Statistical Downscaling of Temperature at Kathmandu Airport

Dissertation Submitted to the Central Department of Hydrology and Meteorology in partial fulfillment of the requirements for the degree of Master of Science in Meteorology

<u>By</u>

Niraj Shankar Pradhananga

Central Department of Hydrology and Meteorology

Tribhuvan University, Kirtipur

T.U. Regd. No: 5-1-37-622-2004

Kathmandu, Nepal

June, 2011





Ph. No.: 4-331418 P.O.Box No.: 20390 G.P.O. Kathmandu, Nepal Office of the Head of Department Kirtipur, Kathmandu, Nepal Fax No.: 977-1-4331964

Ref. No.

Date 22nd June 2011

RECOMMENDATION LETTER

This is to certify that Mr. Niraj Shankar Pradhananga has prepared the Dissertation entitled, "**STATISTICAL DOWNSCALING OF TEMPERATURE AT KATHMANDU AIRPORT**" to fulfill the Degree of Master of Science in Meteorology of the Tribhuvan University is the record of the candidates own work carried by him under our supervision and guidance.

Dissertation Supervisor

.....

Prof. Dr. Lochan Prasad Devkota

Head of Department

Central Department of Hydrology & Meteorology

Tribhuvan University

Kirtipur





Ph. No.: 4-331418 P.O.Box No.: 20390 G.P.O. Kathmandu, Nepal Office of the Head of Department Kirtipur, Kathmandu, Nepal Fax No.: 977-1-4331964

Ref. No.

ci. 70

Date 22nd June 2011

LETTER OF APPROVAL

This Dissertation entitled "STATISTICAL DOWNSCALING OF TEMPERATURE AT KATHMANDU AIRPORT" submitted by Mr. Niraj Shankar Pradhananga has been approved as a partial fulfillment for the Master of Science in Meteorology.

Prof. Dr. Lochan Prasad Devkota	Mr Tirtha Raj Adhikari
Head of Department	Lecturer
Central Department of Hydrology & Meteorology	Central Department of Hydrology & Meteorology
Tribhuvan University	Tribhuvan University
Kirtipur, Nepal	Kirtipur, Nepal

Mr Saraju Kumar Baidya

External Examiner

Senior Divisional Meteorologist

Department of Hydrology and Meteorology

Babarmahal, Nepal





Ph. No. : 4-331418 P.O.Box No.: 20390 G.P.O. Kathmandu, Nepal Office of the Head of Department Kirtipur, Kathmandu, Nepal Fax No.: 977-1-4331964

Ref. No.

Date 22nd June 2011

LETTER OF ACCEPTANCE

This Dissertation submitted by Mr. Niraj Shankar Pradhananga entitled "STATISTICAL **DOWNSCALING OF TEMPERATURE AT KATHMANDU AIRPORT**" towards the partial fulfillment of Degree of Master of Science in Meteorology is hereby accepted. It is based on the original research study. The thesis in part or full is the property of the Central Department of Hydrology and Meteorology (TU), and thereof should not be used for the purpose of awarding the same academic degree in other institution under TU.

Prof. Dr. Lochan Prasad Devkota	Mr Tirtha Raj Adhikari
Head of Department	Lecturer
Central Department of Hydrology & Meteorology	Central Department of Hydrology & Meteorology
Tribhuvan University	Tribhuvan University
Kirtipur, Nepal	Kirtipur, Nepal

Acknowledgement

First, I would like to express my deep and sincere gratitude to my supervisor, Dr. Lochan Prasad Devkota, Head, Central department of Hydrology and Meteorology, Tribhuvan University, Nepal. His wide knowledge and his logical way of thinking have been of great value for me. His understanding, encouraging and personal guidance have provided a good basis for the present report.

I owe my most sincere gratitude to Mr Saraju Kumar Baidya, Senior Divisional Meteorologist, Department of Hydrology and Meteorology, Babarmahal, Nepal for his kind support and valuable advice in every steps of this study.

I wish to express my deepest and most sincere appreciation to Mr. Kamal Prasad Budhathoki Senior Divisional Meteorologist, Department of Hydrology and Meteorology, Babarmahal, Nepal for the encouragement.

I am grateful to all the staff of Department of Hydrology and Meteorology, Nepal and all the teachers and staffs of Central Department of Hydrology and Meteorology, Tribhuvan University, Nepal for their essential assistance.

I would also like to thank my friend Miss Nisha R.C. for her help and support during my thesis period.

I warmly thank my seniors Mr. Raju Dhar Paradhanaga, Mr.Ramchandra Karki, Miss Indira Kandel, Mr.Chiranjibi Bhetwal, Mr. Sami Kunwar, Mr. Binod Parajuli, Mr.Nitesh Shrestha, Miss Bibhuti pokhrel, Miss Finu shrestha and my friends and brothers Mr. Rameswor Rimal and Mr. Gopi Adhikari for their guidance and excellent advice during the preparation of this thesis.

The partial financial support of the Nepal academy of science and technology is gratefully acknowledged.

Lastly, I thank my family for their support during my thesis work.

Niraj Shankar Pradhananga

ABSTRACT

Kathmandu Airport station is located at Tribhuwan International Airport in Kathmandu, spanning 27.70 degrees of latitude and 85.37 degrees of longitude with the elevation of 1337 meters. It is situated in Kathmandu valley which is surrounded by hills in all sides and is almost circular in shape. Elevation of surrounding hills range from 2000 to 2750m and valley is flat with elevation ranging from 1300 to 1400m. The east to west and north to south axes of valley are about 26km and 37km.kathmandu valley lies between 27°32 to 27°49 E and 85°11 to 85° 32 N. The Kathmandu valley, which has the capital city Kathmandu along with four other municipal towns, Lalitpur, Bhaktapur, Kirtipur and Madhyapur-Thimi, is the main urban area of Nepal. The valley is located between the Himalayan in the north and the Mahabharata mountains in the south. In order to best describe the expected climate change impacts for the region, climate change scenarios and climate variables must be developed on a regional, or even site-specific, scale.

To generate the future climate change scenarios in this region statistical downscaling tool was used. For this, daily temperature data from 1968-1990 A.D. was obtained from Department of Hydrology and Meteorology but for the model to run it has to start from 1960 A.D. so the data from 1961 to 1967 A.D. was coated as -999 as missing values for the model to run. This data was used as the basis for developing the initial statistical relationships. Essentially, a predictor-predictand relationship is defined between global climate model values and the observed values at Kathmandu Airport. Future climate variables (predictors) are then extracted from HADCM3 model experiment. The predictors were found to be 500 hPa geo potential height, surface zonal velocity, relative humidity at 850 and 500 hPa and surface specific humidity. Those predictors are used to provide downscaled climate variables (predictand) that are applicable to those specific observed data sites.

From this model it was found the future scenario of temperature in Kathmandu Airport at different time periods was rising.

