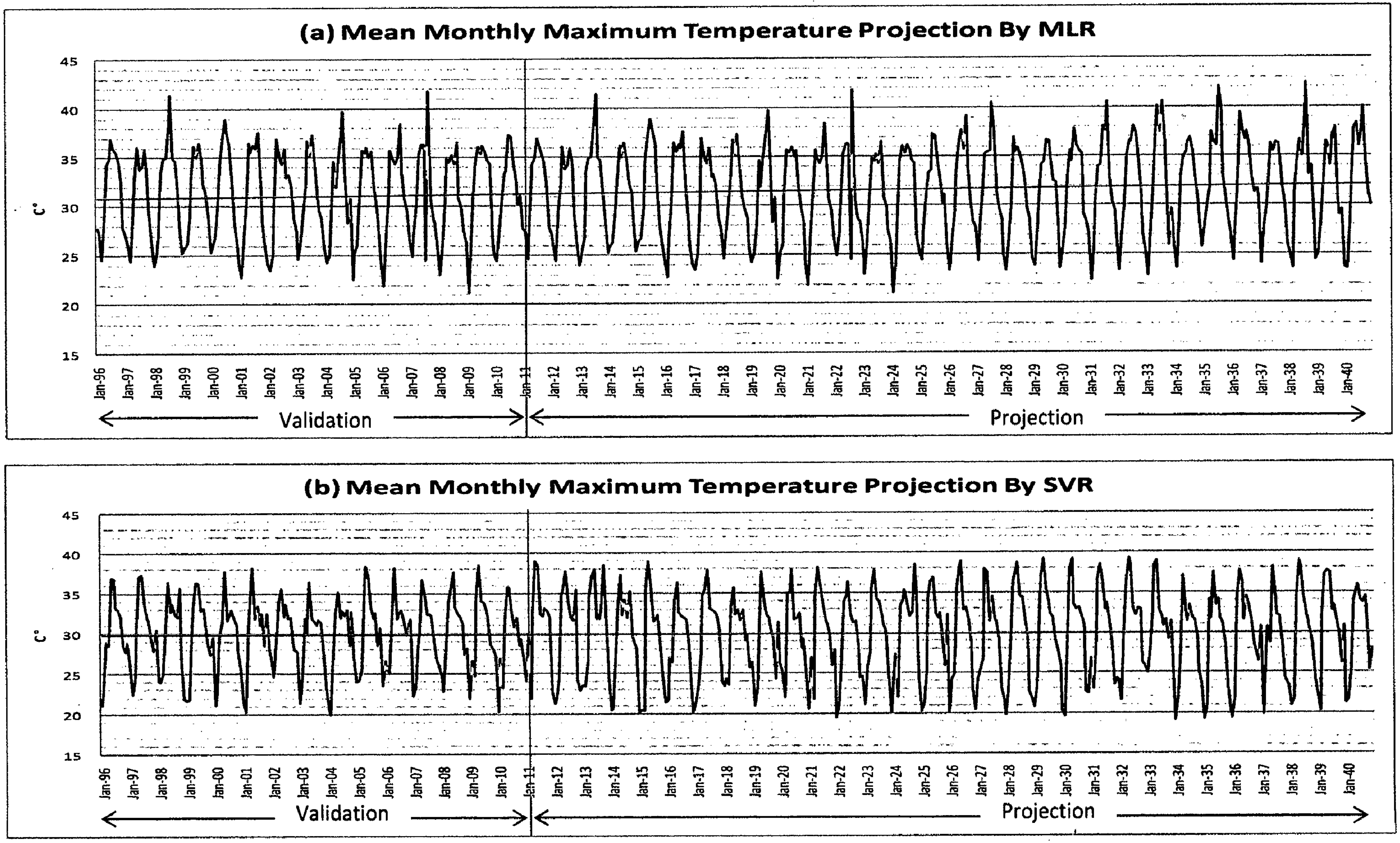


Figure 6.10 Graphical depiction of projected maximum temperature. a) Using MLR, b) Using SVR

CHAPTER VII
CONCLUSIONS

VII.1 CONCLUSIONS

This work has downscaled the climate variables in Roorkee area which are mean monthly precipitation, minimum and maximum temperature by using Support Vector Machine for Regression (SVR) and Multi linear regression (MLR) methods. Based on the result of this study, the following conclusions can be drawn:

- The best combination of predictors for downscaling precipitation for Roorkee area among the available variables are temperature, geopotential height, and specific humidity at 200 mb this means that the values refer to approximately 12,000 m height where the cumulonimbus clouds are formed. This finding is in accordance with Gadgil (2006) that most of the rain over the Indian region comes from Cumulus and Cumulonimbus clouds.
- V (Vertical) or Meridional wind influences the computations when downscaling the minimum temperatures. This probably happens because in the summer, south-west monsoon comes to Roorkee area and brings heavy rain between July and September. In the winter, north-east monsoon sweeps down from the plateaus of Asia and the Himalayas and brings rain and cooler weather between October and December.
- U (horizontal) or Zonal wind influences the computation of the maximum temperature. This probably happens because zonal wind which has west–east direction brings strong, hot "loo" and dry summer wind from the large desert regions of the northwestern Indian subcontinent (Rana, 2007).
- The result of downscaling for precipitation variable shows that SVR result are better computation than the MLR as seen by the improvement of error measurements which are 4.678 % for *r*, 10.931 % for NSE and 5.447 % for RMSE. However, from the performance indices, it can be determined that both

MLR and SVR could not well downscaled precipitation variable in Roorkee Area. The possible reason of this could be that by nature, precipitation is much more erratic and dependant on very local factors than for the other predictand (Berastegi, 2011). Also, for precipitation the spatial variation is very large and it has very poor temporal correlation. Thus, downscaling of precipitation is a challenge and more studies are needed to that.

- The result of SVR downscaling for minimum temperature shows a 4.331 % improvement in *r*, 9.243 % in NSE and 16.504 % in RMSE as compared to MLR.
- The result of SVR downscaling for maximum temperature shows a 14.440 % improvement in *r*, 31.437 % in NSE and 19.541 % in RMSE as compared to MLR.
- The result of downscaling for temperature variables shows that the maximum temperature shows better improvement when the SVR model is used rather than the minimum temperature.
- From the comparison of the results, it can be concluded that, use of SVR can improve correlation in the range 4 – 14 % than MLR, for NSE by 9 - 31 % and for RMSE by 5 – 19 %.
- From the SVR model, the future projection until 2040 for precipitation shows that there will be little increase of precipitation and the future projection for temperature shows that there will be not much change of temperature in Roorkee area.
- More research is needed to confirm these conclusions.

VII.2 SUGGESTIONS FOR FUTURE RESEARCH

- Precipitation is a very important input variable in hydrologic modeling. Long series of predictant variables and data of many related stations will be necessary to get better results from statistical downscaling of precipitation.
- It would be interesting to get more data from various GCM outputs so that other variables which are important in hydrologic modeling such as evaporation, humidity, wind speed, radiation and sunshine hours.

REFFERENCES

B.C, Hewitson, R.G Crane,1995. Climate downscaling: techniques and application, Departement of Enviromental and Geographical Sciences, University of Cape Town.

Berastegi G. Ibarra, Saenz.J, Ezcurra.A, Elias.A, Argandona.J, Errasati, 2011. Downscaling of surface moisture flux and precipitation in the Ebro Valley (spain) using analogues followed by random forests and multiple linear regression

Bernstein.L .et.al, 2007. Synthesis Report, An Assessment of the Intergovernmental Panel on Climate Change.

Charles Stephen. P, Bates Bryson .C, Peter H. Whetton, James P. Hughes, 1999. Validation of downscaling models for changed climate conditions: case study of southwestern Australia.

Chen. Shien-Tsung, Yu.Pao-Sun, Tang Ti-Hsuan, 2010. Statistical Downscaling of Daily Precipitation Using Support Vector Machine and multivariate Analysis.

Chong-Yu Xu 1999. Climate Change and Hydrologic Models: A Review of Existing Gaps and Recent Research Developments.

Dibike YB, Velickov S, Slomatine D, Abbott MB. 2001. Model induction with support vector machines: introduction and applications

De Brabanter.K, et al, 2010. LS-SVMlab Toolbox User's Guide version 1.7

Downie David.L, Brash Kate,Vaughan Kate, 2009. Climate Change : a reference handbook

Environmental Law Institute USA ,2003. Reporting on Climate Change: Understanding the Science, Third Edition

Fealy Rowan ,Sweeney John, 2010. Statistical downscaling of temperature, radiation and potential evapotranspiration to produce a multiple GCM ensemble mean for a selection of sites in Ireland.

Fowller H.J, Blenkinsop.S, Tebaldi.C,2007. Review Linking Climate change modeling to impact studies : advences in downscaling technique for hydrological modeling

Gadgil Sulochana, 2006. The Indian Monsoon, Part 1. Variations in Space and Time, Resonance, Vol.11, No.8.

Gunn Steve.R, 1998. Support Vector Machines for Classification and Regression

Hardy Jhon.T, 2003.Climate Change, Causes, effects and solutions

Hsu, Chih-Wei et al.,2004. A Practical Guide to Support Vector Classification.Department of Computer Science and Information Engineering, National Taiwan University.

IPCC Technical Paper VI 2008, Climate Change and Water.

Jain S.K, Singh V.P ,2006. Water Resources Systems Planning and Management, ELSEVIER

Kumar Satish, 2004. Neural Networks a Calssroom Approach.

Karamouz.M, Fallahi.M, Nazif.S and Farahani.M. Rahimi,2009. Long Lead Rainfall Prediction Using Statistical Downscaling and Artifcial Neural Network Modeling,

Koch Manfred ,2007. Approaches to model the impact of climate change on water resources: From the global to local scale.

Maity.P, Bhagwat et al 2010. Potential of support vector regression for prediction of monthly streamflow using endogenous property.

Mearns L.O, Giorgi.P, whetton, Pabon.D, Hulme.M, Lal.M,2007. Guidelines for use of regional climate model experiments.

Najafi M.reza, Moradkhani.H, Wherry Susan, 2010. Statistical Downscaling of Precipitation using Machine Learning with Optimal Predictor Selection

Nabney I.T., 2002. Netlab: Algorithms for Pattern Recognition, Springer.

Nugroho Anto Satriyo, Witarto Arief Budi, Handoko Dwi, 2003. Support Vector Machine. Bioteknologi LIPI Indonesia

Osuna, Edgar E. et. Al, 1997. Support Vector machines: Training and Applications.MIT.

Pelckmans Kristiaan, Suykens Johan A.K. , Van Gestel. T, De Brabanter.J, L. Lukas, Hamers. B, De Moor and J.Vandewalle , LS-SVMlab: a MATLAB/C toolbox for Least Squares Support Vector Machines.

Pidwirny.M, Scott Jones.S, 1999. Fundamentals of Physical Geography, University of British Columbia Okanagan. www.physicalgeography.net

Rana S.V.S.,2007. Essentials of Ecology and Environmental Science, Prentice Hall of India, ISBN 8120333004

R.L Wilby, SP Charles, E Zorita, B Timbal, P Whetton, LO Mearns,2004. Guidelines for Use of Climate Scenarios Developed From Statistical Methods.

Santosa Budi,2007. Data Mining Terapan Dengan MATLAB.

Santosa Budi,2008. MATLAB untuk Statistika dan Teknik Optimasi .

Sembiring Krisantus ,2007. Penerapan Teknik Support Vector Machine Pada Pendeteksian Intrusi Pada Jaringan. Institute Technology Bandung. Indonesia

Shivam Tripathi, V.V Srinivas, Ravi S.Nanjundiah, 2006. Downscaling of Precipitation for climate change scenario: A support Vector Machine Approach.

Smola A. J, 1996. Regression estimation with support vector learning machines. Master's thesis, Technische Universit¨at M¨unchen.

Soman.K.P, Loganathan.R, V. Ajay, 2009 . Maching learning with SVM and other Kernel Method.

Suykens JAK, Vandewalle J. 1999. Least squares support vector machine classifiers. Neural Processing Letters

Turner.J, et al, 2004. Antarctic Climate Change during the last 50 years.

Vapnik, V., 1995. The Nature of Statistical Learning Theory.Springer-Verlag. New York

Vapnik, V., S. Golowich, A.Smola, 1996. Support vector method for function approximation, regression estimation, and signal processing.

Wang Xiao Hu, 2006. Financial Management in the Public Sector, ME Sharpe New York, USA

APPENDIX A

MULTI LINEAR REGRESSION

PRECIPITATION DATA (CALIBRATION)

PRECIPITATION

NO	Month	Observed Mean Mothly precipitation (Y)	200Mb Temp GCM (X1)	200Mb GPH GCM (X2)	200Mb SpecHum GCM (X3)
1	Jan-81	2.268	-56.898	11941.700	0.025
2	Feb-81	0.361	-57.503	11917.900	0.025
3	Mar-81	0.661	-57.989	12010.800	0.030
4	Apr-81	0.207	-58.716	12044.400	0.041
5	May-81	1.448	-56.976	12174.000	0.069
6	Jun-81	8.200	-53.830	12274.700	0.046
7	Jul-81	12.070	-49.148	12457.300	0.091
8	Aug-81	4.297	-48.848	12485.700	0.118
9	Sep-81	7.720	-51.978	12426.500	0.076
10	Oct-81	0.000	-54.240	12283.600	0.042
11	Nov-81	1.593	-56.047	12143.900	0.047
12	Dec-81	0.123	-57.074	12060.700	0.038
13	Jan-82	1.990	-55.973	11972.400	0.026
14	Feb-82	0.679	-56.757	11977.500	0.036
15	Mar-82	4.965	-57.145	12009.900	0.036
16	Apr-82	1.803	-57.128	12045.200	0.039
17	May-82	0.858	-57.315	12150.100	0.047
18	Jun-82	3.500	-53.622	12293.400	0.052
19	Jul-82	5.961	-48.497	12471.300	0.144
20	Aug-82	5.503	-48.622	12484.600	0.188
21	Sep-82	0.200	-51.205	12417.800	0.067
22	Oct-82	0.000	-54.742	12278.100	0.039
23	Nov-82	0.000	-55.970	12176.600	0.039
24	Dec-82	1.152	-56.708	12010.600	0.031
25	Jan-83	4.058	-55.561	11993.000	0.027
26	Feb-83	0.193	-55.905	12014.700	0.025
27	Mar-83	0.284	-56.674	12008.600	0.035
28	Apr-83	3.131	-58.517	12075.400	0.037
29	May-83	0.917	-57.212	12184.000	0.051
30	Jun-83	3.446	-53.963	12326.200	0.045
31	Jul-83	4.254	-48.756	12462.100	0.117
32	Aug-83	14.645	-48.205	12501.900	0.177
33	Sep-83	3.666	-51.792	12433.200	0.075
34	Oct-83	0.403	-53.765	12257.600	0.041
35	Nov-83	0.000	-55.921	12127.000	0.036
36	Dec-83	1.265	-57.918	12007.000	0.029
37	Jan-84	1.065	-56.701	12025.800	0.037
38	Feb-84	3.804	-56.214	12002.400	0.030
39	Mar-84	0.000	-56.288	11953.200	0.035
40	Apr-84	0.000	-58.221	12047.800	0.043
41	May-84	1.570	-56.379	12135.000	0.043
42	Jun-84	6.517	-53.539	12332.300	0.066
43	Jul-84	8.662	-48.601	12467.700	0.140
44	Aug-84	8.662	-47.915	12508.300	0.167
45	Sep-84	2.680	-51.802	12411.100	0.095
46	Oct-84	0.000	-53.904	12293.600	0.036
47	Nov-84	0.130	-55.824	12117.300	0.036
48	Dec-84	0.010	-56.924	12009.400	0.034
49	Jan-85	0.281	-56.799	11999.200	0.039
50	Feb-85	0.000	-55.953	12059.100	0.035
51	Mar-85	0.000	-57.600	11960.300	0.033
52	Apr-85	0.463	-58.656	12043.700	0.045
53	May-85	0.290	-57.624	12173.400	0.050
54	Jun-85	2.736	-53.238	12353.500	0.052
55	Jul-85	7.668	-49.583	12459.100	0.115
56	Aug-85	13.814	-47.832	12506.200	0.197
57	Sep-85	3.780	-51.628	12423.600	0.067
58	Oct-85	2.916	-54.630	12303.100	0.054
59	Nov-85	0.000	-55.380	12182.200	0.057
60	Dec-85	1.739	-56.966	12045.400	0.035