LIST OF TABLES

No.	Tables	Page No
5.2.1	Result of Quality Control	21
5.3.1	Predictors	21
5.3.2	Predictors for the study	23

LIST OF FIGURES

<u>No.</u>	Figures	Page No
3.1	Flow chart of SDSM Version 4.2	14
4.1	Location Map of Kathmandu Airport in Nepal	18
4.2	Map of Kathmandu Valley And Kathmandu Airport	18
5.1	Grid boxes for Asia and Kathmandu Airport	20
ба	Observed Vs Synthesized Tmax at Kathmandu Airport	26
6b	Observed Vs Synthesized Tmin at Kathmandu Airport	26
6c	Projected 2020s Tmax Change at Kathmandu Airport from A2 scenario	27
6d	Projected 2050s Tmax Change at Kathmandu Airport from A2	27
6e	Projected 2080s Tmax Change at Kathmandu Airport from A2	28
6f	Increment of 95 Percentile of Maximum temperature from base	
	line period of 1961-1990 AD from A2 Scenario	28
6g	Projected 2020s Tmax Change at Kathmandu Airport from B2	29
6h	Projected 2050s Tmax Change at Kathmandu Airport from B2	29
6i	Projected 2080s Tmax Change at Kathmandu Airport from B2	30
6j	Increment of 95 Percentile of Maximum temperature from base	
	line period of 1961-1990 AD from B2 Scenario	30
6k	Projected 2020s Tmin Change at Kathmandu Airport from A2	31
61	Projected 2050s Tmin Change at Kathmandu Airport from A2	31
6m	Projected 2080s Tmin Change at Kathmandu Airport from A2	32
6n	Increment of 5 Percentile of Minimum temperature from base	
	line period of 1961-1990 AD from A2 Scenario	32
60	Projected 2020s Tmin Change at Kathmandu Airport from B2	33

6р	Projected 2050s Tmin Change at Kathmandu Airport from B2	33
6q	Projected 2080s Tmin Change at Kathmandu Airport from B2	34
бr	Increment of 5 Percentile of Minimum temperature from base line	
	period of 1961-1990 AD from B2 Scenario	34
6s	Comparison between A2 and B2 scenarios of 2080s of maximum	
	temperature at Kathmandu Airport	35
бt	Comparison between A2 and B2 scenarios of 2080s of minimum	
	temperature at Kathmandu Airport	35
би	Comparison between change in 95 percentile of minimum temperature	
	generated by A2 and B2 for 2080s	36
бv	Comparison between change in 5 percentile of minimum temperature	
	generated by A2 and B2 for 2080s	36

TABLE OF CONTENTS

ContentsPage No.Recommendation LetterLetter of ApprovalLetter of AcceptanceAcknowledgementAbstractList of FiguresList of Tables

CHAPTER 1: INTRODUCTION

1.1 General Background	1
1.2 Objectives of the Study	2
1.3 Scope of the Work	2
1.4 Limitations of the Study	2
CHAPTER 2: LITERATURE REVIEW	
2.1 Downscaling	3
2.1.1 Spatial Downscaling	3
2.1.2Temporal Downscaling	6
2.2 Emissions Scenarios	7
2.3 Regional Climate Models (RCMs)	9
2.4 Downscaling Tools	10
2.4.1 LARS-WG	11
2.4.2 SDSM	12
2.4.2.1 Assumptions of SDSM	13

CHAPTER 3: DESCRIPTION OF A MODEL

3.1	Quality control and Data transformation	15					
3.2	Screening of downscaling predictors variables	15					
3.3	Model Calibration	15					
3.4	Weather Generator	16					
3.5	Data Analysis	16					
3.6	Graphical analysis	16					
3.7	Scenario Generation	17					
CHAPTER 4	: STUDY AREA	17					
CHAPTER 5	: METHODOLOGY						
5.1	Collection of Data	19					
5.2	Quality Control	21					
5.3 Screening of Downscaling of predictor variables							
5.4 Model Calibration							
5.5	Weather Generator for validation	25					
5.6	Summary Statistics	25					
5.7	Scenario Generator	25					
CHAPTER 6	: RESULT AND DISCUSSION	26					
CHAPTER7	SUMMARY, CONCLUSION AND RECOMMENDATIONS						
7.1	Summary	37					
7.2	Conclusion	38					
7.3	Recommendations	39					
BIBLIOGRA	APHIES						

1. INTRODUCTION

1.1 General Background

After the industrialization period the concentration of green house gases (GHGs) has increased rapidly in the atmosphere and the process is still on. These GHGs are responsible for the climate change; though the climate change was there in the past, rate of climate change has been increased because of these GHGs. Climate change is causing huge problems in different forms such as floods, landslides etc throughout the world. Several basic indicators in our surroundings such as steady rise in temperatures, increasing concentration of greenhouse gases in the atmosphere, and growing weather or climatic uncertainties evidently show that collectively impacts of these changes would not be favorable at all to nature and humanity.

Nepal is a land-locked country. It forms a barrier between the Tibetan plateau and the Gangetic plain along the southern slope of the Himalaya. Kathmandu is the capital city of Nepal. Kathmandu Airport station is located at Tribhuvan International Airport in Kathmandu, spanning 27.70 degrees of latitude and 85.37 degrees of longitude with the elevation of 1337 meters. It is situated in Kathmandu valley which is surrounded by hills in all sides and is almost circular in shape. Elevation of surrounding hills range from 2000 to 2750m and valley is flat with elevation ranging from 1300 to 1400m .The east to west and north to south axes of valley are about 26km and 37km. Kathmandu valley lies between 27°32 to 27°49 E and 85°11 to 85° 32 N .

Temperature of Kathmandu Airport is increasing and to know the future scenario of the maximum temperature and minimum temperature, Statistical Downscaling Model (SDSM) has been used. It is difficult to use Global Climate model to obtain the scenarios for the individual site so it has to be downscaled. For this purpose SDSM is used. After the Calibration and Validation of SDSM it generates the future projection for 2020s, 2050s and 2080s.From this study, it was found that the maximum temperature will rise up to by 7.2°C in 2080s from A2 scenario and by 5.2°C from B2 scenario. Similarly, minimum temperature increases by 1.5°C from A2 scenario and by 1.1oC from B2 scenario.

1.2 Objectives of the Study

SDSM is a tool which is used to downscale global data to individual sites so it is a very useful tool to know the future scenarios of individual sites such as Kathmandu Airport.

The main objectives of this study are as follows:

- 1. To calibrate and validate SDSM for Temperature of Kathmandu Airport.
- 2. To generate future scenarios of Temperature of Kathmandu Airport.

1.3 Scope of the Work

According to the objectives, the scope of the work is to generate the future scenarios of temperature of Kathmandu Airport especially for 2011-2040 A.D., 2041-2070 A.D. and 2071-2099 A.D. This study will help to know how temperature will change in Kathmandu annually, monthly and seasonally because of the Climate Change.

1.4 Limitation of the Study

The following is the limitation of the study:

- The base line time period for SDSM is 1961-1990 A.D. but the temperature data of the Kathmandu airport is available from 1968 A.D. only.
- Only one GCM data has been used.

2. LITERATURE REVIEW

The review of literature is concerned with receiving some knowledge, information ideas relevant to the topic of the study. Every study is based on the past study. The past knowledge or the previous studies should not be ignored as it provides foundation to the present study.

The purpose of reviewing the literature is to develop some expertise in one's area to see what new contributions can be made and to receive some ideas for developing a research design (Howard K. Wolf and Prem Raj Pant, 2003:34)

This chapter deals with review of books, reports, research papers, and unpublished publications related to SDSM.

2.1 Downscaling

For many climate change studies scenarios of climate change derived directly from GCM output are of insufficient spatial and temporal resolution. The spatial resolution of GCMs, in particular, means that the representation of, for example, orography and land surface characteristics, is much simplified in comparison with reality, with consequent loss of some of the characteristics which may have important influences on regional climate.

2.1.1 Spatial Downscaling

Spatial downscaling refers to the techniques used to derive finer resolution climate information from coarser resolution GCM output. The fundamental bases of spatial downscaling are the assumptions that it will be possible to determine significant relationships between local and large-scale climate (thus allowing meaningful site-scale information to be determined from large-scale information alone) and that these relationships will remain valid under future climate conditions. The spatial resolution of most GCMs is between about 250 and 600km. The forcing and circulations which affect regional climate, however, generally occur at much finer spatial scales than these and can lead to significantly different regional climate conditions than are implied by the large-scale state. Spatial downscaling may be able to incorporate some of these regional climate controls and hence add value to coarse-scale GCM output in some areas - although its usefulness will be very much dependent on

the region and climate data available. Each case will be different and may necessitate the investigation of a number of different downscaling techniques before a suitable methodology is identified - and in some cases it will not be possible to improve upon the coarse-scale scenarios of climate change by downscaling.

There are a number of general recommendations concerning spatial downscaling which, if followed, should facilitate the process:

- The GCM being used for spatial downscaling should be able to simulate well those atmospheric features which will influence regional climate, e.g., jet streams and storm tracks.
- The downscaling technique should be based on a climate variable which does not exhibit large sub-grid scale variations, i.e., it is better to use a variable such as mean sea level pressure rather than one such as precipitation.
- The variables used in the downscaling process should also ideally be primary model variables, i.e., they are direct model output (e.g., sea level pressure) and are not based on parameterizations involving other model variables, as is the case with precipitation

Spatial downscaling techniques can be divided into empirical/statistical, statistical/dynamical methods and higher resolution modeling, e.g., regional climate modeling.

Empirical/statistical and statistical/dynamical methods

These techniques refer to methods in which sub-grid scale changes in climate are calculated as a function of larger-scale climate and can be broadly categorized into three classes:

- **Transfer functions** statistical relationships are calculated between large-area and sitespecific surface climate, or between large-scale upper air data and local surface climate.
- Weather typing statistical relationships are determined between particular atmospheric circulation types (e.g., anticyclonic or cyclonic conditions) and local weather.
- **Stochastic weather generators** these statistical models may be conditioned on the large-scale state in order to derive site-specific weather.



Figure 1: 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.

The advantages and disadvantages common to both empirical/statistical and statistical/dynamical spatial downscaling techniques are summarized as follows:

Advantages:

- these techniques may be able to provide more realistic scenarios of climate change at individual sites than the straight application of GCM-derived scenarios to an observed climate data set
- these techniques are much less computationally demanding than physical downscaling using numerical models
- ensembles of high resolution climate scenarios may be produced relatively easily
- statistical/dynamical techniques are based on sensible physical linkages between climate on the large scale and weather on the local scale

Disadvantages:

- large amounts of observational data may be required to establish statistical relationships for the current climate
- specialist knowledge may be required to apply the techniques correctly
- the relationships are only valid within the range of the data used for calibration future projections for some variables may lie outside of this range
- it may not be possible to derive significant relationships for some variables
- a predictor variable which may not appear as the most significant when developing the transfer functions under present climate may be critical for determining climate change
- for statistical/dynamical downscaling the fundamental assumption may not hold differences in relationships between weather type and local climate have occurred at some sites during the observed record (Wilby, 1997)
- for statistical/dynamical downscaling, the scenarios produced are relatively insensitive to
 future climate forcing using GCM pressure fields alone to derive weather types and thence
 local climate does not account for the GCM projected changes in, for example, temperature
 and precipitation, so it may be necessary to include additional variables such as large-scale
 temperature and atmospheric humidity

2.1.2 Temporal downscaling

Temporal downscaling refers to the derivation of fine-scale temporal data from coarser-scale temporal information, e.g., daily data from monthly or seasonal information. Its main application is in scenario studies, particularly for the derivation of daily scenario data from monthly or seasonal scenario information. Monthly model output is available from many GCM experiments, whilst only a small number of experiments have archived daily model output. Also, daily model output is not considered to be as robust as model output at the monthly or seasonal time scales and so is not generally recommended for use in scenario studies without more detailed investigations being undertaken. The simplest method for obtaining daily data for a particular climate change scenario is to apply the monthly or seasonal changes to an historical daily weather record for a particular station. However, this method maintains the current observed climate variability and the same sequences of,

for example, wet and dry days and hot and cold spells. There is also only one time series available for each scenario, which limits the type of analyses for which the daily data can be used.

The advantages and disadvantages associated with the use of stochastic weather generators are briefly summarized as follows:

Advantages:

- the ability to generate time series of unlimited length
- the opportunity to obtain representative weather time series in regions of data sparsity, by interpolating observed data
- the ability to alter the weather generator's parameters in accordance with scenarios of future climate change changes in variability may be incorporated as well as changes in mean values

Disadvantages:

- seldom able to describe all aspects of climate accurately, especially persistent events, rare events and decadal- or century-scale variations
- designed for use independently at individual locations and few account for the spatial correlation of climate

2.2 Emissions Scenarios

Future greenhouse gas (GHG) emissions are the product of very complex dynamic systems, determined by driving forces such as demographic development, socio-economic development and technological change. Their future evolution is highly uncertain. Scenarios are alternative images of how the future might unfold and are an appropriate tool with which to analyse how driving forces may influence future emission outcomes and to assess the associated uncertainties. They assist in climate change analysis, including climate modeling and the assessment of impacts, adaptation, and mitigation. The possibility that any single emissions path will occur as described in scenarios is highly uncertain.

A set of scenarios was developed to represent the range of driving forces and emissions in the scenario literature so as to reflect current understanding and knowledge about underlying uncertainties. They exclude only outlying "surprise" or "disaster" scenarios in the literature. The Special Report on Emissions Scenarios (SRES) is a report prepared by the Intergovernmental Panel on Climate Change (IPCC) that was published in the year 2000. The emissions scenarios described in the Report have been used to make projections of possible future climate change. The SRES scenarios, as they are often called, were used in the IPCC Third Assessment Report (TAR), published in 2001, and in the IPCC Fourth Assessment Report (AR4), published in 2007. The SRES scenarios were designed to improve upon some aspects of the IS92 scenarios, which had been used in the earlier IPCC Second Assessment Report of 1995.[1] At the time they were developed, the range of global emissions projected across all forty of the SRES scenarios covered the 5th% to 95th% percentile range of the emission scenarios literature (Morita et al., 2001, p. 146).

Scenario families

Scenario families contain individual scenarios with common themes. The six families of scenarios discussed in the IPCC's Third Assessment Report (TAR) and Fourth Assessment Report (AR4) are A1FI, A1B, A1T, A2, B1, and B2.

Scenario descriptions are based on those in AR4, which are identical to those in TAR.

A1

The A1 scenarios are of a more integrated world. The A1 family of scenarios is characterized by: Rapid economic growth.

A global population that reaches 9 billion in 2050 and then gradually declines.

The quick spread of new and efficient technologies.

A convergent world - income and way of life converge between regions. Extensive social and cultural interactions worldwide.

There are subsets to the A1 family based on their technological emphasis:

A1FI - An emphasis on fossil-fuels (Fossil Intensive).

A1B - A balanced emphasis on all energy sources.

A1T - Emphasis on non-fossil energy sources.

A2

The A2 scenarios are of a more divided world. The A2 family of scenarios is characterized by: A world of independently operating, self-reliant nations.

Continuously increasing population.

Regionally oriented economic development.

Slower and more fragmented technological changes and improvements to per capita income.

B1

The B1 scenarios are of a world more integrated, and more ecologically friendly. The B1 scenarios are characterized by:

Rapid economic growth as in A1, but with rapid changes towards a service and information economy.

Population rising to 9 billion in 2050 and then declining as in A1.

Reductions in material intensity and the introduction of clean and resource efficient technologies.

An emphasis on global solutions to economic, social and environmental stability.

B2

The B2 scenarios are of a world more divided, but more ecologically friendly. The B2 scenarios are characterized by:

Continuously increasing population, but at a slower rate than in A2.

Emphasis on local rather than global solutions to economic, social and environmental stability.

Intermediate levels of economic development.

Less rapid and more fragmented technological change than in A1 and B1.