NO	Month	Observed Mean Mothly precipitation (Y)	200Mb Temp GCM (X1)	200Mb GPH GCM (X2)	200Mb SpecHum GCM (X3)
61	Jan-86	0.165	-54.962	12035.400	0.029
62	Feb-86	2.171	-55.562	11957.900	0.024
63	Mar-86	0.587	-57.438	11965.600	0.031
64	Apr-86	0.407	-59.273	12003.400	0.035
65	May-86	1.923	-57.393	12182.000	0.043
66	Jun-86	1.481	-52.603	12359.300	0.081
67	Jul-86	3.610	-48.675	12456.800	0.146
68	Aug-86	6.013	-48.394	12503.100	0.190
69	Sep-86	2.027	-51.556	12402.000	0.073
70	Oct-86	2.467	-53.966	12283.300	0.053
71	Nov-86	0.000	-56.298	12113.100	0.034
72	Dec-86	1.003	-57.313	11981.100	0.034
73	Jan-87	1.065	-57.729	11950.700	0.022
74	Feb-87	1.346	-56.195	11991.200	0.026
75	Mar-87	0.787	-56.972	11992.300	0.028
76	Apr-87	0.193	-58.356	11998.900	0.038
77	May-87	3.668	-56.598	12211.200	0.055
78	Jun-87	4.042	-53.099	12317.300	0.057
79	Jul-87	1.565	-48.873	12484.600	0.108
80	Aug-87	4.365	-47.166	12511.100	0.217
81	Sep-87	0.960	-51.563	12412.400	0.076
82	Oct-87	0.161	-53.989	12295.100	0.046
83	Nov-87	0.000	-55.985	12094.000	0.036
84	Dec-87	0.294	-56.736	12047.000	0.035
85	Jan-88	0.000	-57.044	11957.900	0.027
86	Feb-88	2.258	-58.558	11946.700	0.027
87	Mar-88	1.248	-56.982	11965.000	0.036
88	Apr-88	0.417	-56.679	12050.800	0.044
89	May-88	0.206	-57.833	12123.400	0.050
90	Jun-88	1.739	-53.832	12314.400	0.062
91	Jul-88	15.732	-48.205	12484.100	0.131
92	Aug-88	15.839	-48.852	12481.000	0.144
93	Sep-88	9.387	-51.710	12425.200	0.082
94	Oct-88	0.000	-54.222	12239.800	0.034
95	Nov-88	0.000	-56.098	12128.200	0.044
96	Dec-88	0.419	-57.682	12010.900	0.045
97	Jan-89	3.294	-56.961	11943.800	0.025
98	Feb-89	0.132	-56.569	11975.200	0.034
99	Mar-89	0.052	-58.157	11973.800	0.040
100	Apr-89	0.073	-58.191	11995.600	0.036
101	May-89	0.413	-57.293	12165.200	0.042
102	Jun-89	2.184	-52.940	12353.800	0.065
103	Jul-89	8.639	-49.196	12442.300	0.139
104	Aug-89	11.894	-49.106	12475.100	0.156
105	Sep-89	11.404	-51.613	12402.100	0.070
106	Oct-89	0.000	-54.001	12274.500	0.040
107	Nov-89	0.360	-56.388	12140.100	0.055
108	Dec-89	2.258	-56.985	11969.700	0.032
109	Jan-90	1.084	-57.190	11982.400	0.036
110	Feb-90	4.723	-56.089	12038.400	0.029
111	Mar-90	1.729	-56.549	12035.900	0.040
112	Apr-90	2.071	-57.899	12034.000	0.040
113	May-90	2.071	-56.941	12161.700	0.049
114	Jun-90	0.800	-52.272	12368.500	0.063
115	Jul-90	10.900	-47.901	12499.200	0.142
116	Aug-90	12.310	-47.706	12510.500	0.271
117	Sep-90	3.715	-51.648	12421.400	0.077
118	Oct-90	0.087	-54.242	12286.600	0.056
119	Nov-90	0.520	-54.203	12206.500	0.041
120	Dec-90	2.642	-57.519	12042.900	0.048

NO	Month	Observed Mean Mothly precipitation (Y)	200Mb Temp GCM (X1)	200Mb GPH GCM (X2)	200Mb SpecHum GCM (X3)
121	Jan-91	0.000	-55.543	12035.000	0.038
122	Feb-91	0.739	-56.153	12013.300	0.037
123	Mar-91	0.606	-56.721	11969.500	0.032
124	Apr-91	0.813	-58.040	12061.800	0.049
125	May-91	0.000	-57.041	12154.300	0.062
126	Jun-91	2.903	-53.063	12345.200	0.061
127	Jul-91	6.642	-48.426	12489.900	0.148
128	Aug-91	5.342	-47.910	12504.500	0.185
129	Sep-91	7.857	-51.089	12436.500	0.078
130	Oct-91	0.000	-54.367	12279.400	0.044
131	Nov-91	0.567	-56.764	12117.400	0.044
132	Dec-91	1.532	-57.388	12014.700	0.034
133	Jan-92	1.371	-57.105	11973.800	0.036
134	Feb-92	2.317	-55.563	11969.800	0.025
135	Mar-92	0.165	-56.737	11992.400	0.038
136	Apr-92	0.000	-56.767	12029.300	0.044
137	May-92	1.390	-56.930	12154.200	0.045
138	Jun-92	1.290	-52.012	12372.000	0.071
139	Jul-92	4.090	-48.026	12513.100	0.131
140	Aug-92	15.790	-47.323	12523.300	0.148
141	Sep-92	0.010	-51.434	12438.100	0.072
142	Oct-92	0.039	-54.392	12302.500	0.058
143	Nov-92	0.043	-56.360	12098.500	0.037
144	Dec-92	0.000	-57.923	12012.300	0.032
145	Jan-93	0.255	-54.997	11980.500	0.028
146	Feb-93	1.036	-56.339	11958.300	0.036
147	Mar-93	3.816	-56.785	12022.100	0.027
148	Apr-93	1.620	-57.365	12072.700	0.042
149	May-93	1.000	-57.006	12151.400	0.042
150	Jun-93	1.000	-52.302	12360.700	0.048
151	Jul-93	1.753	-49.237	12438.500	0.104
152	Aug-93	3.055	-48.979	12487.400	0.146
153	Sep-93	5.553	-51.344	12421.300	0.104
154	Oct-93	0.000	-54.445	12251.500	0.048
155	Nov-93	0.000	-55.830	12103.500	0.033
156	Dec-93	0.000	-56.988	11987.300	0.024
157	Jan-94	1.026	-56.644	11940.600	0.032
158	Feb-94	2.057	-55.748	12024.400	0.032
159	Mar-94	0.077	-56.416	11987.800	0.035
160	Apr-94	1.137	-57.754	12033.500	0.037
161	May-94	1.129	-56.924	12117.600	0.049
162	Jun-94	1.129	-53.112	12334.900	0.048
163	Jul-94	12.793	-48.828	12475.100	0.122
164	Aug-94	12.480	-48.123	12508.600	0.175
165	Sep-94	1.313	-51.761	12423.700	0.065
166	Oct-94	0.000	-54.071	12328.000	0.049
167	Nov-94	0.000	-55.911	12148.900	0.042
168	Dec-94	0.000	-57.232	12000.100	0.030
169	Jan-95	2.223	-56.108	11977.100	0.032
170	Feb-95	5.021	-56.053	11943.100	0.032
171	Mar-95	0.077	-56.892	11936.700	0.026
172	Apr-95	0.207	-57.514	12067.500	0.043
173	May-95	0.000	-56.537	12166.500	0.051
174	Jun-95	0.000	-52.305	12350.000	0.049
175	Jul-95	17.229	-48.235	12484.800	0.159
176	Aug-95	17.229	-48.273	12491.100	0.194
177	Sep-95	1.313	-51.410	12435.200	0.091
178	Oct-95	0.000	-53.457	12317.900	0.046
179	Nov-95	0.040	-56.540	12107.700	0.048
180	Dec-95	0.029	-56.677	12031.300	0.026

	Coefficients
Intercept	104.501
200Mb Temp GCM (X1)	0.613
200Mb GPH GCM (X2)	-0.006
200Mb SpecHum GCM (X3)	45.053

PRECIPITATION

PRECIPITATION DATA (VALIDATION)

NO	Month	Observed Mean Mothly precipitation (Y)	200Mb Temp GCM (X1)	200Mb GPH GCM (X2)	200Mb SpecHum GCM (X3)	Y REG	Y- Yreg	Y - Ymean	$(Y- Yreg)^2$	$(Y - Ymean)^2$
1	Jan-96	1.087	-56.583	11974.800	0.026	1.070	0.017	-1.769	0.000	3.131
2	Feb-96	4.000	-56.646	11977.400	0.039	1.568	2.432	1.143	5.917	1.308
3	Mar-96	0.294	-56.861	11976.100	0.031	1.081	-0.788	-2.563	0.621	6.569
4	Apr-96	0.007	-58.487	12037.300	0.041	0.183	-0.177	-2.850	0.031	8.122
5	May-96	0.245	-56.814	12176.000	0.048	0.729	-0.484	-2.611	0.235	6.819
6	Jun-96	3.306	-52.202	12387.900	0.074	3.492	-0.186	0.450	0.035	0.202
7	Jul-96	5.168	-48.091	12502.800	0.147	8.640	-3.472	2.311	12.057	5.342
8	Aug-96	15.119	-46.733	12528.600	0.172	10.442	4.677	12.263	21.877	150.377
9	Sep-96	4.307	-51.815	12430.800	0.102	4.739	-0.433	1.450	0.187	2.103
10	Oct-96	2.045	-53.627	12299.100	0.042	1.671	0.374	-0.811	0.140	0.658
11	Nov-96	0.000	-56.794	12136.700	0.054	1.236	-1.236	-2.857	1.529	8.160
12	Dec-96	0.000	-56.850	12045.300	0.039	1.058	-1.058	-2.857	1.119	8.160
13	Jan-97	0.613	-56.194	12065.400	0.040	1.398	-0.785	-2.244	0.617	5.034
14	Feb-97	0.136	-55.083	12031.600	0.026	1.650	-1.514	-2.721	2.293	7.403
15	Mar-97	0.177	-56.788	11987.100	0.037	1.354	-1.176	-2.679	1.384	7.178
16	Apr-97	1.993	-58.005	12059.600	0.043	0.448	1.545	-0.863	2.386	0.746
17	May-97	0.487	-56.424	12168.500	0.054	1.297	-0.810	-2.369	0.657	5.614
18	Jun-97	1.200	-52.225	12365.600	0.068	3.349	-2.149	-1.657	4.618	2.744
19	Jul-97	10.542	-47.691	12499.000	0.166	9.761	0.781	7.685	0.610	59.066
20	Aug-97	8.381	-48.011	12504.100	0.155	9.032	-0.651	5.524	0.424	30.516
21	Sep-97	11.973	-50.606	12433.200	0.090	4.934	7.039	9.117	49.549	83.116
22	Oct-97	2.161	-54.322	12310.700	0.039	1.070	1.091	-0.695	1.190	0.483
23	Nov-97	3.016	-56.752	12122.800	0.041	0.774	2.242	0.160	5.025	0.025
24	Dec-97	3.016	-56.732	12043.000	0.042	1.260	1.756	0.160	3.083	0.025
25	Jan-98	0.103	-55.880	12022.300	0.039	1.779	-1.676	-2.753	2.809	7.581
26	Feb-98	0.893	-55.706	12005.300	0.030	1.602	-0.709	-1.964	0.502	3.856
27	Mar-98	2.587	-56.418	12010.600	0.035	1.329	1.258	-0.269	1.582	0.073
28	Apr-98	2.937	-57.269	12054.000	0.040	0.785	2.152	0.080	4.630	0.006
29	May-98	1.045	-56.054	12225.200	0.063	1.564	-0.519	-1.811	0.269	3.281
30	Jun-98	1.045	-51.373	12379.100	0.061	3.480	-2.435	-1.811	5.931	3.281
31	Jul-98	8.219	-47.683	12486.900	0.145	8.891	-0.671	5.363	0.450	28.760
32	Aug-98	13.407	-48.044	12516.200	0.143	8.392	5.014	10.550	25.143	111.305
33	Sep-98	2.493	-50.819	12458.100	0.099	5.053	-2.559	-0.363	6.549	0.132
34	Oct-98	4.690	-54.190	12263.600	0.033	1.124	3.566	1.834	12.719	3.363
35	Nov-98	0.000	-56.011	12159.400	0.043	1.093	-1.093	-2.857	1.195	8.160
36	Dec-98	0.000	-57.541	11976.100	0.033	0.753	-0.753	-2.857	0.567	8.160
37	Jan-99	2.648	-56.427	11948.700	0.031	1.511	1.137	-0.208	1.293	0.043
38	Feb-99	0.064	-56.040	12009.800	0.035	1.590	-1.526	-2.792	2.329	7.797
39	Mar-99	0.000	-56.136	12033.100	0.038	1.531	-1.531	-2.857	2.345	8.160
40	Apr-99	0.000	-56.497	12035.200	0.038	1.297	-1.297	-2.857	1.684	8.160
41	May-99	0.974	-56.378	12181.100	0.043	0.751	0.223	-1.882	0.050	3.543
42	Jun-99	0.974	-52.077	12361.400	0.062	3.189	-2.215	-1.882	4.907	3.543
43	Jul-99	9.155	-47.299	12504.600	0.103	7.102	2.053	6.298	4.213	39.669
44	Aug-99	5.661	-47.433	12525.600	0.222	12.261	-6.600	2.805	43.558	7.867
45	Sep-99	6.347	-50.795	12456.900	0.119	5.958	0.389	3.490	0.151	12.181
46	Oct-99	0.219	-53.123	12339.200	0.057	2.455	-2.235	-2.637	4.997	6.955
47	Nov-99	0.000	-55.341	12163.500	0.042	1.426	-1.426	-2.857	2.033	8.160
48	Dec-99	0.077	-57.294	12003.700	0.032	0.709	-0.631	-2.779	0.398	7.723
49	Jan-00	1.416	-55.756	11992.500	0.028	1.564	-0.148	-1.440	0.022	2.075
50	Feb-00	0.323	-55.889	12051.600	0.034	1.402	-1.079	-2.534	1.164	6.421
51	Mar-00	8.000	-56.477	12064.400	0.051	1.736	6.264	5.143	39.236	26.455
52	Apr-00	0.100	-57.614	12050.100	0.035	0.403	-0.303	-2.757	0.092	7.598
53	May-00	1.974	-55.469	12269.800	0.058	1.471	0.504	-0.882	0.254	0.779
54	Jun-00	12.717	-52.263	12382.800	0.050	2.398	10.319	9.861	106.477	97.234
55	Jul-00	13.063	-47.175	12505.700	0.170	10.202	2.862	10.207	8.190	104.179
56	Aug-00	15.813	-47.375	12512.000	0.233	12.890	2.923	12.956	8.543	167.868
57	Sep-00	3.803	-51.107	12445.200	0.085	4.325	-0.522	0.947	0.272	0.896
58	Oct-00	0.000	-53.986	12324.300	0.066	2.402	-2.402	-2.857	5.768	8.160
59	Nov-00	0.000	-54.819	12191.000	0.041	1.553	-1.553	-2.857	2.411	8.160
60	Dec-00	0.000	-57.381	12012.900	0.030	0.511	-0.511	-2.857	0.261	8.160

NO	Month	Observed Mean Mothly precipitation (Y)	200Mb Temp GCM (X1)	200Mb GPH GCM (X2)	200Mb SpecHum GCM (X3)	Y REG	Y- Yreg	Y - Ymean	$(Y- Yreg)^2$	$(Y - Ymean)^2$
61	Jan-01	0.535	-56.102	12000.300	0.031	1.413	-0.877	-2.321	0.770	5.387
62	Feb-01	0.648	-55.993	11978.100	0.034	1.752	-1.103	-2.208	1.217	4.876
63	Mar-01	0.000	-55.508	12037.100	0.036	1.783	-1.783	-2.857	3.180	8.160
64	Apr-01	0.347	-57.088	12027.700	0.043	1.198	-0.851	-2.510	0.725	6.299
65	May-01	0.942	-56.338	12181.800	0.048	0.987	-0.045	-1.915	0.002	3.666
66	Jun-01	7.660	-51.896	12405.400	0.095	4.513	3.147	4.803	9.903	23.073
67	Jul-01	9.519	-48.101	12497.700	0.161	9.263	0.256	6.663	0.066	44.393
68	Aug-01	5.342	-48.870	12483.700	0.195	10.422	-5.080	2.485	25.807	6.177
69	Sep-01	0.010	-50.357	12449.700	0.101	5.454	-5.444	-2.847	29.637	8.103
70	Oct-01	0.227	-53.586	12301.500	0.051	2.087	-1.861	-2.630	3.462	6.916
71	Nov-01	0.093	-55.378	12243.300	0.070	2.220	-2.127	-2.763	4.523	7.635
72	Dec-01	0.090	-56.512	12040.500	0.033	1.037	-0.947	-2.766	0.897	7.652
73	Jan-02	0.619	-55.179	12077.500	0.034	1.672	-1.053	-2.237	1.108	5.005
74	Feb-02	0.510	-56.080	12042.500	0.038	1.481	-0.971	-2.347	0.944	5.508
75	Mar-02	0.000	-55.829	12088.300	0.040	1.459	-1.459	-2.857	2.128	8.160
76	Apr-02	0.014	-56.950	12046.400	0.049	1.454	-1.441	-2.843	2.075	8.081
77	May-02	1.639	-57.521	12133.000	0.038	0.107	1.532	-1.218	2.346	1.483
78	Jun-02	2.903	-52.063	12366.600	0.075	3.727	-0.824	0.047	0.679	0.002
79	Jul-02	1.290	-47.649	12500.500	0.174	10.137	-8.846	-1.566	78.260	2.453
80	Aug-02	9.445	-47.215	12509.400	0.196	11.315	-1.869	6.589	3.495	43.410
81	Sep-02	14.113	-52.028	12399.600	0.094	4.423	9.690	11.257	93.899	126.716
82	Oct-02	0.774	-54.226	12284.900	0.047	1.639	-0.865	-2.082	0.748	4.336
83	Nov-02	0.000	-56.633	12128.700	0.045	0.977	-0.977	-2.857	0.954	8.160
84	Dec-02	0.090	-55.710	12092.800	0.042	1.603	-1.512	-2.766	2.287	7.652
85	Jan-03	0.906	-56.006	11971.100	0.029	1.572	-0.665	-1.950	0.443	3.803
86	Feb-03	0.587	-55.869	12082.300	0.042	1.582	-0.995	-2.269	0.989	5.150
87	Mar-03	0.000	-55.802	12078.000	0.040	1.567	-1.567	-2.857	2.457	8.160
88	Apr-03	0.014	-56.654	12076.000	0.031	0.632	-0.618	-2.843	0.382	8.081
89	May-03	0.161	-55.939	12223.300	0.059	1.463	-1.301	-2.695	1.694	7.264
90	Jun-03	2.017	-52.793	12375.200	0.079	3.420	-1.403	-0.840	1.969	0.705
91	Jul-03	7.213	-47.163	12511.700	0.220	12.413	-5.200	4.356	27.040	18.978
92	Aug-03	10.290	-48.241	12507.000	0.209	11.284	-0.993	7.434	0.986	55.261
93	Sep-03	6.777	-50.374	12471.400	0.120	6.189	0.588	3.920	0.346	15.367
94	Oct-03	0.000	-53.428	12340.700	0.050	1.932	-1.932	-2.857	3.732	8.160
95	Nov-03	0.071	-55.883	12127.100	0.028	0.690	-0.619	-2.786	0.383	7.759
96	Dec-03	0.058	-56.796	12013.300	0.029	0.822	-0.764	-2.798	0.584	7.831
97	Jan-04	1.248	-56.102	12003.200	0.032	1.458	-0.209	-1.608	0.044	2.586
98	Feb-04	0.000	-56.145	11990.500	0.042	1.936	-1.936	-2.857	3.749	8.160
99	Mar-04	0.000	-56.801	12020.900	0.036	1.076	-1.076	-2.857	1.159	8.160
100	Apr-04	0.953	-56.973	12059.900	0.041	1.002	-0.048	-1.903	0.002	3.622
101	May-04	0.665	-56.490	12171.100	0.056	1.334	-0.669	-2.192	0.448	4.805
102	Jun-04	1.767	-51.881	12349.100	0.064	3.455	-1.688	-1.090	2.850	1.188
103	Jul-04	9.219	-47.770	12492.100	0.137	8.433	0.786	6.363	0.618	40.486
104	Aug-04	9.897	-46.577	12537.400	0.235	13.334	-3.438	7.040	11.817	49.565
105	Sep-04	1.167	-50.639	12448.600	0.099	5.238	-4.072	-1.690	16.577	2.856
106	Oct-04	0.000	-53.480	12320.600	0.048	1.938	-1.938	-2.857	3.757	8.160
107	Nov-04	0.173	-55.045	12172.500	0.054	2.121	-1.948	-2.683	3.793	7.200
108	Dec-04	0.052	-56.810	12058.400	0.039	1.030	-0.978	-2.805	0.957	7.866
109	Jan-05	1.248	-56.901	12021.800	0.036	1.036	0.212	-1.608	0.045	2.586
110	Feb-05	2.455	-56.002	11997.600	0.030	1.463	0.992	-0.402	0.985	0.161
111	Mar-05	0.000	-56.537	12041.200	0.036	1.160	-1.160	-2.857	1.346	8.160
112	Apr-05	0.000	-57.663	12088.200	0.039	0.291	-0.291	-2.857	0.085	8.160
113	May-05	0.694	-57.070	12179.300	0.043	0.304	0.389	-2.163	0.152	4.678
114	Jun-05	2.990	-52.323	12380.200	0.071	3.338	-0.347	0.134	0.121	0.018
115	Jul-05	7.648	-48.306	12496.000	0.150	8.646	-0.998	4.792	0.995	22.962
116	Aug-05	6.829	-47.888	12514.700	0.193	10.767	-3.938	3.973	15.509	15.781
117	Sep-05	12.553	-50.267	12473.100	0.093	5.035	7.519	9.697	56.532	94.028
118	Oct-05	0.226	-53.975	12313.000	0.066	2.495	-2.270	-2.631	5.151	6.921
119	Nov-05	0.100	-55.422	12124.500	0.041	1.579	-1.479	-2.757	2.189	7.598
120	Dec-05	0.000	-56.963	11984.300	0.035	1.145	-1.145	-2.857	1.311	8.160

NO	Month	Observed Mean Mothly precipitation (Y)	200Mb Temp GCM (X1)	200Mb GPH GCM (X2)	200Mb SpecHum GCM (X3)	Y REG	Y- Yreg	Y - Ymean	$(Y-Yreg)^2$	$(Y-Ymean)^2$
121	Jan-06	0.258	-56.087	12008.000	0.036	1.625	-1.367	-2.598	1.870	6.752
122	Feb-06	0.881	-55.438	12060.700	0.032	1.525	-0.645	-1.976	0.416	3.904
123	Mar-06	0.000	-56.498	12032.800	0.043	1.544	-1.544	-2.857	2.383	8.160
124	Apr-06	0.000	-57.273	12066.400	0.041	0.756	-0.756	-2.857	0.572	8.160
125	May-06	3.306	-56.796	12183.200	0.041	0.376	2.930	0.450	8.587	0.202
126	Jun-06	2.687	-52.780	12385.300	0.075	3.207	-0.521	-0.170	0.271	0.029
127	Jul-06	13.000	-46.978	12492.000	0.087	6.680	6.320	10.143	39.943	102.890
128	Aug-06	2.258	-47.804	12523.700	0.167	9.574	-7.316	-0.598	53.521	0.358
129	Sep-06	1.313	-51.428	12433.200	0.106	5.138	-3.824	-1.543	14.626	2.381
130	Oct-06	1.661	-53.685	12339.400	0.038	1.223	0.438	-1.195	0.192	1.429
131	Nov-06	0.000	-56.370	12110.900	0.054	1.628	-1.628	-2.857	2.652	8.160
132	Dec-06	0.210	-56.687	12039.300	0.043	1.376	-1.166	-2.647	1.360	7.006
133	Jan-07	0.232	-55.704	11949.200	0.030	1.933	-1.701	-2.624	2.892	6.887
134	Feb-07	1.397	-56.127	11983.800	0.034	1.618	-0.221	-1.460	0.049	2.131
135	Mar-07	10.400	-56.237	12033.400	0.041	1.602	8.798	7.543	77.413	56.904
136	Apr-07	1.153	-57.192	12089.500	0.047	0.974	0.180	-1.703	0.032	2.901
137	May-07	1.200	-56.604	12191.600	0.049	0.791	0.409	-1.657	0.167	2.744
138	Jun-07	5.830	-52.533	12386.300	0.047	2.078	3.752	2.973	14.077	8.842
139	Jul-07	2.258	-47.929	12496.000	0.125	7.792	-5.534	-0.598	30.627	0.358
140	Aug-07	9.181	-47.649	12529.300	0.204	11.310	-2.129	6.324	4.534	39.994
141	Sep-07	1.407	-50.830	12425.500	0.101	5.344	-3.937	-1.450	15.501	2.102
142	Oct-07	0.000	-52.873	12348.300	0.051	2.275	-2.275	-2.857	5.174	8.160
143	Nov-07	0.097	-56.746	12118.100	0.050	1.206	-1.109	-2.760	1.229	7.616
144	Dec-07	0.135	-57.356	12008.000	0.027	0.431	-0.296	-2.721	0.088	7.404
145	Jan-08	0.077	-56.311	12029.700	0.035	1.319	-1.241	-2.779	1.541	7.723
146	Feb-08	0.000	-55.442	11985.700	0.027	1.731	-1.731	-2.857	2.995	8.160
147	Mar-08	0.000	-56.798	12058.100	0.045	1.293	-1.293	-2.857	1.673	8.160
148	Apr-08	0.607	-55.645	12079.300	0.040	1.662	-1.056	-2.250	1.115	5.062
149	May-08	1.329	-56.017	12162.400	0.049	1.346	-0.016	-1.527	0.000	2.332
150	Jun-08	8.300	-52.621	12360.300	0.052	2.380	5.920	5.443	35.045	29.631
151	Jul-08	12.871	-47.260	12520.100	0.192	11.078	1.793	10.014	3.214	100.289
152	Aug-08	5.590	-47.093	12524.800	0.206	11.770	-6.180	2.734	38.189	7.474
153	Sep-08	3.200	-50.637	12470.400	0.135	6.698	-3.498	0.343	12.239	0.118
154	Oct-08	0.632	-53.056	12320.600	0.033	1.511	-0.878	-2.224	0.771	4.947
155	Nov-08	0.473	-55.955	12128.800	0.042	1.250	-0.776	-2.383	0.603	5.680
156	Dec-08	0.019	-57.791	12011.800	0.042	0.831	-0.812	-2.837	0.659	8.050
157	Jan-09	0.090	-55.430	12037.000	0.032	1.677	-1.586	-2.766	2.516	7.652
158	Feb-09	0.219	-55.057	11966.200	0.029	2.174	-1.954	-2.637	3.820	6.955
159	Mar-09	0.000	-57.424	11959.000	0.026	0.640	-0.640	-2.857	0.410	8.160
160	Apr-09	0.547	-57.591	12028.300	0.051	1.240	-0.693	-2.310	0.481	5.335
161	May-09	0.877	-55.513	12211.300	0.049	1.357	-0.480	-1.979	0.230	3.917
162	Jun-09	1.227	-53.139	12364.900	0.048	1.854	-0.628	-1.630	0.394	2.656
163	Jul-09	9.223	-47.542	12501.100	0.090	6.411	2.812	6.366	7.905	40.527
164	Aug-09	8.868	-47.055	12538.900	0.177	10.411	-1.544	6.011	2.383	36.135
165	Sep-09	9.170	-49.838	12490.300	0.083	4.757	4.413	6.313	19.471	39.860
166	Oct-09	0.226	-53.694	12310.500	0.035	1.281	-1.055	-2.631	1.113	6.921
167	Nov-09	0.027	-57.009	12120.400	0.036	0.390	-0.363	-2.830	0.132	8.008
168	Dec-09	0.000	-56.672	12044.800	0.041	1.265	-1.265	-2.857	1.599	8.160
169	Jan-10	0.348	-56.896	11967.400	0.035	1.321	-0.972	-2.508	0.945	6.291
170	Feb-10	0.000	-54.953	12040.100	0.032	1.952	-1.952	-2.857	3.810	8.160
171	Mar-10	0.000	-56.332	12029.000	0.036	1.359	-1.359	-2.857	1.846	8.160
172	Apr-10	0.000	-55.453	12085.200	0.045	1.966	-1.966	-2.857	3.863	8.160
173	May-10	0.619	-55.920	12145.900	0.054	1.700	-1.081	-2.237	1.168	5.005
174	Jun-10	0.807	-53.733	12317.000	0.046	1.719	-0.913	-2.050	0.833	4.202
175	Jul-10	21.137	-47.816	12507.800	0.118	7.470	13.667	18.281	186.780	334.179
176	Aug-10	8.133	-47.185	12526.400	0.287	15.365	-7.232	5.276	52.305	27.837
177	Sep-10	15.427	-49.677	12459.300	0.103	5.921	9.505	12.570	90.350	158.008
178	Oct-10	0.432	-53.330	12306.600	0.040	1.722	-1.290	-2.424	1.663	5.877
179	Nov-10	0.020	-55.649	12119.200	0.031	1.019	-0.999	-2.837	0.998	8.046
180	Dec-10	0.000	-57.169	11995.300	0.044	1.361	-1.361	-2.857	1.851	8.160
SUM		514.175			R :	0.714			1621.971	3195.799
MEAN		2.857								

NASH : 0.492

RMSE : 3.002

MINIMUM TEMPERATURE

MINIMUM TEMPERATURE DATA (CALIBRATION)

No	Month	Mean MIN Temp observed (Y)	500Mb Temp GCM (X1)	850Mb GPH (X2)	850Mb SpecHum GCM (X3)	500 Mb V Wind (X4)
1	Jan-81	7.80	-18.036	1528.950	0.002	6.882
2	Feb-81	11.02	-18.939	1523.600	0.003	3.828
3	Mar-81	14.08	-15.988	1528.680	0.003	1.603
4	Apr-81	20.00	-13.716	1498.340	0.007	3.345
5	May-81	22.37	-10.172	1482.460	0.008	-3.306
6	Jun-81	24.08	-7.619	1457.340	0.008	3.408
7	Jul-81	26.59	-2.200	1386.040	0.009	2.434
8	Aug-81	26.86	-1.740	1404.580	0.010	1.465
9	Sep-81	22.89	-3.539	1452.030	0.007	2.384
10	Oct-81	15.49	-8.965	1528.500	0.004	3.954
11	Nov-81	11.48	-12.378	1537.370	0.005	-3.507
12	Dec-81	5.65	-14.334	1531.700	0.004	2.329
13	Jan-82	6.89	-17.577	1524.450	0.002	7.831
14	Feb-82	8.64	-17.374	1530.950	0.002	-7.226
15	Mar-82	12.32	-15.665	1510.690	0.003	-1.271
16	Apr-82	17.24	-13.738	1479.980	0.006	-1.765
17	May-82	21.26	-10.667	1485.390	0.008	-9.168
18	Jun-82	24.40	-6.558	1436.070	0.008	2.905
19	Jul-82	26.26	-1.930	1384.440	0.010	4.298
20	Aug-82	26.26	-1.561	1400.370	0.012	3.860
21	Sep-82	22.39	-3.514	1451.100	0.007	1.143
22	Oct-82	26.12	-8.185	1523.790	0.004	4.414
23	Nov-82	17.15	-11.804	1543.280	0.004	7.283
24	Dec-82	12.37	-16.235	1531.830	0.003	-2.323
25	Jan-83	5.75	-17.187	1533.070	0.002	-2.114
26	Feb-83	8.62	-16.562	1519.170	0.002	3.590
27	Mar-83	12.81	-16.132	1511.690	0.006	6.460
28	Apr-83	16.86	-12.900	1499.100	0.006	-3.184
29	May-83	21.55	-9.793	1485.150	0.008	2.398
30	Jun-83	23.47	-5.518	1448.070	0.005	2.633
31	Jul-83	24.92	-2.403	1402.560	0.008	7.468
32	Aug-83	25.04	-1.122	1393.130	0.010	2.950
33	Sep-83	23.53	-3.540	1459.390	0.006	8.460
34	Oct-83	16.66	-9.610	1523.770	0.005	7.754
35	Nov-83	9.88	-13.072	1537.530	0.003	4.016
36	Dec-83	6.44	-15.708	1544.140	0.003	-3.987
37	Jan-84	5.79	-16.211	1533.100	0.004	1.793
38	Feb-84	7.39	-16.501	1519.110	0.003	6.573
39	Mar-84	13.29	-16.810	1487.030	0.004	7.837
40	Apr-84	17.17	-13.587	1494.910	0.006	2.189
41	May-84	22.51	-11.444	1483.210	0.006	2.895
42	Jun-84	24.50	-5.789	1441.080	0.006	-4.452
43	Jul-84	25.79	-2.239	1406.270	0.011	1.931
44	Aug-84	25.79	-1.137	1399.080	0.010	4.342
45	Sep-84	23.92	-3.508	1440.690	0.008	-9.385
46	Oct-84	16.66	-8.092	1517.800	0.004	4.972
47	Nov-84	10.64	-13.751	1550.940	0.002	6.896
48	Dec-84	7.65	-16.088	1540.730	0.004	-9.952
49	Jan-85	7.48	-16.489	1531.700	0.005	3.590
50	Feb-85	7.60	-14.754	1514.140	0.004	4.186
51	Mar-85	13.29	-16.070	1494.060	0.005	5.519
52	Apr-85	18.65	-13.198	1489.250	0.008	1.530
53	May-85	24.51	-9.535	1488.960	0.006	-1.657
54	Jun-85	24.51	-4.698	1442.280	0.005	-1.945
55	Jul-85	24.98	-1.685	1388.860	0.010	1.277
56	Aug-85	27.68	-0.765	1396.570	0.010	2.429
57	Sep-85	24.89	-3.646	1452.640	0.006	3.943
58	Oct-85	19.57	-7.399	1509.040	0.004	4.157
59	Nov-85	12.01	-11.204	1535.410	0.006	3.655
60	Dec-85	9.57	-15.243	1544.910	0.004	-2.928