2.3 Regional climate models (RCMs)

• An alternative to downscaling using statistical techniques is the use of a regional climate models (RCM). These numerical models are similar to global climate models, but are of higher resolution and therefore contain a better representation of, for example, the underlying topography within the model domain and, depending on the model resolution, may also be

able to resolve some of the atmospheric processes which are parameterised in a global climate model.

The general approach is to 'nest' an RCM within the 'driving' global climate model so that the high resolution model simulates the climate features and physical processes in much greater detail for a limited area of the globe, whilst drawing information about initial conditions, time-dependent lateral meteorological conditions and surface boundary conditions from the GCM. Most nesting techniques are one-way, i.e., there is no feedback from the RCM simulation to the driving GCM. The global model simulates the response of the global circulation to large-scale forcing, whilst the RCM accounts for sub-GCM grid scale forcing, such as complex topographical features and land cover in homogeneity, in a physically-based way and thus enhances the simulations of atmospheric and climatic variables at finer spatial scales. However, the RCM is susceptible to any systematic errors in the driving fields provided by the global models, and these may be exacerbated in the RCM thus resulting in a poor simulation of the regional climate. High frequency, i.e., 6 hourly, time-dependent GCM fields are required to provide the boundary conditions for the RCM; these are generally not routinely stored by global climate modelers, and so there needs to be careful co-ordination between the global and regional climate modeling groups in order to ensure that the appropriate data are available. Also, RCM simulations may be computationally demanding, depending on the domain size and resolution, and this has limited the length of many experiments.

2.4 Downscaling Tools

Although there is no 'standard' approach to downscaling, i.e., obtaining finer resolution scenarios of climate change from the coarser resolution GCM output, there are pieces of software available which can be used to undertake spatial and temporal downscaling such as:

- LARS-WG, a stochastic weather generator developed by Mikhail Semenov, also in the UK.
- SDSM, a Statistical DownScaling Model, developed by Rob Wilby and Christian Dawson in the UK, and

2.4.1 LARS-WG

LARS-WG, based on the serial approach, is one of the most readily available stochastic weather generators. The software consists of three main sections:

- 1. Analysis: the first step in the weather generation process is the analysis of the observed station data in order to calculate the weather generator parameters, i.e., the statistical characteristics of the data. LARS-WG requires observations for precipitation and one or all of maximum and minimum temperature and sunshine hours (or solar radiation; if sunshine hours are supplied the data are converted using an algorithm based on that of Rietveld (1978). The analysis process uses semi-empirical distributions, i.e., frequency distributions calculated from the observed data, for wet and dry series duration, precipitation amount and solar radiation. Maximum and minimum temperature is described using Fourier series. The resulting parameter file is then used in the generation process.
- 2. Generator: LARS-WG generates synthetic weather data by combining a scenario file containing information about changes in precipitation amount, wet and dry series duration, mean temperature, temperature variability and solar radiation with the parameter files generated in step (1). If LARS-WG is being used to generate synthetic data in order to determine how well the model is simulating observed conditions, or to simulate a longer time series of data for a station with only a short observational record, then the scenario file contains no changes. However, if LARS-WG is being used to generate daily data for a particular scenario of climate change, then the scenario file will contain the appropriate monthly changes.
- 3. **Qtest**: LARS-WG simplifies the procedure for determining how well it is simulating observed conditions by providing the Qtest option. In this step, the statistical characteristics of the observed data are compared with those of synthetic data generated using the parameters derived from the observed station data. A number of statistical tests, the chi-squared test,

Student's t test and the F test, are used to determine whether the distributions, mean values and standard deviations, respectively, of the synthetic data are significantly different from those of the original observed data set.

The main use of LARS-WG is in the generation of daily data from monthly climate change scenario information. The advantage of using a stochastic weather generator rather than simply applying the scenario changes to an observed daily time series is that a number of different daily time series representing the scenario can be generated by using a different random number to control the stochastic component of the model. Hence, these time series all have the same statistical characteristics, but they vary on a day-to-day basis. This permits risk analyses to be undertaken.

2.4.2 SDSM

SDSM permits the spatial downscaling of daily predictor-predictand relationships using multiple linear regression techniques. The *predictor* variables provide daily information concerning the large-scale state of the atmosphere, whilst the predictand describes conditions at the site scale. The software reduces the task of statistically downscaling daily weather series into a number of discrete processes:

- Preliminary screening of potential downscaling predictor variables identifies those largescale predictor variables which are significantly correlated with observed station (predictand) data. A number of variables derived from mean sea level pressure fields are included, e.g., air flow strength, meridional and zonal components of air flow, vorticity etc.
- 2. Assembly and calibration of statistical downscaling model(s) the large-scale predictor variables identified in (1) are used in the determination of multiple linear regression relationships between these variables and the local station data. Statistical models may be built on a monthly, seasonal or annual basis. Information regarding the amount of variance explained by the model(s) and the standard error is given in order to determine the viability of spatial downscaling for the variable and site in question.
- 3. Synthesis of ensembles of current weather data using observed predictor variables once statistical downscaling models have been determined they can be verified by using an independent data set of observed predictors. The stochastic component of SDSM allows the

generation of up to 100 ensembles of data which have the same statistical characteristics but which vary on a day-to-day basis.

4. Generation of ensembles of future weather data using GCM-derived predictor variables - provision of the appropriate GCM-derived predictor variables allows the generation of ensembles of future weather data by using the statistical relationships calculated in (2).

Diagnostic testing/analysis of observed data and climate change scenarios - it is possible to calculate the statistical characteristics of both the observed and synthetic data in order for easy comparison and thus determination of the effect of spatial downscaling.

2.4.2.1 Assumption of SDSM:

There is a great effect of Global Circulation in the local climate so SDSM does regression analysis of local parameter and global predictor and it assumes that the analysis will valid till 2100 A.D.

3. DESCRIPTION OF MODEL

SDSM 4.2 (Statistical DownScaling Model) facilitates the rapid development of multiple, low– cost, single–site scenarios of daily surface weather variables under present and future climate forcing. Additionally, the software performs ancillary tasks of data quality control and transformation, predictor variable pre–screening, automatic model calibration, basic diagnostic testing, statistical analyses and graphing of climate data. SDSM Version 4.2 was supported by the Environment Agency of England and Wales as part of the Thames Estuary 2100 project. SDSM is coded in Visual Basic 6.0. The structure and operation of SDSM with respect to seven tasks are as follows:

- 1. Quality control and data transformation;
- 2. Screening of potential downscaling predictor variables;
- 3. Model calibration;
- 4. Generation of ensembles of present weather data using observed predictor variables;
- 5. Statistical analysis of observed data and climate change scenarios;
- 6. Graphing model output;
- 7. Generation of ensembles of future weather data using GCM-derived predictor variables.



Fig 3.1 Flow chart of SDSM Version 4.2 Climate Scenario Generation

Within the taxonomy of downscaling techniques, SDSM is best described as a hybrid of the stochastic weather generator and transfer function methods. This is because large–scale circulation patterns and atmospheric moisture variables are used to condition local–scale weather generator parameters (e.g., precipitation occurrence and intensity). Additionally, stochastic techniques are used to artificially inflate the variance of the downscaled daily time series to better accord with observations. To date, the downscaling algorithm of SDSM has been applied to a host of meteorological, hydrological and environmental assessments, as well as a range of geographical contexts including Africa, Europe, North America and Asia.

The following sections outline the software's seven core operations.

3.1 Quality control and data transformation

Few meteorological stations have 100% complete and/or fully accurate data sets. Handling of missing and imperfect data is necessary for most practical situations. Simple **Quality Control** checks in SDSM enable the identification of gross data errors, specification of missing data codes and outliers prior to model calibration.