No	Month	Mean MIN Temp observed (Y)	500Mb Temp GCM (X1)	850Mb GPH (X2)	850Mb SpecHum GCM (X3)	500 Mb V Wind (X4)
61	Jan-86	6.71	-15.733	1529.380	0.003	-3.486
62	Feb-86	9.18	-17.928	1511.740	0.003	4.315
63	Mar-86	14.55	-16.834	1515.460	0.004	5.293
64	Apr-86	18.66	-14.089	1491.600	0.006	2.808
65	May-86	21.83	-9.214	1483.070	0.008	-2.130
66	Jun-86	24.63	-5.135	1433.030	0.010	7.142
67	Jul-86	25.92	-1.966	1382.260	0.011	3.506
68	Aug-86	25.85	-1.281	1408.730	0.013	9.826
69	Sep-86	23.29	-4.281	1460.250	0.009	2.218
70	Oct-86	18.46	-8.404	1516.090	0.007	5.072
71	Nov-86	13.32	-14.105	1565.940	0.003	6.085
72	Dec-86	8.30	-16.128	1514.070	0.006	1.782
73	Jan-87	8.47	-18.108	1534.890	0.002	-1.655
74	Feb-87	11.89	-17.089	1517.880	0.003	2.578
75	Mar-87	16.11	-15.886	1507.130	0.004	7.722
76	Apr-87	20.05	-14.736	1491.850	0.006	-4.947
77	May-87	21.72	-9.284	1488.550	0.009	5.892
78	Jun-87	24.52	-6.223	1453.150	0.011	5.952
79	Jul-87	28.20	-1.183	1392.820	0.010	1.202
80	Aug-87	26.94	-1.085	1402.490	0.012	2.456
81	Sep-87	25.57	-4.380	1461.910	0.006	1.324
82	Oct-87	18.92	-8.217	1523.000	0.005	-1.747
83	Nov-87	12.00	-13.876	1534.760	0.004	7.388
84	Dec-87	9.10	-14.964	1531.930	0.003	7.008
85	Jan-88	8.27	-18.026	1541.800	0.003	4.804
86	Feb-88	10.91	-17.465	1539.070	0.003	2.718
87	Mar-88	14.38	-16.327	1502.340	0.006	5.356
88	Apr-88	20.43	-13.563	1495.420	0.007	3.887
89	May-88	25.41	-11.093	1486.460	0.009	-5.665
90	Jun-88	26.96	-5.926	1447.810	0.009	-4.510
91	Jul-88	26.44	-1.080	1382.470	0.013	-1.596
92	Aug-88	26.28	-1.567	1400.400	0.012	3.678
93	Sep-88	25.31	-3.186	1446.290	0.006	1.797
94	Oct-88	17.51	-10.049	1528.300	0.004	5.122
95	Nov-88	12.49	-12.965	1547.350	0.003	-4.167
96	Dec-88	9.29	-15.611	1530.670	0.005	1.412
97	Jan-89	7.49	-17.924	1530.270	0.002	2.112
98	Feb-89	8.94	-17.086	1518.820	0.002	4.549
99	Mar-89	14.14	-16.266	1516.710	0.005	2.604
100	Apr-89	18.11	-14.790	1494.870	0.005	5.630
101	May-89	23.88	-10.053	1484.390	0.007	-5.796
102	Jun-89	24.74	-5.612	1455.510	0.009	4.381
103	Jul-89	26.76	-3.387	1408.810	0.010	4.649
104	Aug-89	25.59	-1.607	1408.290	0.012	6.948
105	Sep-89	24.92	-4.623	1467.510	0.008	4.623
106	Oct-89	18.46	-9.445	1539.400	0.004	-6.485
107	Nov-89	12.05	-12.417	1542.180	0.006	-7.023
108	Dec-89	8.73	-17.187	1539.690	0.004	4.456
109	Jan-90	9.89	-16.994	1531.780	0.004	1.879
110	Feb-90	11.26	-15.764	1519.340	0.004	4.857
111	Mar-90	12.59	-15.251	1519.320	0.006	2.114
112	Apr-90	16.54	-13.856	1495.590	0.006	-2.565
113	May-90	23.32	-10.386	1488.860	0.009	-3.666
114	Jun-90	25.90	-4.533	1429.940	0.007	3.294
115	Jul-90	25.34	-1.109	1386.800	0.010	2.866
116	Aug-90	26.28	-1.405	1394.710	0.012	3.571
117	Sep-90	24.50	-3.393	1446.600	0.009	1.531
118	Oct-90	18.05	-7.735	1513.910	0.007	5.442
119	Nov-90	12.12	-10.404	1532.560	0.005	1.947
120	Dec-90	7.98	-15.112	1543.880	0.005	3.713

No	Month	Mean MIN Temp observed (Y)	500Mb Temp GCM (X1)	850Mb GPH (X2)	850Mb SpecHum GCM (X3)	500 Mb V Wind (X4)
121	Jan-91	5.93	-16.554	1544.960	0.003	-5.909
122	Feb-91	9.68	-16.528	1536.160	0.004	-1.622
123	Mar-91	14.45	-16.997	1519.970	0.005	3.256
124	Apr-91	17.93	-12.995	1491.290	0.006	-1.104
125	May-91	22.73	-10.312	1484.990	0.009	-5.987
126	Jun-91	24.90	-4.888	1450.930	0.008	5.282
127	Jul-91	26.30	-1.785	1400.910	0.009	5.993
128	Aug-91	25.48	-1.057	1390.700	0.012	1.980
129	Sep-91	23.60	-3.484	1448.270	0.008	2.979
130	Oct-91	15.37	-8.981	1528.920	0.004	4.155
131	Nov-91	10.36	-13.593	1549.400	0.004	-8.092
132	Dec-91	8.54	-15.548	1532.660	0.004	-1.705
133	Jan-92	7.52	-17.200	1527.910	0.004	7.361
134	Feb-92	10.78	-17.219	1513.020	0.003	1.779
135	Mar-92	8.64	-15.993	1503.070	0.004	-9.581
136	Apr-92	17.84	-14.301	1494.680	0.005	2.994
137	May-92	21.52	-10.385	1488.380	0.006	4.273
138	Jun-92	25.09	-5.116	1447.960	0.009	7.101
139	Jul-92	25.10	-0.999	1392.420	0.008	2.530
140	Aug-92	28.44	-0.938	1401.250	0.010	2.287
141	Sep-92	23.61	-3.070	1441.750	0.007	1.315
142	Oct-92	16.40	-8.356	1532.220	0.005	2.081
143	Nov-92	16.58	-13.529	1539.910	0.004	2.239
144	Dec-92	7.15	-15.809	1543.350	0.003	-2.910
145	Jan-93	7.26	-16.404	1502.260	0.001	3.017
146	Feb-93	10.78	-16.536	1499.480	0.004	6.858
147	Mar-93	12.76	-15.755	1514.940	0.004	-1.040
148	Apr-93	17.87	-13.626	1501.740	0.006	-5.426
149	May-93	23.12	-10.582	1477.540	0.006	-5.315
150	Jun-93	25.72	-5.355	1437.270	0.005	2.892
151	Jul-93	26.18	-2.560	1398.760	0.011	4.096
152	Aug-93	26.02	-1.218	1398.260	0.013	1.975
153	Sep-93	23.38	-3.336	1440.340	0.011	1.127
154	Oct-93	11.38	-9.284	1524.510	0.005	2.045
155	Nov-93	11.38	-13.543	1541.040	0.003	7.186
156	Dec-93	6.90	-17.397	1564.680	0.004	-2.556
157	Jan-94	8.32	-17.746	1522.670	0.004	-1.845
158	Feb-94	14.64	-16.202	1524.800	0.004	1.644
159	Mar-94	14.89	-16.474	1513.580	0.003	2.480
160	Apr-94	17.19	-14.214	1509.600	0.006	-3.120
161	May-94	22.60	-10.992	1481.800	0.011	-2.772
162	Jun-94	26.80	-5.603	1446.190	0.008	1.328
163	Jul-94	25.87	-1.932	1404.800	0.009	5.672
164	Aug-94	25.32	-1.170	1401.420	0.010	1.500
165	Sep-94	23.47	-3.926	1459.400	0.007	1.706
166	Oct-94	15.87	-6.369	1506.490	0.005	6.824
167	Nov-94	10.67	-12.265	1544.210	0.004	2.630
168	Dec-94	7.87	-16.505	1541.940	0.005	-1.267
169	Jan-95	6.06	-17.067	1519.060	0.003	3.385
170	Feb-95	9.34	-17.704	1511.980	0.003	5.540
171	Mar-95	12.92	-16.460	1479.810	0.004	-1.014
172	Apr-95	17.68	-13.061	1494.670	0.005	-9.769
173	May-95	23.22	-10.457	1488.900	0.007	-1.519
174	Jun-95	25.52	-5.263	1432.540	0.010	2.653
175	Jul-95	25.14	-1.379	1381.680	0.012	1.319
176	Aug-95	24.96	-1.139	1394.090	0.011	1.392
177	Sep-95	24.08	-2.741	1441.550	0.007	4.651
178	Oct-95	18.87	-7.602	1529.380	0.005	3.421
179	Nov-95	11.43	-13.427	1543.770	0.005	1.203
180	Dec-95	8.15	-15.315	1532.090	0.004	4.642

MINIMUM TEMPERATURE

MINIMUM TEMPERATURE DATA (VALIDATION)

No	Month	Mean MIN Temp observed (Y)	500Mb Temp GCM (X1)	850Mb GPH (X2)	850Mb SpecHum GCM (X3)	500 Mb V Wind (X4)	Yreg	Y- Yreg	Y - Ymean	$(Y- Yreg)^2$	$(Y - Ymean)^2$
1	Jan-96	6.95	-17.5277	1541.480	0.002	-3.185	9.527	-2.579	-10.802	6.651	116.683
2	Feb-96	9.71	-17.1682	1529.200	0.004	6.763	10.305	-0.595	-8.040	0.354	64.642
3	Mar-96	15.19	-16.5924	1502.640	0.005	-1.584	12.513	2.680	-2.557	7.185	6.537
4	Apr-96	18.06	-14.1167	1504.230	0.004	-2.375	13.976	4.081	0.306	16.652	0.094
5	May-96	22.28	-9.84026	1480.550	0.009	-1.822	19.970	2.308	4.527	5.326	20.494
6	Jun-96	25.40	-4.01313	1438.660	0.009	-1.239	24.870	0.526	7.646	0.277	58.466
7	Jul-96	25.89	-0.952298	1396.540	0.010	-4.988	28.457	-2.563	8.143	6.570	66.311
8	Aug-96	24.95	-0.86872	1393.360	0.011	-3.604	29.051	-4.099	7.201	16.805	51.858
9	Sep-96	23.46	-3.44713	1453.070	0.007	-2.896	23.539	-0.075	5.713	0.006	32.638
10	Oct-96	17.89	-8.22989	1520.740	0.005	-5.811	17.646	0.247	0.143	0.061	0.020
11	Nov-96	10.71	-12.4956	1548.230	0.005	-2.331	14.073	-3.359	-7.037	11.286	49.520
12	Dec-96	5.83	-14.9318	1529.180	0.005	1.672	12.872	-7.043	-11.921	49.601	142.119
13	Jan-97	5.18	-14.9851	1537.550	0.004	3.144	12.057	-6.879	-12.573	47.326	158.079
14	Feb-97	7.63	-15.3362	1516.550	0.003	1.774	11.949	-4.321	-10.122	18.667	102.451
15	Mar-97	17.18	-16.0198	1511.570	0.004	2.368	11.892	5.292	-0.567	28.002	0.321
16	Apr-97	17.78	-13.011	1505.750	0.006	1.183	14.951	2.828	0.029	7.999	0.001
17	May-97	26.02	-10.0517	1488.830	0.008	-4.281	19.012	7.008	8.269	49.108	68.376
18	Jun-97	29.10	-4.71525	1444.720	0.008	-1.581	23.567	5.533	11.350	30.616	128.814
19	Jul-97	26.06	-1.31621	1396.600	0.012	-7.913	29.907	-3.848	8.308	14.811	69.018
20	Aug-97	25.58	-1.35044	1406.740	0.013	-5.686	29.737	-4.160	7.827	17.303	61.263
21	Sep-97	24.15	-3.87967	1455.090	0.006	-1.569	22.721	1.433	6.403	2.053	40.998
22	Oct-97	17.00	-7.64256	1529.680	0.003	-3.278	16.678	0.319	-0.754	0.102	0.568
23	Nov-97	12.78	-13.3356	1560.290	0.005	-1.626	12.958	-0.181	-4.974	0.033	24.738
24	Dec-97	9.21	-15.0094	1533.410	0.006	1.203	13.267	-4.061	-8.544	16.489	72.999
25	Jan-98	6.73	-16.0345	1529.110	0.004	2.743	11.117	-4.385	-11.018	19.228	121.399
26	Feb-98	10.19	-16.2498	1506.560	0.003	1.128	11.440	-1.247	-7.558	1.555	57.116
27	Mar-98	12.87	-15.6164	1512.580	0.004	2.946	12.343	0.525	-4.883	0.275	23.840
28	Apr-98	18.59	-13.2783	1498.020	0.004	-8.002	14.751	3.839	0.840	14.736	0.705
29	May-98	23.34	-8.77009	1487.820	0.007	-1.114	19.430	3.908	5.588	15.276	31.229
30	Jun-98	26.60	-4.48909	1430.020	0.008	-2.836	24.288	2.309	8.846	5.331	78.257
31	Jul-98	26.25	-1.32218	1382.960	0.011	-3.245	29.178	-2.926	8.501	8.561	72.271
32	Aug-98	25.45	-1.2493	1409.390	0.011	-5.301	28.776	-3.330	7.696	11.088	59.233
33	Sep-98	24.89	-3.24567	1454.660	0.007	-3.456	23.883	1.010	7.143	1.021	51.022
34	Oct-98	25.64	-8.87445	1521.830	0.007	-2.035	18.004	7.635	7.888	58.290	62.226
35	Nov-98	13.21	-12.2702	1547.930	0.004	1.185	13.245	-0.032	-4.537	0.001	20.585
36	Dec-98	7.49	-17.0614	1542.200	0.003	-7.289	10.714	-3.224	-10.260	10.396	105.275
37	Jan-99	8.30	-17.6495	1522.750	0.003	-1.338	10.137	-1.837	-9.450	3.376	89.310
38	Feb-99	10.66	-15.7196	1509.080	0.003	-3.704	12.194	-1.534	-7.090	2.352	50.263
39	Mar-99	13.80	-14.8353	1503.710	0.005	1.231	13.512	0.285	-3.954	0.081	15.631
40	Apr-99	17.97	-13.8236	1483.850	0.006	1.958	15.510	2.457	0.216	6.037	0.047
41	May-99	22.30	-10.3645	1489.280	0.007	-1.087	17.865	4.435	4.550	19.674	20.699
42	Jun-99	31.72	-5.10442	1438.170	0.008	-1.472	23.239	8.485	13.973	71.989	195.243
43	Jul-99	26.08	-1.40685	1395.510	0.009	-4.128	27.812	-1.731	8.330	2.996	69.393
44	Aug-99	26.91	-1.09345	1409.080	0.012	-4.682	29.602	-2.696	9.156	7.267	83.834
45	Sep-99	23.82	-2.39634	1445.850	0.012	-1.386	27.432	-3.612	6.070	13.046	36.840
46	Oct-99	18.19	-6.78567	1520.950	0.004	-2.676	18.008	0.185	0.443	0.034	0.196
47	Nov-99	11.20	-12.1263	1549.930	0.003	-1.058	13.311	-2.114	-6.554	4.470	42.951
48	Dec-99	7.59	-15.8549	1542.350	0.004	1.271	11.049	-3.455	-10.157	11.939	103.161
49	Jan-00	7.26	-17.2487	1529.490	0.002	1.599	9.511	-2.253	-10.492	5.078	110.089
50	Feb-00	8.14	-16.2574	1550.310	0.003	-1.813	10.408	-2.267	-9.609	5.137	92.333
51	Mar-00	12.96	-14.4727	1510.590	0.005	5.616	13.143	-0.178	-4.786	0.032	22.904
52	Apr-00	20.79	-13.7243	1500.340	0.005	4.643	14.333	6.457	3.040	41.689	9.239
53	May-00	24.35	-7.58382	1476.250	0.008	-1.043	20.830	3.521	6.601	12.398	43.576
54	Jun-00	24.61	-4.22871	1448.790	0.005	5.329	21.510	3.097	6.857	9.594	47.012
55	Jul-00	26.45	-1.79864	1393.700	0.010	-3.644	28.224	-1.778	8.696	3.160	75.625
56	Aug-00	25.56	-1.37871	1398.460	0.013	-5.259	29.855	-4.297	7.808	18.466	60.960
57	Sep-00	22.88	-3.60119	1460.840	0.007	-2.933	23.566	-0.682	5.133	0.466	26.347
58	Oct-00	18.81	-7.01549	1520.020	0.006	2.582	18.557	0.250	1.056	0.062	1.115
59	Nov-00	12.74	-11.2769	1540.710	0.003	2.588	13.610	-0.874	-5.015	0.764	25.149
60	Dec-00	6.67	-16.0718	1547.060	0.003	1.565	10.184	-3.517	-11.083	12.367	122.825

No	Month	Mean MIN Temp observed (Y)	500Mb Temp GCM (X1)	850Mb GPH (X2)	850Mb SpecHum GCM (X3)	500 Mb V Wind (X4)	Yreg	Y- Yreg	Y - Ymean	$(Y-Yreg)^2$	$(Y-Ymean)^2$
61	Jan-01	5.98	-16.8964	1529.520	0.002	-3.076	10.373	-4.389	-11.767	19.260	138.451
62	Feb-01	8.93	-17.8013	1540.780	0.003	-2.647	9.870	-0.945	-8.825	0.893	77.887
63	Mar-01	13.20	-15.0586	1498.280	0.005	1.163	13.689	-0.486	-4.547	0.236	20.677
64	Apr-01	18.56	-14.4617	1495.010	0.007	4.830	14.874	3.686	0.810	13.583	0.655
65	May-01	24.22	-10.2609	1487.980	0.008	-1.405	18.543	5.679	6.472	32.254	41.889
66	Jun-01	25.55	-3.74989	1423.980	0.009	-3.372	25.684	-0.134	7.800	0.018	60.834
67	Jul-01	26.64	-0.964186	1373.160	0.011	-5.214	30.077	-3.435	8.892	11.797	79.060
68	Aug-01	26.43	-1.63063	1409.980	0.014	-4.444	30.351	-3.919	8.682	15.359	75.375
69	Sep-01	23.44	-3.10253	1449.700	0.009	-4.500	25.543	-2.103	5.690	4.422	32.372
70	Oct-01	19.43	-8.43268	1526.890	0.005	-1.042	16.997	2.437	1.683	5.938	2.832
71	Nov-01	11.85	-9.53713	1539.000	0.006	-1.753	16.712	-4.859	-5.897	23.608	34.775
72	Dec-01	8.06	-15.5905	1540.510	0.005	3.562	12.016	-3.955	-9.689	15.639	93.878
73	Jan-02	7.21	-14.9562	1533.900	0.004	2.915	11.893	-4.680	-10.537	21.901	111.038
74	Feb-02	9.98	-15.8893	1545.390	0.004	-1.501	11.141	-1.159	-7.768	1.343	60.346
75	Mar-02	15.25	-13.962	1512.010	0.004	-2.105	13.759	1.493	-2.499	2.228	6.244
76	Apr-02	19.43	-13.9096	1501.090	0.007	1.832	15.459	3.971	1.680	15.766	2.821
77	May-02	24.52	-10.637	1491.720	0.007	-2.723	18.118	6.398	6.766	40.930	45.775
78	Jun-02	25.56	-4.81223	1439.470	0.012	-3.525	26.107	-0.544	7.813	0.296	61.042
79	Jul-02	26.03	-0.878893	1374.410	0.013	-4.896	31.222	-5.190	8.282	26.936	68.590
80	Aug-02	28.00	-1.39397	1395.780	0.013	-4.566	29.973	-1.976	10.246	3.905	104.989
81	Sep-02	22.67	-4.30191	1462.960	0.012	-4.374	25.897	-3.224	4.923	10.392	24.235
82	Oct-02	18.01	-8.71682	1530.070	0.005	-2.923	16.908	1.102	0.259	1.214	0.067
83	Nov-02	11.46	-12.9291	1555.910	0.005	1.180	13.305	-1.847	-6.292	3.412	39.593
84	Dec-02	8.47	-14.2307	1541.040	0.004	2.556	12.382	-3.907	-9.276	15.268	86.048
85	Jan-03	6.49	-17.643	1532.740	0.002	-4.471	9.937	-3.450	-11.263	11.903	126.862
86	Feb-03	10.09	-14.7119	1534.960	0.003	-1.891	11.915	-1.829	-7.665	3.345	58.747
87	Mar-03	14.38	-14.0199	1510.200	0.006	1.145	14.406	-0.029	-3.373	0.001	11.377
88	Apr-03	18.88	-13.0682	1498.990	0.003	-2.624	13.978	4.904	1.132	24.053	1.282
89	May-03	21.40	-8.94064	1486.570	0.007	-5.351	19.286	2.117	3.653	4.484	13.343
90	Jun-03	26.11	-4.20136	1438.370	0.009	-1.843	24.856	1.254	8.360	1.573	69.883
91	Jul-03	26.16	-0.742531	1379.560	0.014	-6.000	31.462	-5.301	8.411	28.100	70.743
92	Aug-03	25.63	-1.02785	1398.610	0.014	-3.841	30.867	-5.235	7.882	27.402	62.124
93	Sep-03	24.50	-1.77208	1435.340	0.009	-4.656	26.552	-2.052	6.750	4.209	45.557
94	Oct-03	16.60	-6.51935	1515.910	0.006	-5.866	19.956	-3.359	-1.154	11.281	1.331
95	Nov-03	11.27	-13.4823	1556.650	0.003	-3.529	11.971	-0.703	-6.483	0.495	42.025
96	Dec-03	9.53	-15.9815	1541.400	0.003	-4.215	11.049	-1.520	-8.221	2.309	67.591
97	Jan-04	8.60	-16.0974	1517.130	0.003	3.191	10.920	-2.316	-9.147	5.363	83.662
98	Feb-04	10.58	-16.8542	1523.730	0.003	-4.354	11.122	-0.547	-7.175	0.299	51.486
99	Mar-04	15.28	-14.9209	1504.640	0.004	1.012	13.173	2.105	-2.473	4.430	6.116
100	Apr-04	20.27	-13.5829	1505.880	0.006	-1.242	14.767	5.503	2.520	30.284	6.348
101	May-04	22.60	-10.213	1492.130	0.010	7.295	18.950	3.647	4.846	13.300	23.488
102	Jun-04	25.06	-5.18374	1446.510	0.007	-3.261	22.608	2.456	7.313	6.030	53.479
103	Jul-04	25.71	-1.57738	1396.160	0.010	-3.223	27.964	-2.255	7.959	5.083	63.350
104	Aug-04	25.39	-0.436458	1385.910	0.014	-4.087	31.753	-6.366	7.637	40.526	58.319
105	Sep-04	24.26	-2.9306	1457.970	0.008	-3.132	24.632	-0.369	6.513	0.136	42.419
106	Oct-04	15.87	-7.89688	1522.850	0.004	-2.516	17.290	-1.422	-1.883	2.023	3.544
107	Nov-04	12.12	-11.6191	1532.920	0.007	3.354	15.609	-3.493	-5.634	12.198	31.739
108	Dec-04	8.60	-14.8945	1549.200	0.004	2.919	11.691	-3.088	-9.147	9.533	83.662
109	Jan-05	6.56	-16.374	1543.720	0.004	-9.462	11.962	-5.404	-11.192	29.201	125.268
110	Feb-05	10.00	-16.8737	1519.850	0.004	7.010	10.928	-0.932	-7.754	0.868	60.124
111	Mar-05	22.31	-15.3879	1524.910	0.004	-1.638	12.415	9.894	4.559	97.895	20.787
112	Apr-05	17.96	-12.0355	1496.530	0.005	-1.294	15.564	2.400	0.213	5.759	0.045
113	May-05	21.84	-10.1083	1502.010	0.008	-1.352	18.370	3.465	4.085	12.006	16.688
114	Jun-05	24.61	-4.33689	1443.610	0.008	-2.025	23.625	0.982	6.856	0.964	47.006
115	Jul-05	25.51	-1.73203	1403.300	0.010	-2.334	27.942	-2.429	7.763	5.899	60.257
116	Aug-05	25.26	-0.929587	1408.770	0.013	-3.105	29.685	-4.427	7.508	19.601	56.365
117	Sep-05	23.93	-2.20726	1447.580	0.007	-2.044	24.692	-0.759	6.183	0.576	38.229
118	Oct-05	18.40	-7.53045	1524.290	0.005	1.351	17.750	0.653	0.653	0.426	0.426
119	Nov-05	9.91	-13.016	1536.250	0.006	3.558	14.030	-4.123	-7.844	17.002	61.524
120	Dec-05	5.61	-16.5635	1530.980	0.004	1.373	11.016	-5.409	-12.144	29.259	147.475

No	Month	Mean MIN Temp observed (Y)	500Mb Temp GCM (X1)	850Mb GPH (X2)	850Mb SpecHum GCM (X3)	500 Mb V Wind (X4)	Yreg	Y- Yreg	Y - Ymean	$(Y-Yreg)^2$	$(Y-Ymean)^2$
121	Jan-06	6.80	-17.1996	1544.330	0.005	-8.554	11.387	-4.590	-10.954	21.067	119.981
122	Feb-06	11.78	-15.2603	1521.310	0.004	-7.407	12.858	-1.079	-5.971	1.164	35.654
123	Mar-06	14.46	-15.5639	1523.800	0.004	-2.748	12.382	2.076	-3.292	4.312	10.839
124	Apr-06	19.04	-13.3213	1508.060	0.006	1.726	14.765	4.278	1.293	18.304	1.672
125	May-06	24.24	-9.71684	1489.810	0.008	-3.271	19.028	5.214	6.492	27.189	42.140
126	Jun-06	24.76	-3.69075	1443.000	0.010	-5.038	25.895	-1.139	7.006	1.297	49.088
127	Jul-06	26.48	-2.16926	1393.190	0.012	-1.937	28.697	-2.216	8.730	4.912	76.218
128	Aug-06	25.89	-0.911121	1405.040	0.012	-5.726	29.589	-3.702	8.137	13.707	66.206
129	Sep-06	23.68	-3.34812	1453.100	0.010	-3.539	25.270	-1.587	5.933	2.518	35.200
130	Oct-06	18.42	-6.855	1524.800	0.003	-1.038	17.372	1.044	0.666	1.089	0.443
131	Nov-06	12.12	-13.0071	1537.120	0.006	1.906	14.290	-2.174	-5.634	4.728	31.745
132	Dec-06	8.09	-14.5487	1516.330	0.006	5.176	13.825	-5.735	-9.660	32.885	93.317
133	Jan-07	5.27	-17.6811	1520.860	0.003	-1.003	10.335	-5.060	-12.476	25.607	155.655
134	Feb-07	10.27	-17.2408	1529.440	0.004	-1.505	10.729	-0.458	-7.479	0.210	55.935
135	Mar-07	13.48	-15.4395	1515.220	0.005	1.300	12.623	0.855	-4.273	0.730	18.258
136	Apr-07	20.36	-12.3803	1498.220	0.005	-1.404	15.730	4.630	2.610	21.434	6.810
137	May-07	23.52	-10.2316	1501.620	0.009	-1.195	19.123	4.393	5.766	19.299	33.244
138	Jun-07	20.36	-3.97703	1443.220	0.007	-3.925	23.695	-3.335	2.610	11.122	6.810
139	Jul-07	25.62	-1.47481	1392.030	0.010	-3.430	28.160	-2.539	7.871	6.447	61.951
140	Aug-07	25.63	-0.484387	1397.840	0.012	-5.531	30.415	-4.785	7.879	22.901	62.073
141	Sep-07	24.78	-3.64439	1460.130	0.009	-3.788	24.834	-0.050	7.033	0.003	49.462
142	Oct-07	16.49	-7.029	1524.310	0.005	-1.331	18.291	-1.798	-1.257	3.232	1.580
143	Nov-07	11.35	-13.2175	1550.720	0.004	-1.230	13.031	-1.679	-6.399	2.819	40.944
144	Dec-07	6.58	-16.2081	1544.880	0.002	-1.559	10.245	-3.661	-11.167	13.402	124.691
145	Jan-08	6.34	-15.6663	1529.220	0.004	-4.534	12.051	-5.715	-11.415	32.664	130.300
146	Feb-08	7.18	-16.8229	1517.580	0.002	2.923	10.300	-3.124	-10.575	9.759	111.820
147	Mar-08	14.32	-14.3156	1513.890	0.004	-2.027	13.255	1.068	-3.428	1.140	11.750
148	Apr-08	18.32	-13.3358	1489.840	0.008	1.969	16.265	2.052	0.566	4.209	0.321
149	May-08	21.56	-10.9389	1496.370	0.007	8.331	17.072	4.486	3.808	20.126	14.498
150	Jun-08	24.43	-5.06171	1446.280	0.008	-1.400	23.437	0.996	6.683	0.993	44.662
151	Jul-08	25.62	-0.531326	1382.750	0.010	-2.986	29.140	-3.519	7.871	12.382	61.951
152	Aug-08	24.72	-1.08244	1401.990	0.012	-4.667	29.642	-4.917	6.974	24.181	48.643
153	Sep-08	22.76	-2.31609	1448.290	0.010	-2.517	26.047	-3.282	5.014	10.773	25.140
154	Oct-08	18.18	-7.41825	1521.620	0.006	-2.593	18.550	-0.373	0.427	0.139	0.182
155	Nov-08	12.49	-12.6605	1539.040	0.004	2.350	13.277	-0.784	-5.257	0.615	27.637
156	Dec-08	9.77	-15.4672	1527.540	0.005	1.654	12.177	-2.403	-7.976	5.776	63.620
157	Jan-09	8.67	-15.6556	1527.210	0.003	1.255	11.385	-2.714	-9.079	7.368	82.436
158	Feb-09	10.27	-17.3652	1507.090	0.003	5.982	10.209	0.059	-7.483	0.004	55.988
159	Mar-09	13.86	-16.7036	1523.660	0.004	-1.533	11.224	2.641	-3.886	6.973	15.100
160	Apr-09	18.89	-13.7638	1489.080	0.007	3.936	15.396	3.490	1.136	12.182	1.291
161	May-09	22.67	-9.20561	1485.090	0.008	-2.955	19.715	2.959	4.923	8.755	24.235
162	Jun-09	25.05	-5.09099	1448.510	0.007	-3.625	22.888	2.162	7.300	4.676	53.284
163	Jul-09	25.99	-1.73559	1394.970	0.009	-4.416	27.581	-1.590	8.240	2.529	67.897
164	Aug-09	25.69	-0.67928	1399.190	0.011	-4.580	29.321	-3.634	7.937	13.206	62.991
165	Sep-09	24.26	-1.68517	1432.180	0.006	-1.100	24.518	-0.258	6.510	0.067	42.375
166	Oct-09	17.05	-8.01521	1527.260	0.004	-4.566	17.351	-0.303	-0.702	0.092	0.493
167	Nov-09	12.41	-13.6919	1569.100	0.003	-5.240	11.751	0.655	-5.344	0.429	28.555
168	Dec-09	7.81	-14.7176	1534.370	0.004	8.822	11.680	-3.870	-9.941	14.979	98.818
169	Jan-10	7.17	-17.2756	1529.300	0.003	4.933	10.091	-2.920	-10.579	8.528	111.924
170	Feb-10	9.60	-15.5465	1500.580	0.004	4.843	12.230	-2.627	-8.147	6.899	66.370
171	Mar-10	15.69	-15.2278	1512.780	0.003	-7.620	12.593	3.094	-2.063	9.572	4.257
172	Apr-10	21.44	-13.3021	1502.060	0.006	2.668	15.180	6.256	3.686	39.141	13.589
173	May-10	23.87	-11.199	1490.970	0.008	8.998	17.591	6.280	6.121	39.438	37.462
174	Jun-10	24.92	-6.14131	1459.610	0.010	-2.320	23.386	1.530	7.166	2.342	51.356
175	Jul-10	25.07	-1.40752	1397.630	0.010	-3.379	28.348	-3.277	7.321	10.738	53.591
176	Aug-10	25.15	-0.476104	1392.140	0.015	-3.498	31.705	-6.559	7.395	43.025	54.683
177	Sep-10	23.49	-2.46344	1433.010	0.009	-3.331	26.295	-2.802	5.743	7.849	32.982
178	Oct-10	18.91	-7.78091	1533.650	0.004	-2.688	17.008	1.905	1.163	3.630	1.351
179	Nov-10	13.00	-13.5221	1547.600	0.002	-2.426	12.014	0.987	-4.750	0.973	22.563
180	Dec-10	7.83	-16.5806	1545.050	0.005	2.158	10.947	-3.122	-9.925	9.745	98.513
	SUM :	3195.07				R :	0.882			2142.199	9149.599
	MEAN :	17.75									