In many instances it may be appropriate to transform predictors and/or the predictand prior to model calibration. The **Transform** facility takes chosen data files and applies selected transformations (e.g., logarithm, power, inverse, lag, binomial, etc).

3.2 Screening of downscaling predictor variables

Identifying empirical relationships between gridded predictors (such as mean sea level pressure) and single site predictands (such as station precipitation) is central to all statistical downscaling methods.

The main purpose of the **Screen Variables** operation is to assist the user in the selection of appropriate downscaling predictor variables. This is one of the most challenging stages in the development of any statistical downscaling model since the choice of predictors largely determines the character of the downscaled climate scenario. The decision process is also complicated by the fact that the explanatory power of individual predictor variables varies both spatially and temporally. **Screen Variables** facilitates the examination of seasonal variations in predictor skill.

3.3 Model calibration

The **Calibrate Model** operation takes a User–specified predictand along with a set of predictor variables, and computes the parameters of multiple regression equations via an optimisation algorithm (either dual simplex of ordinary least squares).

The User specifies the model structure: whether monthly, seasonal or annual sub-models are required; whether the process is unconditional or conditional. In unconditional models a direct link is assumed between the predictors and predictand (e.g., local wind speeds may be a function of regional airflow indices). In conditional models, there is an intermediate process between regional forcing and local weather (e.g., local precipitation amounts depend on the occurrence of wet-days, which in turn depend on regional-scale predictors such as humidity and atmospheric pressure).

3.4 Weather generator

The **Weather Generator** operation generates ensembles of synthetic daily weather series given observed (or NCEP re–analysis) atmospheric predictor variables. The procedure enables the verification of calibrated models (using independent data) and the synthesis of artificial time series for present climate conditions.

The User selects a calibrated model and SDSM automatically links all necessary predictors to model weights. The User must also specify the period of record to be synthesized as well as the desired number of ensemble members. Synthetic time series are written to specific output files for later statistical analysis, graphing and/or impacts modeling.

3.5 Data analysis

SDSM provides means of interrogating both downscaled scenarios and observed climate data with the **Summary Statistics** and **Frequency Analysis** screens.

In both cases, the User must specify the sub-period, output file name and chosen statistics. For model output, the ensemble member or mean must also be specified. In return, SDSM displays a suite of diagnostics including monthly/ seasonal/ annual means, measures of dispersion, serial correlation and extremes.

3.6 Graphical analysis

Three options for graphical analysis are provided by SDSM 4.2 through the **Frequency Analysis**, **Compare Results**, and the **Time Series Analysis** screens.

The **Frequency Analysis** screen allows the User to plot extreme value statistics of the chosen data file(s). Analyses include Empirical, Gumbel, Stretched Exponential and Generalised Extreme Value distributions.

The **Compare Results** screen enables the User to plot monthly statistics produced by the **Summary Statistics** screen. Having specified the necessary input file, either bar or line charts may be chosen for display purposes. The graphing option allows simultaneous comparison of two data sets and hence rapid assessment of downscaled versus observed, or present versus future climate scenarios.

The **Time Series Analysis** screen allows the User to produce time series plots for up to a maximum of five variables. The data can be analysed as monthly, seasonal, annual or water year periods for statistics such as Sum, Mean, Maximum, Winter/Summer ratios, Partial Duration Series, Percentiles and Standardized Precipitation Index.

3.7 Scenario generation

Finally, the **Scenario Generator** operation produces ensembles of synthetic daily weather series given atmospheric predictor variables supplied by a climate model (either for present or future climate experiments), rather than observed predictors. This function is identical to that of the **Weather Generator** operation in all respects except that it may be necessary to specify a different convention for model dates and source directory for predictor variables. The input files for both the **Weather Generator** and **Scenario Generator** options need not be the same length as those used to obtain the model weights during the calibration phase.

4. STUDY AREA

The study area is the Kathmandu Airport station in Kathmandu valley. Kathmandu Valley is located between latitude 27.34° N and 27.50° N and longitude 85.11° E and 85.32° E. The valley is almost a circular bowl-shaped and surrounded on all sides (although the narrow gap in the south) by the mountains which have a height of about 2,122m on average., its east-west axis being about 25 km in length with a maximum north-south width of nearly 19 km. Its area is approximately 339 sq. km. The valley lies at an average altitude of 1350 m above mean sea level (msl), with hills and mountain ranges rising rather steeply on all sides completely enclosing the valley. Kathmandu Airport station is located at Tribhuwan International Airport in Kathmandu, spanning 27.70 degrees of latitude and 85.37 degrees of longitude with the elevation of 1337 meters.



Location Map of Kathmandu Airport in Nepal





Map of Kathmandu Valley and Kathmandu Airport



5. METHODOLOGY

The methodology in the study using SDSM basically involved collection of different types of data and processing them into standard formats followed by calibration and validation of the model. Most of these data were available in the public domain of different web sites. Followings are the steps involved in the study:

- 1. Collection of data
- 2. Quality Control
- 3. Screening of variables
- 4. Calibration of SDSM
- 5. Weather Generator and Validation
- 6. Summary Statistics
- 7. Frequency Analysis
- 8. Scenario Generator
- 9. Compare Results
- 10. Time Series Analysis

5.1 Collection of data

The observed daily data of maximum and minimum temperature for the SDSM from 1968-1990 A.D. was collected from DHM. The predictor variables were obtained from the web portal of The Canadian Institute for Climate Studies. The website is http://www.cics.uvic.ca/scenarios/index.cgi?Scenarios. In this study HADCM3 model has been chosen. From that model, grid box Y= 24 latitude 27.5°C and X= 24 Longitude=86.25°C was selected for study of Kathmandu Airport.



Grid boxes for Asia and Kathmandu Airport



The data downloaded from the HADCM3 are:

- a) H3A2a_1961-2099
- b) H3B2a_1961-2099
- c) NCEP_1961-2001

5.2 Quality Control

Quality control of observed daily maximum and minimum temperature data was done by using Quality Control of SDSM.

Results	Maximum Temperature	Minimum Temperature				
Minimum value	6.9	-3.5				
Maximum value	36.6	22.4				
Mean	24.81	11.74				
No. of values in file	14975	14975				
Missing Values	2579	2597				
No. of values ok	12396	12378				
Missing value code	-999	-999				

5.2.1 Result of Quality Control

5.3 Screening of Downscaling of predictor variables

Identifying empirical relationships between gridded predictors (such as mean sea level pressure) and single site predictands (such as temperature) is central to all statistical downscaling methods and is often the most time consuming step in the process. There are altogether 26 predictors available and to determine the best predictors for the predictand, Screen Variables option was used. Followings are the 26 predictors:

5.3.1 Predictors

Predictor	Code	Predictor	Code		
Mean sea level pressure	ncepmslpas	500 hpa divergence	ncepp5zhas		
Surface airflow strength	ncepp_fas	850 hpa air flow strength	ncepp8_fas		
Surface zonal velocity	ncepp_uas	850 hpa zonal velocity	ncepp8_uas		
Surface meridional velocity	ncepp_vas	850 hpa meridional velocity	ncepp8_vas		
Surface vorticity	ncepp_zas	850 hpa vorticity	ncepp8_zas		
Surface wind direction	ncepp_thas	850 hpa geopotential height	ncepp850as		
Surface divergence	ncepp_zhas	850 hpa wind direction	ncepp8thas		
500 hpa airflow strength	ncepp5_fas	850 hpa divergence	ncepp8zhas		
500 hpa zonal velocity	ncepp5_uas	Relative humidity at 500 hpa	ncepr500as		