NASH : **0.766**

RMSE : **3.450**

MAXIMUM TEMPERATURE

MEAN MONTHLY MAXIMUM TEMPERATURE (CALIBRATION)

NO	MONTH	Mean MAX Temp Observed (Y)	500Mb Temp GCM (X1)	500Mb GPH GCM (X2)	850Mb SpecHum GCM (X3)	200Mb U Wind (X4)
1	Jan-81	19.230	-18.036	5635.060	0.002	5.975
2	Feb-81	23.539	-18.939	5633.410	0.003	5.665
3	Mar-81	26.342	-15.988	5704.590	0.003	4.491
4	Apr-81	35.738	-13.716	5737.780	0.007	3.227
5	May-81	37.865	-10.172	5776.050	0.008	2.280
6	Jun-81	38.687	-7.619	5794.920	0.008	1.510
7	Jul-81	33.147	-2.200	5799.230	0.009	2.845
8	Aug-81	33.871	-1.740	5820.060	0.010	-5.556
9	Sep-81	32.500	-3.539	5842.890	0.007	4.204
10	Oct-81	31.216	-8.965	5806.900	0.004	2.426
11	Nov-81	25.993	-12.378	5757.670	0.005	3.895
12	Dec-81	22.868	-14.334	5708.160	0.004	4.872
13	Jan-82	21.019	-17.577	5643.400	0.002	5.461
14	Feb-82	21.271	-17.374	5650.170	0.002	5.432
15	Mar-82	24.458	-15.665	5676.680	0.003	4.974
16	Apr-82	32.690	-13.738	5697.390	0.006	4.525
17	May-82	35.481	-10.667	5766.270	0.008	2.492
18	Jun-82	37.171	-6.558	5802.470	0.008	1.247
19	Jul-82	35.477	-1.930	5796.120	0.010	-4.659
20	Aug-82	32.535	-1.561	5803.850	0.012	-6.933
21	Sep-82	34.187	-3.514	5824.420	0.007	1.321
22	Oct-82	31.050	-8.185	5799.800	0.004	2.474
23	Nov-82	25.931	-11.804	5761.300	0.004	3.971
24	Dec-82	21.226	-16.235	5678.690	0.003	5.327
25	Jan-83	18.248	-17.187	5643.920	0.002	5.526
26	Feb-83	22.271	-16.562	5644.250	0.002	6.117
27	Mar-83	27.990	-16.132	5683.490	0.006	5.486
28	Apr-83	31.403	-12.900	5755.570	0.006	3.350
29	May-83	35.555	-9.793	5782.640	0.008	2.038
30	Jun-83	38.687	-5.518	5818.090	0.005	1.608
31	Jul-83	35.148	-2.403	5795.120	0.008	1.008
32	Aug-83	33.381	-1.122	5799.950	0.010	-6.960
33	Sep-83	33.907	-3.540	5832.250	0.006	5.441
34	Oct-83	32.123	-9.610	5788.980	0.005	2.622
35	Nov-83	27.723	-13.072	5741.640	0.003	4.102
36	Dec-83	24.242	-15.708	5709.270	0.003	4.457
37	Jan-84	19.526	-16.211	5682.400	0.004	5.374
38	Feb-84	21.632	-16.501	5643.170	0.003	5.655
39	Mar-84	30.390	-16.810	5632.440	0.004	5.619
40	Apr-84	33.614	-13.587	5716.180	0.006	4.330
41	May-84	37.248	-11.444	5755.940	0.006	3.275
42	Jun-84	35.357	-5.789	5807.800	0.006	1.156
43	Jul-84	32.466	-2.239	5798.600	0.011	-4.851
44	Aug-84	32.466	-1.137	5809.150	0.010	-8.830
45	Sep-84	32.807	-3.508	5820.800	0.008	0.799
46	Oct-84	33.197	-8.092	5817.420	0.004	2.131
47	Nov-84	28.063	-13.751	5741.810	0.002	4.328
48	Dec-84	24.287	-16.088	5696.770	0.004	4.903
49	Jan-85	20.181	-16.489	5677.440	0.005	5.055
50	Feb-85	24.213	-14.754	5664.600	0.004	5.679
51	Mar-85	31.787	-16.070	5660.320	0.005	4.925
52	Apr-85	34.917	-13.198	5723.030	0.008	3.539
53	May-85	39.097	-9.535	5779.170	0.006	2.169
54	Jun-85	36.832	-4.698	5812.590	0.005	1.300
55	Jul-85	33.023	-1.685	5804.760	0.010	1.482
56	Aug-85	33.400	-0.765	5800.550	0.010	-1.157
57	Sep-85	31.753	-3.646	5815.290	0.006	3.278
58	Oct-85	29.400	-7.399	5808.240	0.004	2.138
59	Nov-85	26.647	-11.204	5764.530	0.006	3.414
60	Dec-85	22.552	-15.243	5710.930	0.004	4.982

NO	MONTH	Mean MAX Temp Observed (Y)	500Mb Temp GCM (X1)	500Mb GPH GCM (X2)	850Mb SpecHum GCM (X3)	200Mb U Wind (X4)
61	Jan-86	20.894	-15.733	5659.290	0.003	5.542
62	Feb-86	21.971	-17.928	5625.930	0.003	5.741
63	Mar-86	27.571	-16.834	5680.980	0.004	4.994
64	Apr-86	33.960	-14.089	5711.870	0.006	3.451
65	May-86	35.726	-9.214	5775.830	0.008	2.127
66	Jun-86	35.352	-5.135	5791.240	0.010	1.027
67	Jul-86	32.061	-1.966	5778.620	0.011	-2.753
68	Aug-86	31.952	-1.281	5808.010	0.013	-1.048
69	Sep-86	32.093	-4.281	5815.470	0.009	6.986
70	Oct-86	29.797	-8.404	5807.350	0.007	2.098
71	Nov-86	27.177	-14.105	5765.120	0.003	3.544
72	Dec-86	20.829	-16.128	5676.910	0.006	5.009
73	Jan-87	21.723	-18.108	5650.100	0.002	6.094
74	Feb-87	24.121	-17.089	5632.820	0.003	6.058
75	Mar-87	29.400	-15.886	5666.280	0.004	5.047
76	Apr-87	33.863	-14.736	5699.350	0.006	3.828
77	May-87	33.790	-9.284	5781.290	0.009	2.387
78	Jun-87	36.381	-6.223	5790.770	0.011	1.866
79	Jul-87	36.587	-1.183	5810.450	0.010	1.030
80	Aug-87	33.658	-1.085	5796.420	0.012	-6.296
81	Sep-87	33.970	-4.380	5825.980	0.006	7.444
82	Oct-87	32.232	-8.217	5804.480	0.005	2.032
83	Nov-87	28.033	-13.876	5725.100	0.004	4.404
84	Dec-87	22.945	-14.964	5693.770	0.003	5.498
85	Jan-88	21.481	-18.026	5669.830	0.003	5.495
86	Feb-88	24.283	-17.465	5680.640	0.003	5.004
87	Mar-88	26.535	-16.327	5667.530	0.006	4.418
88	Apr-88	35.947	-13.563	5712.840	0.007	3.970
89	May-88	39.242	-11.093	5749.030	0.009	3.066
90	Jun-88	35.461	-5.926	5795.890	0.009	1.580
91	Jul-88	32.110	-1.080	5795.680	0.013	-1.903
92	Aug-88	30.310	-1.567	5808.350	0.012	-2.789
93	Sep-88	32.500	-3.186	5819.360	0.006	6.302
94	Oct-88	30.948	-10.049	5783.950	0.004	2.765
95	Nov-88	27.233	-12.965	5750.680	0.003	4.342
96	Dec-88	22.813	-15.611	5697.190	0.005	5.326
97	Jan-89	18.661	-17.924	5643.800	0.002	5.689
98	Feb-89	22.439	-17.086	5649.220	0.002	5.737
99	Mar-89	27.387	-16.266	5691.480	0.005	4.640
100	Apr-89	33.037	-14.790	5701.550	0.005	3.824
101	May-89	37.103	-10.053	5766.900	0.007	2.687
102	Jun-89	33.716	-5.612	5800.580	0.009	1.229
103	Jul-89	34.106	-3.387	5796.280	0.010	2.133
104	Aug-89	32.113	-1.607	5797.040	0.012	-6.762
105	Sep-89	32.058	-4.623	5823.920	0.008	1.218
106	Oct-89	32.239	-9.445	5808.570	0.004	2.320
107	Nov-89	26.290	-12.417	5758.680	0.006	3.680
108	Dec-89	19.874	-17.187	5681.560	0.004	4.686
109	Jan-90	20.568	-16.994	5663.480	0.004	6.133
110	Feb-90	25.687	-15.764	5664.500	0.004	5.780
111	Mar-90	25.687	-15.251	5680.660	0.006	5.438
112	Apr-90	32.981	-13.856	5720.450	0.006	3.923
113	May-90	35.113	-10.386	5774.170	0.009	2.493
114	Jun-90	36.823	-4.533	5811.760	0.007	1.173
115	Jul-90	32.568	-1.109	5805.840	0.010	-2.107
116	Aug-90	32.490	-1.405	5793.820	0.012	-1.204
117	Sep-90	30.677	-3.393	5816.520	0.009	4.890
118	Oct-90	29.829	-7.735	5795.940	0.007	2.039
119	Nov-90	28.143	-10.404	5766.020	0.005	3.440
120	Dec-90	22.290	-15.112	5729.300	0.005	4.533

NO	MONTH	Mean MAX Temp Observed (Y)	500Mb Temp GCM (X1)	500Mb GPH GCM (X2)	850Mb SpecHum GCM (X3)	200Mb U Wind (X4)
121	Jan-91	19.445	-16.554	5688.820	0.003	5.210
122	Feb-91	23.400	-16.528	5678.470	0.004	5.449
123	Mar-91	26.577	-16.997	5678.120	0.005	4.483
124	Apr-91	32.647	-12.995	5725.490	0.006	3.824
125	May-91	37.932	-10.312	5756.460	0.009	3.157
126	Jun-91	35.587	-4.888	5805.110	0.008	1.115
127	Jul-91	35.010	-1.785	5806.320	0.009	-2.564
128	Aug-91	32.442	-1.057	5796.970	0.012	-6.694
129	Sep-91	31.950	-3.484	5820.090	0.008	2.743
130	Oct-91	29.603	-8.981	5809.080	0.004	2.445
131	Nov-91	24.513	-13.593	5750.890	0.004	4.363
132	Dec-91	21.103	-15.548	5701.870	0.004	4.901
133	Jan-92	19.906	-17.200	5658.750	0.004	5.834
134	Feb-92	20.503	-17.219	5631.430	0.003	5.985
135	Mar-92	27.113	-15.993	5668.570	0.004	5.276
136	Apr-92	33.660	-14.301	5703.300	0.005	4.323
137	May-92	36.661	-10.385	5755.860	0.006	2.988
138	Jun-92	37.807	-5.116	5804.020	0.009	1.801
139	Jul-92	33.319	-0.999	5817.750	0.008	-2.015
140	Aug-92	31.700	-0.938	5814.250	0.010	-6.138
141	Sep-92	32.257	-3.070	5827.620	0.007	7.932
142	Oct-92	30.784	-8.356	5817.970	0.005	2.486
143	Nov-92	26.827	-13.529	5734.300	0.004	3.974
144	Dec-92	22.006	-15.809	5704.480	0.003	5.088
145	Jan-93	18.990	-16.404	5619.410	0.001	5.913
146	Feb-93	24.489	-16.536	5634.290	0.004	5.704
147	Mar-93	25.332	-15.755	5678.220	0.004	5.412
148	Apr-93	33.393	-13.626	5736.420	0.006	3.920
149	May-93	36.310	-10.582	5767.560	0.006	3.236
150	Jun-93	37.193	-5.355	5823.510	0.005	1.226
151	Jul-93	34.361	-2.560	5798.180	0.011	6.131
152	Aug-93	33.987	-1.218	5810.300	0.013	-2.008
153	Sep-93	30.207	-3.336	5822.770	0.011	5.182
154	Oct-93	32.168	-9.284	5792.600	0.005	2.384
155	Nov-93	27.617	-13.543	5734.480	0.003	3.990
156	Dec-93	23.216	-17.397	5701.020	0.004	4.681
157	Jan-94	21.716	-17.746	5648.690	0.004	5.180
158	Feb-94	22.479	-16.202	5648.070	0.004	6.004
159	Mar-94	30.055	-16.474	5658.610	0.003	5.655
160	Apr-94	33.393	-14.214	5723.990	0.006	3.412
161	May-94	37.019	-10.992	5744.340	0.011	2.312
162	Jun-94	38.557	-5.603	5802.270	0.008	1.207
163	Jul-94	33.813	-1.932	5806.080	0.009	6.801
164	Aug-94	32.337	-1.170	5806.730	0.010	-7.672
165	Sep-94	33.213	-3.926	5826.750	0.007	5.805
166	Oct-94	31.945	-6.369	5812.950	0.005	1.463
167	Nov-94	27.213	-12.265	5759.840	0.004	3.945
168	Dec-94	22.540	-16.505	5700.340	0.005	4.853
169	Jan-95	19.303	-17.067	5648.790	0.003	5.770
170	Feb-95	22.589	-17.704	5638.980	0.003	5.410
171	Mar-95	26.816	-16.460	5632.830	0.004	5.346
172	Apr-95	34.050	-13.061	5732.810	0.005	3.873
173	May-95	38.703	-10.457	5764.630	0.007	3.082
174	Jun-95	39.113	-5.263	5800.750	0.010	1.453
175	Jul-95	33.377	-1.379	5801.750	0.012	1.904
176	Aug-95	31.719	-1.139	5799.020	0.011	-4.768
177	Sep-95	32.886	-2.741	5818.520	0.007	3.643
178	Oct-95	30.955	-7.602	5820.880	0.005	1.620
179	Nov-95	27.667	-13.427	5752.610	0.005	3.983
180	Dec-95	22.645	-15.315	5695.860	0.004	5.218

MAXIMUM TEMPERATURE

MEAN MONTHLY MAXIMUM TEMPERATURE (VALIDATION)

NO	MONTH	Mean MAX Temp Observed Y	500Mb Temp GCM X1	500Mb GPH GCM X2	850Mb SpecHum GCM X3	200Mb U Wind X4	Y Reg	Y-Yreg	Y-Ymean	$(Y\text{-}Yreg)^2$	$(Y\text{-}Ymean)^2$
1	Jan-96	20.268	-17.528	5665.670	0.002	5.259	23.153	-2.885	-9.986	8.323	99.720
2	Feb-96	23.190	-17.168	5663.960	0.004	5.456	24.710	-1.520	-7.064	2.312	49.901
3	Mar-96	28.352	-16.592	5661.370	0.005	4.959	25.101	3.250	-1.902	10.564	3.618
4	Apr-96	35.033	-14.117	5719.460	0.004	4.472	27.921	7.112	4.780	50.578	22.845
5	May-96	37.742	-9.840	5766.250	0.009	2.705	34.190	3.552	7.488	12.614	56.073
6	Jun-96	36.307	-4.013	5804.440	0.009	1.558	34.351	1.955	6.053	3.823	36.638
7	Jul-96	33.123	-0.952	5816.880	0.010	-1.561	33.932	-0.809	2.869	0.654	8.230
8	Aug-96	30.829	-0.869	5809.640	0.011	-5.461	34.046	-3.217	0.575	10.348	0.331
9	Sep-96	31.177	-3.447	5830.060	0.007	8.214	33.920	-2.743	0.923	7.524	0.852
10	Oct-96	30.645	-8.230	5813.840	0.005	2.213	32.092	-1.446	0.391	2.092	0.153
11	Nov-96	26.883	-12.496	5765.810	0.005	3.877	31.002	-4.119	-3.370	16.967	11.359
12	Dec-96	22.235	-14.932	5695.870	0.005	5.355	27.404	-5.169	-8.018	26.717	64.292
13	Jan-97	20.087	-14.985	5693.050	0.004	5.577	26.418	-6.331	-10.167	40.083	103.360
14	Feb-97	22.354	-15.336	5658.250	0.003	5.444	22.968	-0.615	-7.900	0.378	62.412
15	Mar-97	26.610	-16.020	5681.820	0.004	4.911	25.510	1.100	-3.644	1.210	13.279
16	Apr-97	31.500	-13.011	5748.760	0.006	3.250	30.538	0.962	1.246	0.925	1.553
17	May-97	36.442	-10.052	5762.700	0.008	2.720	32.557	3.885	6.188	15.095	38.294
18	Jun-97	36.327	-4.715	5799.080	0.008	1.467	32.934	3.393	6.073	11.510	36.881
19	Jul-97	33.665	-1.316	5785.870	0.012	-4.363	34.289	-0.625	3.411	0.390	11.634
20	Aug-97	32.432	-1.350	5817.560	0.013	-6.420	36.999	-4.567	2.179	20.855	4.746
21	Sep-97	32.397	-3.880	5823.410	0.006	7.893	32.882	-0.485	2.143	0.235	4.592
22	Oct-97	28.806	-7.643	5825.030	0.003	2.381	30.963	-2.156	-1.447	4.650	2.095
23	Nov-97	23.800	-13.336	5767.300	0.005	3.499	31.097	-7.297	-6.454	53.242	41.650
24	Dec-97	16.974	-15.009	5712.230	0.006	5.063	29.594	-12.620	-13.280	159.253	176.346
25	Jan-98	18.477	-16.035	5685.420	0.004	5.230	25.322	-6.845	-11.776	46.854	138.681
26	Feb-98	22.861	-16.250	5634.540	0.003	6.187	21.259	1.602	-7.393	2.566	54.656
27	Mar-98	25.377	-15.616	5680.630	0.004	5.236	25.761	-0.383	-4.876	0.147	23.778
28	Apr-98	34.253	-13.278	5716.970	0.004	4.088	26.640	7.613	4.000	57.965	15.997
29	May-98	38.765	-8.770	5790.140	0.007	2.571	33.620	5.144	8.511	26.463	72.434
30	Jun-98	37.140	-4.489	5804.240	0.008	9.246	34.086	3.054	6.886	9.324	47.421
31	Jul-98	33.781	-1.322	5797.480	0.011	-2.440	33.947	-0.166	3.527	0.028	12.439
32	Aug-98	31.353	-1.249	5814.970	0.011	-7.671	34.918	-3.564	1.100	12.706	1.209
33	Sep-98	33.363	-3.246	5837.130	0.007	4.924	34.442	-1.078	3.110	1.163	9.670
34	Oct-98	30.855	-8.874	5802.220	0.007	2.079	33.561	-2.706	0.601	7.321	0.361
35	Nov-98	27.770	-12.270	5760.920	0.004	4.366	29.257	-1.487	-2.484	2.212	6.169
36	Dec-98	21.703	-17.061	5689.540	0.003	5.025	25.778	-4.075	-8.550	16.602	73.109
37	Jan-99	17.574	-17.650	5642.830	0.003	5.694	22.174	-4.600	-12.680	21.156	160.770
38	Feb-99	23.789	-15.720	5654.820	0.003	5.753	22.674	1.116	-6.464	1.245	41.789
39	Mar-99	30.006	-14.835	5672.750	0.005	5.659	25.417	4.590	-0.247	21.066	0.061
40	Apr-99	38.600	-13.824	5699.410	0.006	3.905	28.366	10.234	8.346	104.728	69.660
41	May-99	37.781	-10.365	5786.450	0.007	2.729	33.158	4.623	7.527	21.373	56.655
42	Jun-99	36.963	-5.104	5824.690	0.008	1.187	34.504	2.459	6.710	6.047	45.019
43	Jul-99	33.416	-1.407	5810.280	0.009	3.324	33.521	-0.105	3.162	0.011	10.001
44	Aug-99	31.353	-1.093	5813.380	0.012	-1.005	36.782	-5.429	1.100	29.472	1.209
45	Sep-99	32.900	-2.396	5816.220	0.012	3.921	37.890	-4.990	2.646	24.903	7.003
46	Oct-99	32.655	-6.786	5818.270	0.004	2.037	31.144	1.510	2.401	2.281	5.765
47	Nov-99	28.270	-12.126	5759.250	0.003	4.032	28.767	-0.497	-1.984	0.247	3.935
48	Dec-99	26.290	-15.855	5713.400	0.004	4.459	27.340	-1.050	-3.964	1.103	15.711
49	Jan-00	18.097	-17.249	5652.540	0.002	5.757	21.822	-3.725	-12.157	13.874	147.791
50	Feb-00	21.541	-16.257	5694.090	0.003	5.459	25.445	-3.904	-8.712	15.238	75.905
51	Mar-00	28.700	-14.473	5693.390	0.005	5.438	26.599	2.101	-1.554	4.416	2.414
52	Apr-00	36.787	-13.724	5718.400	0.005	3.737	28.603	8.183	6.533	66.967	42.679
53	May-00	37.448	-7.584	5804.180	0.008	1.485	34.625	2.823	7.195	7.969	51.763
54	Jun-00	34.345	-4.229	5823.580	0.005	1.360	31.269	3.076	4.091	9.459	16.737
55	Jul-00	33.767	-1.799	5802.350	0.010	-6.337	33.436	0.331	3.513	0.110	12.341
56	Aug-00	32.632	-1.379	5805.850	0.013	-1.094	36.545	-3.913	2.379	15.312	5.657
57	Sep-00	33.037	-3.601	5831.710	0.007	7.599	34.678	-1.641	2.783	2.693	7.745
58	Oct-00	33.135	-7.015	5811.660	0.006	2.292	32.797	0.339	2.882	0.115	8.305
59	Nov-00	27.216	-11.277	5761.040	0.003	3.919	28.095	-0.879	-3.038	0.772	9.227
60	Dec-00	23.555	-16.072	5714.130	0.003	4.664	26.437	-2.883	-6.699	8.310	44.875

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61	Jan-01	18.655	-16.896	5651.060	0.002	5.962	22.088	-3.433	-11.599	11.788	134.534
62	Feb-01	25.514	-17.801	5665.360	0.003	5.253	24.266	1.249	-4.739	1.559	22.462
63	Mar-01	29.042	-15.059	5660.980	0.005	5.292	24.934	4.108	-1.212	16.873	1.468
64	Apr-01	34.687	-14.462	5705.770	0.007	3.858	29.678	5.009	4.433	25.090	19.651
65	May-01	37.377	-10.261	5779.440	0.008	2.683	33.624	3.753	7.124	14.088	50.747
66	Jun-01	34.570	-3.750	5820.610	0.009	6.626	36.047	-1.477	4.316	2.181	18.630
67	Jul-01	34.106	-0.964	5805.620	0.011	-1.265	34.962	-0.856	3.853	0.733	14.844
68	Aug-01	34.310	-1.631	5803.450	0.014	-7.277	37.838	-3.528	4.056	12.449	16.451
69	Sep-01	35.217	-3.103	5829.830	0.009	3.696	36.256	-1.039	4.963	1.080	24.631
70	Oct-01	34.117	-8.433	5813.550	0.005	2.279	32.195	1.922	3.863	3.694	14.922
71	Nov-01	28.700	-9.537	5793.700	0.006	2.861	32.602	-3.902	-1.554	15.226	2.414
72	Dec-01	22.661	-15.591	5708.720	0.005	4.695	28.624	-5.963	-7.592	35.556	57.645
73	Jan-02	20.048	-14.956	5680.980	0.004	5.493	24.951	-4.903	-10.205	24.036	104.149
74	Feb-02	23.089	-15.889	5696.020	0.004	5.072	26.106	-3.017	-7.164	9.102	51.329
75	Mar-02	29.442	-13.962	5689.700	0.004	5.178	25.572	3.870	-0.812	14.974	0.659
76	Apr-02	35.633	-13.910	5715.680	0.007	3.679	30.445	5.188	5.380	26.918	28.940
77	May-02	37.903	-10.637	5763.040	0.007	2.072	32.192	5.711	7.650	32.619	58.515
78	Jun-02	35.850	-4.812	5791.110	0.012	9.837	37.495	-1.645	5.596	2.707	31.318
79	Jul-02	36.152	-0.879	5797.180	0.013	-3.084	36.282	-0.131	5.898	0.017	34.785
80	Aug-02	32.774	-1.394	5803.900	0.013	-8.480	35.921	-3.147	2.520	9.905	6.353
81	Sep-02	32.233	-4.302	5820.300	0.012	7.484	39.250	-7.017	1.980	49.236	3.919
82	Oct-02	31.419	-8.717	5821.150	0.005	2.314	32.953	-1.533	1.166	2.351	1.359
83	Nov-02	25.806	-12.929	5771.230	0.005	3.498	31.542	-5.736	-4.447	32.899	19.778
84	Dec-02	23.839	-14.231	5719.080	0.004	5.215	27.746	-3.907	-6.415	15.265	41.152
85	Jan-03	15.816	-17.643	5654.920	0.002	5.968	22.759	-6.943	-14.438	48.201	208.444
86	Feb-03	22.893	-14.712	5690.540	0.003	5.461	24.650	-1.757	-7.361	3.087	54.182
87	Mar-03	28.116	-14.020	5700.480	0.006	5.168	28.045	0.072	-2.138	0.005	4.569
88	Apr-03	35.207	-13.068	5718.850	0.003	4.148	25.811	9.396	4.953	88.276	24.534
89	May-03	37.384	-8.941	5792.650	0.007	2.421	33.131	4.252	7.130	18.083	50.839
90	Jun-03	37.690	-4.201	5826.330	0.009	7.348	36.683	1.007	7.436	1.014	55.298
91	Jul-03	34.645	-0.743	5798.810	0.014	-5.991	36.456	-1.811	4.391	3.279	19.285
92	Aug-03	33.048	-1.028	5806.220	0.014	-7.712	37.476	-4.427	2.795	19.602	7.810
93	Sep-03	32.127	-1.772	5826.950	0.009	5.759	35.167	-3.040	1.873	9.243	3.508
94	Oct-03	32.339	-6.519	5816.770	0.006	1.821	33.500	-1.161	2.085	1.348	4.347
95	Nov-03	25.758	-13.482	5755.940	0.003	3.968	28.247	-2.489	-4.496	6.195	20.211
96	Dec-03	20.958	-15.982	5693.940	0.003	4.961	25.331	-4.373	-9.296	19.125	86.409
97	Jan-04	18.568	-16.097	5664.380	0.003	5.314	22.976	-4.408	-11.686	19.435	136.562
98	Feb-04	25.368	-16.854	5661.450	0.003	5.787	23.689	1.679	-4.886	2.819	23.872
99	Mar-04	32.452	-14.921	5689.190	0.004	4.881	26.074	6.377	2.198	40.669	4.831
100	Apr-04	36.583	-13.583	5718.250	0.006	4.272	28.655	7.929	6.330	62.866	40.064
101	May-04	37.871	-10.213	5775.610	0.010	2.554	35.471	2.400	7.617	5.758	58.023
102	Jun-04	35.433	-5.184	5807.330	0.007	9.874	33.158	2.276	5.180	5.179	26.828
103	Jul-04	34.742	-1.577	5806.510	0.010	-3.943	33.297	1.445	4.488	2.089	20.144
104	Aug-04	33.310	-0.436	5799.640	0.014	-1.062	37.610	-4.301	3.056	18.496	9.339
105	Sep-04	33.997	-2.931	5836.960	0.008	2.663	35.311	-1.314	3.743	1.726	14.010
106	Oct-04	31.945	-7.897	5825.480	0.004	2.168	32.305	-0.360	1.691	0.129	2.861
107	Nov-04	26.467	-11.619	5752.280	0.007	3.844	31.465	-4.999	-3.787	24.986	14.342
108	Dec-04	22.763	-14.895	5728.650	0.004	4.864	28.692	-5.929	-7.491	35.149	56.111
109	Jan-05	19.790	-16.374	5700.370	0.004	5.294	27.557	-7.767	-10.463	60.323	109.483
110	Feb-05	23.029	-16.874	5650.620	0.004	5.798	24.000	-0.971	-7.225	0.943	52.203
111	Mar-05	29.542	-15.388	5701.820	0.004	5.013	27.020	2.521	-0.712	6.358	0.507
112	Apr-05	34.777	-12.036	5745.520	0.005	2.711	28.955	5.822	4.523	33.892	20.457
113	May-05	37.548	-10.108	5778.570	0.008	2.465	33.683	3.866	7.295	14.943	53.212
114	Jun-05	37.490	-4.337	5805.920	0.008	1.394	32.791	4.700	7.237	22.087	52.368
115	Jul-05	32.058	-1.732	5802.190	0.010	-1.662	33.896	-1.838	1.804	3.380	3.256
116	Aug-05	33.106	-0.930	5811.750	0.013	-8.522	36.055	-2.949	2.853	8.695	8.138
117	Sep-05	31.417	-2.207	5825.720	0.007	2.830	33.044	-1.627	1.163	2.649	1.352
118	Oct-05	32.594	-7.530	5813.970	0.005	2.564	32.378	0.216	2.340	0.046	5.475
119	Nov-05	28.363	-13.016	5744.030	0.006	3.742	30.411	-2.047	-1.890	4.192	3.574
120	Dec-05	23.923	-16.564	5677.400	0.004	5.104	25.306	-1.384	-6.331	1.915	40.083