500 hpa meridional velocity	ncepp5_vas	Relative humidity at 850 hpa	ncepr850as
500 hpa vorticity	ncepp5_zas	Near surface relative humidity	nceprhumas
500 hpa geopotential height	ncepp500as	Surface specific humidity	ncepshumas
500 hpa wind direction	ncepp5thas	Mean temperature at 2m	nceptempas

Data from 1968-1985 A.D. was used for screening of the variables. Correlation between the predictors and Tmax are as follows:

RESULTS: EXPLAINED VARIANCE

Analysis Period: 1/1/1961 - 12/31/2001 Significance level: 0.05

Total missing values: 23211

Predictand: TMAX1030.DAT

Predictors:	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
ncepmslpas.dat	0.021	0.007	0.023	0.026	0.029	0.030	0.020	0.018		0.012	0.060	0.088
nceppfas.dat	0.021	0.051	0.040	0.086	0.108	0.091	0.131	0.136	0.033	0.145	0.270	0.164
nceppuas.dat	0.026	0.052	0.041	0.089	0.117	0.093	0.132	0.150	0.043	0.154	0.274	0.175
nceppvas.dat	0.064	0.071	0.009	0.009	0.006	0.017	0.023	0.011			0.192	0.074
nceppzas.dat	0.045	0.019		0.009	0.057	0.011	0.021	0.009			0.005	0.016
ncepp_thas.dat	0.021	0.030	0.005		0.044	0.031	0.048	0.097	0.056	0.015	0.102	0.040
ncepp_zhas.dat		0.007	0.007				0.008		0.012	0.020	0.020	
ncepp5_fas.dat	0.027	0.028		0.008			0.028	0.032		0.097	0.155	0.165

RESULTS: EXPLAINED VARIANCE

Analysis Period: 1/1/1961 - 12/31/2001 Significance level: 0.05

Total missing values: 23211

Predictand: TMAX1030.DAT

Predictors:	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
ncepp5_uas.dat ncepp5_vas.dat ncepp5_zas.dat ncepp500as.dat ncepp5thas.dat ncepp5zhas.dat ncepp8_fas.dat ncepp8_uas.dat	0.017 0.019 0.079 0.234 0.022 0.021 0.028 0.061	0.016 0.092 0.272 0.017	0.006 0.070 0.254 0.012 0.022	0.023 0.045 0.112 0.023 0.006 0.014	0.005 0.048 0.101 0.125 0.006 0.059 0.005	0.007 0.044 0.005 0.005	0.119 0.008 0.061 0.058 0.080 0.011 0.053 0.107	0.153 0.074 0.091 0.113 0.008 0.067 0.124	0.028 0.008 0.006 0.091 0.021 0.012 0.012 0.012	0.063 0.094 0.200 0.096 0.101	0.123 0.073 0.262 0.169 0.175	0.145 0.100 0.365 0.027 0.005 0.198 0.217

RESULTS: EXPLAINED VARIANCE

Analysis Period: 1/1/1961 - 12/31/2001 Significance level: 0.05

Total missing values: 25790

Predictand: TMAX1030.DAT

Predictors:	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
ncepp8_vas.dat	0.015	0.000	0.007	0.006		0.000	0.013	0.008		0.008	0.053	0.005
nceppo_zas.dat pcepp850as.dat	CUU.U	0.006	0.024	0.011		0.008	0.046	0.049	0 009		0.014	0.005
ncepp8thas.dat	0.048	0.022	0.010	0.008		0.011	0.024	0.115	0.012		0.069	0.110
ncepp8zhas.dat	0.013	0.005	0.016				0.010	0.008		0.009	0.054	
ncepr500as.dat	0.119	0.065	0.134	0.137	0.175	0.174	0.093	0.080	0.078	0.020	0.043	0.090
ncepr850as.dat	0.090	0.165	0.277	0.285	0.300	0.168	0.084	0.074	0.055	0.005		0.048
nceprhumas.dat	0.090	0.165	0.277	0.285	0.300	0.168	0.084	0.074	0.055	0.005		0.048
ncepshumas.dat			0.008	0.085	0.113	0.084	0.011			0.018	0.037	0.021

In the similar way the correlation between Predictors and Tmin was generated and the predictors were choosen for the study. They are as follows:

5.3.2 Predictors for the study

	Maximum Temperature	Minimum Temperature			
Predictors	ncepp500as.dat	ncepshumas.dat			
Treaterons	ncepp_uas.dat	ncepp500as.dat			
	ncepr850as.dat	ncepp_uas.dat			

Where,

ncepp500as.dat= 500 hPa geopotential height

ncepp_uas.dat =Surface zonal velocity

ncepr850as.dat= Relative humidity at 850 hPa

ncepshumas.dat= Surface specific humidity

5.4 Model Calibration

For the model calibration, model type was chosen to be monthly, process was unconditional and the period from 1968-1985 A.D. was selected for the model calibration. As we don't have the data of 1961-1967 A.D. we're unable to use the earlier data for calibration.

5.4.1 Result of model calibration of Tmax

Predictand: TMAX1030.DAT

Predictors: ncepp__uas.dat ncepp500as.dat ncepr850as.dat

Unconditional Statistics

RSquared	SE
0.260	1.799
0.440	2.028
0.540	1.940
0.396	2.133
0.442	1.872
0.281	1.787
0.200	1.364
0.206	1.472
0.127	1.822
0.234	1.764
0.400	1.371
0.359	1.585
0.324	1.745
	RSquared 0.260 0.440 0.540 0.396 0.442 0.281 0.200 0.206 0.127 0.234 0.400 0.359 0.324

5.5 Weather Generator for Validation

The **Weather Generator** operation produces ensembles of synthetic daily weather series given observed (or NCEP re–analysis) atmospheric predictor variables and regression model weights produced by the **Calibrate Model** operation. The **Weather Generator** enables the verification of calibrated models (assuming the availability of independent data) as well as the synthesis of artificial time series representative of present climate conditions. The **Weather Generator** can also be used to reconstruct predictands or to infill missing data.

For this purpose, the output file generated from the calibration part is used as input file and the validation period was 1986-2001 A.D. Validation output is given in the result section; Fig 6a and Fig 6b.

5.6 Summary Statistics

In summary statistics, statistics which has to be performed for this study i.e. mean, 95 percentile and percentile selected. Both observed and modeled data were used for analysis and future scenarios generation. The result of summary statistics is given in the result section; Fig 6c-Fig 6n.

5.8 Scenario Generator

From Scenario generator ensembles of synthetic daily weather series given daily atmospheric predictor variables supplied by a GCM was produced. In this study, scenarios of A2 and B2 for the temperature at Kathmandu Airport were generated from HADCM3 model. The result of scenario generator is given in the result section; Fig 6c-Fig 6n.

6. RESULT AND DISSCUSION

Downscaled SDSM results for Tmax and Tmin at Kathmandu Airport, for the three tri-decadal periods ceni Maximum Temperature at Kathmandu Airport from 1986-2001 A.D.



Fig 6a: Observed Vs Synthesized Tmax at Kathmandu Airport

Here the model has underestimated the observed data from January to May while over estimated in June and for rest of the months it simulated quite well. The model has underestimated the observed data the most in the month of January while in June it has over estimated the most. In December it simulated quite well.



Minimum temperature at Kathmandu Airport from 1986-2001

Fig 6b: Observed Vs Synthesized Tmin at Kathmandu Airport

The model has shown that the minimum temperature can be accurately simulated by SDSM as it rarely over and underestimated the observed data.



Fig 6c: Projected 2020s Tmax Change at Kathmandu Airport from A2

The future scenario from H3A2 shows that when compared with current climate, the annual increment of Maximum Temperature would be 0.46° C in 2020s. The most warming amplitude may happen in April with the increment by 1.06° C and the lowest increment of 0.20° C was found in the Month of January. Similarly, spring season recorded the highest increment with 0.77° C while summer, the lowest with the increment of 0.29° C.