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121	Jan-06	21.529	-17.200	5683.110	0.005	5.535	26.766	-5.237	-8.725	27.427	76.120
122	Feb-06	28.064	-15.260	5676.250	0.004	5.529	24.795	3.269	-2.189	10.685	4.794
123	Mar-06	28.161	-15.564	5697.430	0.004	5.131	26.722	1.440	-2.092	2.072	4.378
124	Apr-06	35.690	-13.321	5733.280	0.006	3.699	29.805	5.885	5.436	34.636	29.553
125	May-06	36.142	-9.717	5772.730	0.008	2.373	32.931	3.211	5.888	10.311	34.671
126	Jun-06	36.290	-3.691	5812.230	0.010	7.612	36.546	-0.256	6.036	0.065	36.437
127	Jul-06	33.877	-2.169	5792.740	0.012	2.781	35.298	-1.421	3.624	2.019	13.131
128	Aug-06	34.732	-0.911	5826.330	0.012	-3.942	36.778	-2.046	4.479	4.185	20.057
129	Sep-06	34.283	-3.348	5826.470	0.010	7.001	36.525	-2.242	4.030	5.026	16.238
130	Oct-06	31.952	-6.855	5833.300	0.003	1.976	31.599	0.352	1.698	0.124	2.883
131	Nov-06	27.074	-13.007	5742.440	0.006	4.272	30.622	-3.548	-3.180	12.590	10.109
132	Dec-06	22.468	-14.549	5687.470	0.006	5.319	27.782	-5.314	-7.786	28.244	60.621
133	Jan-07	21.903	-17.681	5639.890	0.003	5.500	22.313	-0.410	-8.350	0.168	69.731
134	Feb-07	23.054	-17.241	5659.350	0.004	5.637	24.127	-1.073	-7.200	1.151	51.842
135	Mar-07	27.513	-15.440	5686.440	0.005	5.234	26.315	1.198	-2.741	1.435	7.512
136	Apr-07	36.613	-12.380	5738.790	0.005	3.647	29.501	7.112	6.360	50.585	40.445
137	May-07	36.919	-10.232	5798.310	0.009	2.396	36.741	0.179	6.666	0.032	44.431
138	Jun-07	36.357	-3.977	5821.420	0.007	1.169	33.150	3.206	6.103	10.280	37.246
139	Jul-07	33.877	-1.475	5819.410	0.010	3.281	34.876	-0.999	3.624	0.998	13.131
140	Aug-07	33.619	-0.484	5821.250	0.012	-6.702	36.646	-3.026	3.366	9.158	11.328
141	Sep-07	34.103	-3.644	5829.610	0.009	8.705	36.911	-2.807	3.850	7.881	14.820
142	Oct-07	32.697	-7.029	5823.780	0.005	1.868	32.830	-0.133	2.443	0.018	5.969
143	Nov-07	26.355	-13.218	5756.220	0.004	4.185	29.859	-3.504	-3.899	12.280	15.201
144	Dec-07	22.719	-16.208	5699.300	0.002	4.448	25.107	-2.388	-7.534	5.702	56.767
145	Jan-08	20.803	-15.666	5683.560	0.004	5.567	25.313	-4.510	-9.450	20.338	89.312
146	Feb-08	22.876	-16.823	5640.240	0.002	5.767	21.273	1.602	-7.378	2.568	54.433
147	Mar-08	31.065	-14.316	5706.240	0.004	5.058	26.527	4.538	0.811	20.595	0.658
148	Apr-08	34.557	-13.336	5708.560	0.008	4.466	30.000	4.557	4.303	20.764	18.515
149	May-08	36.174	-10.939	5773.130	0.007	2.796	33.367	2.807	5.920	7.879	35.052
150	Jun-08	33.707	-5.062	5804.480	0.008	1.420	33.763	-0.056	3.453	0.003	11.923
151	Jul-08	32.419	-0.531	5807.960	0.010	-1.477	33.452	-1.033	2.166	1.066	4.690
152	Aug-08	32.248	-1.082	5812.550	0.012	-8.368	35.733	-3.485	1.995	12.143	3.979
153	Sep-08	33.060	-2.316	5828.430	0.010	3.552	35.991	-2.931	2.806	8.590	7.875
154	Oct-08	31.345	-7.418	5811.670	0.006	1.949	32.759	-1.414	1.091	2.000	1.191
155	Nov-08	28.257	-12.661	5748.280	0.004	4.332	28.749	-0.493	-1.997	0.243	3.988
156	Dec-08	23.974	-15.467	5698.750	0.005	4.800	27.068	-3.093	-6.280	9.569	39.432
157	Jan-09	21.177	-15.656	5674.500	0.003	5.290	24.089	-2.912	-9.076	8.477	82.379
158	Feb-09	25.386	-17.365	5618.670	0.003	6.173	20.363	5.023	-4.868	25.232	23.697
159	Mar-09	30.258	-16.704	5680.100	0.004	4.483	25.280	4.978	0.004	24.781	0.000
160	Apr-09	36.243	-13.764	5708.280	0.007	3.766	29.243	7.000	5.990	48.999	35.876
161	May-09	37.387	-9.206	5778.990	0.008	2.238	33.621	3.766	7.133	14.184	50.885
162	Jun-09	39.680	-5.091	5833.920	0.007	1.796	34.775	4.905	9.426	24.055	88.855
163	Jul-09	35.045	-1.736	5816.870	0.009	2.151	33.940	1.105	4.791	1.221	22.958
164	Aug-09	33.777	-0.679	5818.420	0.011	-5.239	35.058	-1.281	3.524	1.640	12.416
165	Sep-09	32.563	-1.685	5830.520	0.006	-7.351	30.609	1.954	2.310	3.818	5.334
166	Oct-09	32.039	-8.015	5823.580	0.004	1.735	32.365	-0.326	1.785	0.106	3.186
167	Nov-09	27.683	-13.692	5778.120	0.003	3.871	30.189	-2.506	-2.570	6.280	6.607
168	Dec-09	23.639	-14.718	5700.280	0.004	4.931	26.395	-2.756	-6.615	7.596	43.758
169	Jan-10	17.535	-17.276	5671.620	0.003	5.084	24.758	-7.223	-12.718	52.169	161.753
170	Feb-10	24.693	-15.547	5640.170	0.004	5.973	22.195	2.498	-5.561	6.242	30.923
171	Mar-10	31.661	-15.228	5679.580	0.003	5.233	24.000	7.661	1.408	58.698	1.981
172	Apr-10	37.626	-13.302	5723.270	0.006	4.515	29.721	7.904	7.372	62.481	54.348
173	May-10	36.681	-11.199	5756.690	0.008	2.899	33.393	3.288	6.427	10.808	41.305
174	Jun-10	37.080	-6.141	5806.180	0.010	1.885	36.170	0.910	6.826	0.828	46.598
175	Jul-10	32.742	-1.408	5815.630	0.010	-3.373	34.508	-1.766	2.488	3.119	6.191
176	Aug-10	30.784	-0.476	5803.240	0.015	-7.192	37.678	-6.894	0.530	47.530	0.281
177	Sep-10	29.507	-2.463	5821.760	0.009	4.998	35.453	-5.946	-0.747	35.357	0.558
178	Oct-10	31.126	-7.781	5823.810	0.004	1.940	31.963	-0.838	0.872	0.701	0.761
179	Nov-10	26.947	-13.522	5740.820	0.002	4.297	27.012	-0.065	-3.307	0.004	10.937
180	Dec-10	22.950	-16.581	5709.510	0.005	4.607	28.345	-5.395	-7.304	29.101	53.344
	SUM	5435.683								2795.352	5940.381
	MEAN	30.254				R :	0.732				

NASH : 0.529

RMSE : 3.941

APPENDIX B

SUPPORT VECTOR REGRESSION ON MATLAB TOOLBOX

Precipitation

```
% DOWNSCALING PRECIPITATION WITH SVR
clear all;
clc
load  Ucc.mat
load  Uvv.mat
load  Rcc.mat
load  Rvv.mat

To = Ucc(:,1);
Go = Ucc(:,2);
H = Ucc(:,3);

LTo= length(To);

T=To+100;
G=Go+100;
%scaling
Tmin = min(T);
Tmax = max(T);
Gmax = max(G);
Gmin = min(G);
Hmax = max(H);
Hmin = min(H);

Ts =(T-Tmin)/(Tmax - Tmin);
Gs =(G-Gmin)/(Gmax - Gmin);
Hs =(H-Hmin)/(Hmax - Hmin);

Xs = [Ts, Gs, Hs];
Rmin = min(Rcc);
Rmax = max(Rcc);
Rcs = (Rcc-Rmin)/(Rmax - Rmin);

gam =0.33;
sig2 =1.8;
type = 'function estimation';

fprintf('Calibration Precipitation....\n');
[alpha,b] = trainlssvm({Xs,Rcs,type,gam,sig2,'RBF_kernel','preprocess'});
Rcst =
simlssvm({Xs,Rcs,type,gam,sig2,'RBF_kernel','preprocess'},{alpha,b},Xs);
Rct  = Rcst*(Rmax - Rmin) + Rmin;

STDc = std(Rcc);
ssqc = sumsqr(Rcc - Rct);
sq2  = sumsqr(Rcc - mean(Rcc));
NMSEc= (ssqc/LTo)/(STDc)^2 %Normalized Mean Square error
NASHc = 1.0 - ssqc/sq2 %nash-sutcliffe efficiency
RMSEc = sqrt(ssqc/LTo) %root mean square error
cor  = corrcoef(Rcc , Rct);
```

```
CORc   = [cor(1,2)]
r2c = [cor(1,2)]^2
% plot (Rct, Rcc, 'k.')
% -------------------VALIDATION------------------------------
fprintf('Validation Precipitation....\n');
% for validation
Tov = Uvv(:,1);
Gov = Uvv(:,2);
Hv = Uvv(:,3);

LTov= length(Tov);

Tv=Tov + 100;
Gv=Gov + 100;

%scaling
Tvmin = min(Tv);
Tvmax = max(Tv);
Gvmax = max(Gv);
Gvmin = min(Gv);
Hvmax = max(Hv);
Hvmin = min(Hv);

Tsv =(Tv-Tvmin)/(Tvmax - Tvmin);
Gsv =(Gv-Gvmin)/(Gvmax - Gvmin);
Hsv =(Hv-Hvmin)/(Hvmax - Hvmin);

Xsv = [Tsv, Gsv, Hsv];
Rvmin = min(Rvv);
Rvmax = max(Rvv);
Rvs = (Rvv-Rvmin)/(Rvmax - Rvmin);

%type = 'function estimation';
%[alpha,b] = trainlssvm({Xsv,Rvs,type,gam,sig2,'RBF_kernel','preprocess'});
Rvst =
simlssvm({Xsv,Rvs,type,gam,sig2,'RBF_kernel','preprocess'},{alpha,b},Xsv);
Rvt   = Rvst*(Rvmax - Rvmin) + Rvmin;

STDv = std(Rvv);
NMSEv= (ssqc/LTov)/(STDv)^2
ssqcv = sumsqr(Rvv - Rvt);
sq2v  = sumsqr(Rvv - mean(Rvv));
NASHv = 1.0 - ssqcv/sq2v
RMSEv = sqrt(ssqcv/LTov)
corv  = corrcoef(Rvv, Rvt);
CORv  = [corv(1,2)]
r2v = [corv(1,2)]^2

Compare_Rvv_Rvt =[Rvv Rvt]
plot (Rvv, Rvt, 'k.')
```

Minimum Temperature

```
% DOWNSCALING MEAN MONTHLY MINIMUM TEMPERATURE
clear all;
clc
load  GMINc.mat
load  GMINv.mat
load  MINc.mat
load  MINv.mat

To = GMINc(:,1);
Go = GMINc(:,2);
H = GMINc(:,3);
Vo = GMINc(:,4);
LTo= length(To);

T=To+100;
G=Go+100;
V=Vo+100;

%scaling
Tmin = min(T);
Tmax = max(T);
Gmax = max(G);
Gmin = min(G);
Hmax = max(H);
Hmin = min(H);
Vmax = max(V);
Vmin = min(V);

Ts =(T-Tmin)/(Tmax - Tmin);
Gs =(G-Gmin)/(Gmax - Gmin);
Hs =(H-Hmin)/(Hmax - Hmin);
Vs =(V-Vmin)/(Vmax - Vmin);

Xs = [Ts, Gs, Hs, Vs];
Mmin = min(MINc);
Mmax = max(MINc);
MINcs = (MINc-Mmin)/(Mmax - Mmin);

gam =0.45;
sig2=2;

type = 'function estimation';
fprintf('.....MINIMUM TEMPERATURE......\n');
fprintf('Calibration MINIMUM TEMPERATURE ....\n');
[alpha,b] = trainlssvm({Xs,MINcs,type,gam,sig2,'RBF_kernel','preprocess'});
MINcst =
simlssvm({Xs,MINcs,type,gam,sig2,'RBF_kernel','preprocess'},{alpha,b},Xs);
MINct  = MINcst*(Mmax - Mmin) + Mmin;
STDc = std(MINc);
ssqc = sumsqr(MINc - MINct);
sq2  = sumsqr(MINc - mean(MINc));
```

```
NMSEc= (ssqc/LTo)/(STDc)^2 %Normalized Mean Square error
NASHc = 1.0 - ssqc/sq2 %Nash-Sutcliffe model efficiency coefficient,
RMSEc = sqrt(ssqc/LTo)
cor  = corrcoef(MINc , MINct);
CORc  = [cor(1,2)]
r2c = [cor(1,2)]^2
% -------------------VALIDATION------------------------------
fprintf('Validation MINIMUM TEMPERATURE....\n');
% for validation
Tov = GMINv(:,1);
Gov = GMINv(:,2);
Hv = GMINv(:,3);
Vov = GMINv(:,4);
LTov= length(Tov);

Tv=Tov + 100;
Gv=Gov + 100;
Vv=Vov + 100;

%scaling
Tvmin = min(Tv);
Tvmax = max(Tv);
Gvmax = max(Gv);
Gvmin = min(Gv);
Hvmax = max(Hv);
Hvmin = min(Hv);
Vvmax = max(Vv);
Vvmin = min(Vv);

Tsv =(Tv-Tvmin)/(Tvmax - Tvmin);
Gsv =(Gv-Gvmin)/(Gvmax - Gvmin);
Hsv =(Hv-Hvmin)/(Hvmax - Hvmin);
Vsv =(Vv-Vvmin)/(Vvmax - Vvmin);

Xsv = [Tsv, Gsv, Hsv, Vsv];
Mvmin = min(MINv);
Mvmax = max(MINv);
MINvs = (MINv-Mvmin)/(Mvmax - Mvmin);

MINvst =
simlssvm({Xsv,MINvs,type,gam,sig2,'RBF_kernel','preprocess'},{alpha,b},Xsv);
MINvt  = MINvst*(Mvmax - Mvmin) + Mvmin;

STDv = std(MINv);
ssqcv = sumsqr(MINv - MINvt);
sq2v  = sumsqr(MINv - mean(MINv));
NMSEv= (ssqc/LTov)/(STDv)^2
NASHv = 1.0 - ssqcv/sq2v
RMSEv = sqrt(ssqcv/LTov)
corv  = corrcoef(MINv , MINvt);
CORv  = [corv(1,2)]
Compare_MINv_MINvt =[MINv MINvt]
plot (MINv, MINvt, 'k.')
```

Maximum Temperature

```
% DOWNSCALING MEAN MONTHLY MAXIMUM TEMPERATURE
clear all;
clc
load  GMAXc.mat
load  GMAXv.mat
load  MAXc.mat
load  MAXv.mat

To = GMAXc(:,1);
Go = GMAXc(:,2);
H = GMAXc(:,3);
Uo = GMAXc(:,4);
LTa= length(To);

T=To+100;
G=Go+100;
U=Uo+100;

%scaling
Tmin = min(T);
Tmax = max(T);
Gmax = max(G);
Gmin = min(G);
Hmax = max(H);
Hmin = min(H);
Umax = max(U);
Umin = min(U);

Ts =(T-Tmin)/(Tmax - Tmin);
Gs =(G-Gmin)/(Gmax - Gmin);
Hs =(H-Hmin)/(Hmax - Hmin);
Us =(U-Umin)/(Umax - Umin);

Xs = [Ts, Gs, Hs, Us];
Mmin = min(MAXc);
Mmax = max(MAXc);
MAXcs = (MAXc-Mmin)/(Mmax - Mmin);

gam =0.9;
sig2 =0.2;

type = 'function estimation';
fprintf('.....MAXIMUM TEMPERATURE ....\n');
fprintf('Calibration ....\n');
[alpha,b] = trainlssvm({Xs,MAXcs,type,gam,sig2,'RBF_kernel','preprocess'});
MAXcst =
simlssvm({Xs,MAXcs,type,gam,sig2,'RBF_kernel','preprocess'},{alpha,b},Xs);
MAXct  = MAXcst*(Mmax - Mmin) + Mmin;

STDc = std(MAXc);
```

```
ssqc = sumsqr(MAXc - MAXct);
sq2  = sumsqr(MAXc - mean(MAXc));
NMSEc= (ssqc/LTa)/(STDc)^2 %Normalized Mean Square error
NASHc = 1.0 - ssqc/sq2
RMSEc = sqrt(ssqc/LTa)
cor  = corrcoef(MAXc , MAXct);
CORc  = [cor(1,2)] % nash
r2c  = [cor(1,2)]^2
% ------------------VALIDATION-----------------------------
fprintf('Validation ....\n');
% for validation
Tov = GMAXv(:,1);
Gov = GMAXv(:,2);
Hv = GMAXv(:,3);
Vov = GMAXv(:,4);
LTav= length(Tov);

Tv=Tov + 100;
Gv=Gov + 100;
Vv=Vov + 100;

%scaling
Tvmin = min(Tv);
Tvmax = max(Tv);
Gvmax = max(Gv);
Gvmin = min(Gv);
Hvmax = max(Hv);
Hvmin = min(Hv);
Vvmax = max(Vv);
Vvmin = min(Vv);

Tsv =(Tv-Tvmin)/(Tvmax - Tvmin);
Gsv =(Gv-Gvmin)/(Gvmax - Gvmin);
Hsv =(Hv-Hvmin)/(Hvmax - Hvmin);
Vsv =(Vv-Vvmin)/(Vvmax - Vvmin);

Xsv = [Tsv, Gsv, Hsv, Vsv];
Mvmin = min(MAXv);
Mvmax = max(MAXv);
MAXvs = (MAXv-Mvmin)/(Mvmax - Mvmin);

MAXvst =
simlssvm({Xsv,MAXvs,type,gam,sig2,'RBF_kernel','preprocess'},{alpha,b},Xsv);
MAXvt  = MAXvst*(Mvmax - Mvmin) + Mvmin;

STDv = std(MAXv);
ssqcv = sumsqr(MAXv - MAXvt);
sq2v  = sumsqr(MAXv - mean(MAXv));
NMSEv= (ssqc/LTav)/(STDv)^2
NASHv = 1.0 - ssqcv/sq2v
RMSEv = sqrt(ssqcv/LTav)
corv  = corrcoef(MAXv , MAXvt);
CORv  = [corv(1,2)] % nash

Compare_MAXv_MAXvt =[MAXv MAXvt]
plot (MAXv, MAXvt, 'k.')
```