Fig 6d: Projected 2050s Tmax Change at Kathmandu Airport from A2

With the same scenario, the annual increment of Maximum Temperature would be 0.95°C in 2050s. In April, maximum temperature will rise by 1.40°C while in July it will rise by 0.57°C which is the lowest. In winter it will rise by 0.88°C while spring records the highest rise by 1.24°C.In summer the increment is the lowest with the value of 0.75°C.

Increment in Maximum Temperature at Kathmandu in 2080s from A2 Scenario



Fig 6e: Projected 2080s Tmax Change at Kathmandu Airport from A2

The future scenario from H3A2 shows that when compared with current climate, the annual increment of Maximum Temperature would be 1.74° C in 2080s. The most warming amplitude may happen in April with the increment by 3.01° C and the lowest increment of 1.03° C was found in the Month of July. Similarly, spring season recorded the highest increment with 2.66° C while summer, the lowest with the increment of 1.21° C.



Fig 6f: Increment of 95 Percentile of Maximum temperature from base line period of 1961-1990 AD from A2 Scenario

In case of 95 percentile, from A2 scenario we can see that the rise in annual maximum temperature will be 0.53°C, 1.11°C and 1.99°C for 2020s, 2050s and 2080s respectively. A rising limb can be seen from January to April then retreating line can be seen till July and it again starts rising till September. From the figure it has been seen that the rise is less in summer and high in spring.



Fig 6g: Projected 2020s Tmax Change at Kathmandu Airport from B2

The future scenario from H3A2 shows that when compared with current climate, the annual increment of Minimum Temperature would be 0.50° C in 2020s. The most warming amplitude may happen in June with the increment by 0.98° C and the lowest increment of 0.14° C was found in the Month of January. Similarly, spring season recorded the highest increment with 0.70° C while winter, the lowest with the increment of 0.34° C.



Fig 6h: Projected 2050s Tmax Change at Kathmandu Airport from B2

With the same scenario, the annual increment of Maximum Temperature would be 0.78° C in 2050s. In March, maximum temperature will rise by 1.27° C while in July it will rise by 0.42° C which is the lowest. In winter it will rise by 0.75° C while spring records the highest rise by 1.10° C.In summer the increment is the lowest with the value of 0.61° C.



Fig 6i: Projected 2080s Tmax Change at Kathmandu Airport from B2

The future scenario from H3B2 shows that when compared with current climate, the annual increment of Maximum Temperature would be 1.26° C in 2080s. The most warming amplitude may happen in March with the increment by 1.97° C and the lowest increment of 0.71° C was found in the month of July. Similarly, spring season recorded the highest increment with 1.72° C while summer, the lowest with the increment of 1.00° C.



Fig 6j: Increment of 95 Percentile of Maximum temperature from base line period of 1961-1990 AD from B2 Scenario

In case of 95 percentile, from B2 scenario we can see that the rise in annual maximum temperature will be 0.63°C, 0.82°C and 1.37°C for 2020s, 2050s and 2080s respectively. A rising limb can be seen from winter to summer in 2020s and 2080s.



Fig 6k: Projected 2020s Tmin Change at Kathmandu Airport from A2

The future scenario from H3A2 shows that when compared with current climate, the annual increment of Minimum Temperature would be 0.4° C in 2020s. The most warming amplitude may happen in October with the increment by 0.8° C and the lowest increment of 0.2° C was found in the Month of February. Similarly, autumn season recorded the highest increment with 0.6° C while winter, the lowest with the increment of 0.3° C.



Fig 61: Projected 2050s Tmin Change at Kathmandu Airport from A2

With the same scenario, the annual increment of Minimum Temperature would be 1.0° C in 2050s. In October, minimum temperature will rise by 1.6° C while in August it will rise by 0.5° C which is the lowest. In winter it will rise by 0.7° C while autumn records the highest rise by 1.3° C.In summer the increment is the lowest with the value of 0.7° C.



Fig 6m: Projected 2080s Tmin Change at Kathmandu Airport from A2

The future scenario from H3A2 shows that when compared with current climate, the annual increment of Minimum Temperature would be 1.5° C in 2080s. The most warming amplitude may happen in October with the increment by2.7°C and the lowest increment of 0.6°C was found in the Month of February. Similarly, autumn season recorded the highest increment with 2.3°C while winter, the lowest with the increment of 1.0° C.



Fig 6n: Increment of 5 Percentile of Minimum temperature from base line period of 1961-1990 AD from A2 Scenario

In case of 5 percentile, from A2 scenario we can see that the rise in annual minimum temperature will be 0.38°C, 0.66°C and 1.05°C for 2020s, 2050s and 2080s respectively. A recession limb can be seen from May to August. From the figure it has been seen that the rise is less in winter and high in autumn.



Fig 60: Projected 2020s Tmin Change at Kathmandu Airport from B2

The future scenario from H3B2 shows that when compared with current climate, the annual increment of Minimum Temperature would be 0.60° C in 2020s. The most warming amplitude may happen in October with the increment by 1.2° C and the lowest increment of -0.1° C was found in the Month of June. Similarly, autumn season recorded the highest increment with 0.90° C while summer, the lowest with the increment of 0.34° C.



Fig 6p: Projected 2050s Tmin Change at Kathmandu Airport from B2

With the same scenario, the annual increment of Minimum Temperature would be 0.8° C in 2050s. In November, minimum temperature will rise by 1.1° C while in February it will rise by 0.3° C which is the lowest. In winter it will rise by 0.5° C while autumn records the highest rise by 1.1° C.



Fig 6q: Projected 2080s Tmin Change at Kathmandu Airport from B2

The future scenario from H3B2 shows that when compared with current climate, the annual increment of Minimum Temperature would be 1.1° C in 2080s. The most warming amplitude may happen in November with the increment by 1.82° C and the lowest increment of 0.7° C was found in the Month of January. Similarly, autumn season recorded the highest increment with 1.7° C while winter, the lowest with the increment of 0.8° C.



Fig 6r: Increment of 5 Percentile of Minimum temperature from base line period of 1961-1990 AD from B2 Scenario

In case of 5 percentile, from B2 scenario we can see that the rise in annual minimum temperature will be 0.50°C, 0.50oC and 0.72°C for 2020s, 2050s and 2080s respectively. A recession limb can be seen from May to August. From the figure it has been seen that the rise is less in winter and high in autumn.





Fig 6s: Comparison between A2 and B2 scenarios of 2080s of maximum temperature at Kathmandu Airport

Comparing the results of A2 and B2 scenarios it was found that the annual increment of maximum temperature varied between 1.26 and 1.74. It is obvious that the result of A2 will give high value than B2. In spring the increment was the highest with 2.66 from A2 and 1.72 from B2 while the lowest was found to be 1.00 from B2 and 1.21 from A2 in summer. The result from A2 and B2 was almost coinciding in the month of June with the values 1.48 and 1.43 respectively.



Fig 6t: Comparison between A2 and B2 scenarios of 2080s of minimum temperature at Kathmandu Airport

Minimum temperature varied between 1.13 and 1.51 with the highest value in autumn.

In February the value from A2 was less than that of B2. The figure above is quite similar except in February.

Comparison between change in 95 percentile of maximum temperature generated by A2 and B2 for 2080s



Fig 6u: Comparison between change in 95 percentile of minimum temperature generated by A2 and B2 for 2080s

Comparing the results of A2 and B2 scenarios it was found that the annual increment in 95 percentile varied between 1.37 and 1.99. It is obvious that the result of A2 will give high value than B2. In spring the increment was the highest with 2.43 from A2and in summer 1.52 from B2 while the lowest was found to be 1.23 in winter from B2 and 1.24 from A2 in summer.



Fig 6v: Comparison between change in 5 percentile of minimum temperature generated by A2 and B2 for 2080s

Comparing the results of A2 and B2 scenarios it was found that the annual increment in 5 percentile varied between 0.72 and 1.05. It is obvious that the result of A2 will give high value than B2. From the figure it is clear that that starting from winter to autumn the trend is in rising form. In February they all most collide other than that line graphs from A2 and B2 look similar except that the values from A2 are higher than that of B2.

7. SUMMARY, CONCLUSION AND RECOMMENDATIONS

7.1 Summary

Downscaling methods can be broadly divided into two classes: dynamical downscaling (DD) and statistical (empirical) downscaling (SD). In DD, the GCM outputs are used as boundary conditions to drive a Regional Climate Model or Limited Area Model and produce regional-scale information up to 5~50 km. This method has superior capability in complex terrain or with changed land cover (Wang et al. 2004; Kite 1997). However, this method entails higher computation cost and relies strongly on the boundary conditions provided by GCMs. In contrast, SD gains local or station-scale meteorological time series (predictands) by appropriate statistical or empirical relationships with surface or troposphere atmospheric features (predictors; Xu 1999; Wilby and Wigley 1997; Fowler et al. 2007). Since this method is inexpensive to use and is as powerful as its dynamic competitor, it has been widely employed in climate change impact assessments. However, its drawback is that it needs much longer historical time series to build the appropriate statistical relationship. In addition, one of the assumptions of SD, which is the built statistical relationship, is still valid in the future; this assumption cannot be tested at present.

SDSM refers to Statistical Downscaling Method, which has been used for projection of the temperature at Kathmandu Airport in this study. Kathmandu Airport station is located at Tribhuvan International Airport in Kathmandu, spanning 27.70 degrees of latitude and 85.37 degrees of longitude with the elevation of 1337 meters.

Every model has uncertainty, to remove this uncertainty in SDSM we have to use no. of models such as hadcm3, cgcm3 etc. More the number of models used lesser will be the uncertainty. We can also used numbers of scenarios to reduce the uncertainty and in SDSM it has facility of ensemble mean which also reduces the uncertainty.

The data for the station is available from 1968 A.D. so for the calibration of SDSM, data of maximum and minimum temperature from 1968-1985 A.D. was used. For the validation of the SDSM, data from 1986-2001 A.D. was used. The predictors were selected for both maximum and minimum temperature for the analysis before the calibration was started. After that, from the weather generator, maximum and minimum temperatures were generated for the validation. Then both observed and downscaled data were compared. The future scenarios were generated from scenario

generation. From the summary statistics, scenarios of 2011-2040 A.D. (2020s), 2041-2070A.D. (2050s) and 2071-2099 A.D. (2080s) were generated for the maximum as well as minimum temperature at Kathmandu Airport. Different analyses were done for the maximum and minimum temperature to get the idea of the climate change scenarios of those parameters.

7.2 Conclusions

SDSM was used to generate future scenarios of maximum and minimum temperature at Kathmandu Airport. From the results obtained from the model following conclusions can be drawn:

- 1. The annual maximum temperature will increase by 0.46° C in 2020s from A2.
- 2. The annual maximum temperature will increase by 0.95°C in 2050s from A2.
- 3. The annual maximum temperature will increase by 1.74° C in 2080s from A2.
- 4. In case of 95 percentile, from A2 scenario we can see that the rise in annual maximum temperature will be 0.53°C, 1.11°C and 1.99°C for 2020s, 2050s and 2080s respectively.
- 5. The future scenario from H3B2 shows that when compared with current climate, the annual maximum temperature will increase by about 0.50°C in 2020s.
- 6. In 2050s annual maximum temperature may rise up to 0.78°C from B2.
- 7. In 2080s, it was seen that the annual maximum temperature may rise up to 1.26°C from B2.
- 8. In case of 95 percentile, from B2 scenario we can see that the rise in annual maximum temperature will be 0.63°C, 0.82°C and 1.37°C for 2020s, 2050s and 2080s respectively.
- The future scenario from H3A2 shows that when compared with current climate, the annual minimum temperature would increase by about 0.4°C in 2020s.
- The future scenario from H3A2 shows in 2050s period, the warming may be up to 1.0°C in annual minimum temperature.
- 11. The annual minimum temperature will rise by 1.5°C during 2080s from H3A2 scenario.
- 12. In case of 5 percentile, from A2 scenario we can see that the rise in annual minimum temperature will be 0.38°C, 0.66°C and 1.05°C for 2020s, 2050s and 2080s respectively.
- The future scenario from H3B2 shows that when compared with current climate, the annual minimum temperature will increase by 0.6°C during 2020s.
- 14. The annual minimum temperature would increase by about 0.8°C in 2050s from B2.
- 15. In 2080s, the annual minimum temperature may rise up to 1.1° C from B2.

- 16. In case of 5 percentile, from B2 scenario we can see that the rise in annual minimum temperature will be 0.50°C, 0.50oC and 0.72°C for 2020s, 2050s and 2080s respectively.
- 17. Comparing the results of A2 and B2 scenarios it was found that the annual increment of maximum temperature varied between 1.26 and 1.74.
- 18. Comparing the results of A2 and B2 scenarios it was found that the annual increment in 95 percentile varied between 1.37 and 1.99.
- 19. Comparing the results of A2 and B2 scenarios it was found that the annual increment in 5 percentile varied between 0.72 and 1.05.

7.3 Recommendations

On the basis of analysis and findings of the study, following recommendations are made to improve the efficiency of the model.

- 1. The SDSM can be used to generate future climate change scenarios of different parameters such as temperature and precipitation.
- 2. As research of this type is very less in our country, more research need to be done using such a tool.
- 3. Using the output of the SDSM we can introduce lots of programs relating adaptation and mitigation to reduce the impact of climate change.
- 4. Using the results from SDSM, policy makers can make good policy which will lead to better life for those sites which are vulnerable to landslides and floods by reducing the impact of those disasters.

BIBLIOGRAPHIES

- Wilby, R.L., Dawson, C.W. and Barrow, E.M. 2001. SDSM a decision support tool for the assessment of regional climate change impacts. Environmental and Modelling Software, **17**, 145–157.
- Lines, G.S. and Pancura, M. 2005. Building climate change scenarios of temperature and precipitation in Atlantic Canada using the Statistical DownScaling Model (SDSM). Meteorological Service of Canada, Atlantic Region. Science Report series 2005-9, Dartmouth, Canada, pp41.
- Wilby, R.L., Hassan, H. and Hanaki, K. 1998b. Statistical downscaling of hydrometeorological variables using general circulation model output. Journal of Hydrology, **205**, 1-19.
- Wilby, R.L. and Wigley, T.M.L. 1997. Downscaling general circulation model output: a review of methods and limitations. Progress in Physical Geography, 21, 530 548.
- Wilby, R.L., Charles, S., Mearns, L.O., Whetton, P., Zorito, E. and Timbal, B. 2004. Guidelines for Use of Climate Scenarios Developed from Statistical Downscaling Methods. IPCC Task Group on Scenarios for Climate Impact Assessment (TGCIA).
- Wilby, R.L., Hay, L.E. and Leavesley, G.H. 1999. A comparison of downscaled and raw GCM output: implications for climate change scenarios in the San Juan River basin, Colorado. Journal of Hydrology 225, 67-91.

J T Chu, J Xia, C Y Xu, V P Singh, Statistical downscaling of daily mean temperature, pan evaporation and precipitation for climate change scenarios in Haihe River, China.

а

b