

# Assessment of Temperature for Future Time Series Over Lower Godavari Sub-Basin, Maharashtra State, India



Y. J. Barokar and D. G. Regulwar

**Abstract** Climate change can cause various negative impacts on water resources system, ecosystem, etc. To deal with these effects, it is necessary to study the climate change. There are various ways to study climate change in which one of the way is the study of downscaling. Downscaling is the procedure in which prediction of information is done for local scale area from the available information of a large scale area. In the downscaling of climatic variables, General Circulation Model (GCM) plays an important role. GCM gives larger scale climatic variables. With the help of this downscaling, we can predict different climatic variables such as temperature, precipitation for future time period over the selected area. To perform this downscaling there are different ways, we can classify it as statistical downscaling and dynamical downscaling. In statistical downscaling, we can find relation between predictant and predictors and this statistical relation we use for the future prediction of the selected climatic variable. In dynamical downscaling, we use Regional Climatic Model (RCM), and with the help of this, we carry out downscaling procedure. In this study, statistical downscaling has studied for temperature parameter ( $T_{max}$  and  $T_{min}$ ) by considering the basic equation given by Wilby in (Inter-research 10:163–178 [1]). The study area selected for this study is lower Godavari Sub-basin, Maharashtra State, India (Latitude:  $19^{\circ} 11'$ , Longitude:  $76^{\circ} 33'$ ). In this study, in the first step, statistical downscaling has been done with the help of statistical downscaling model (SDSM) software by using HadCM3 GCM with A2a and B2a scenarios for temperature parameter for the future time period up to 2099. In second step, the

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statistical downscaling again performed by using basic equation given by Wilby (Inter-research 10:163–178 [1]) in excel which is named as “Excel Model.” Temperature values predicted up to 2099. These results are considered with three different series such as 2020s, 2050s, and 2080s. Downscaled results of temperature parameter by “SDSM” model and “Excel Model” were compared for future series. After study of these results, it is concluded that SDSM gives higher value of change in mean monthly daily value of  $T_{max}$  and  $T_{min}$  than that of “Excel Model.”

**Keywords** SDSM · Excel model · HadCM3 · A2a · B2a ·  $T_{max}$  ·  $T_{min}$

## 1 Introduction

Climate change is [1] the major issue faced by many sectors; there are different causes of changing climate in which one of the major cause is increase in the greenhouse gases. Disturbance in the climate is caused by increase in  $CO_2$  and other greenhouse gases [2]. Global warming causes change in the climatic parameters which affects on the weather patterns [3]. To study these effects, downscaling is the more suitable way in which we can forecast the future climatic variables with the help of General Circulation Models (GCMs) [4]. Downscaling can be carried out with the help of dynamical or statistical methods, but statistical downscaling is preferable than dynamical downscaling [5]. Dynamical downscaling can be carried out with the help of Regional Circulation Model (RCM), whereas statistical downscaling is based on statistical relation between predictor and predictant [5]. Statistical downscaling model is the tool in which we can form statistical relation between predictor and predictant [6]. Such relation we can execute for the future forecasting of the climatic parameters. In the study of the Mahmood and Babel [2], authors have used statistical downscaling model (SDSM) and downscaled the climatic variables with application of bias correction over the trans-boundary region of Jhelum River. In the present study, SDSM has been used for predicting the future values of temperature parameter ( $T_{max}$ ,  $T_{min}$ ) over Lower Godavari Sub-basin, Maharashtra State, India. In addition to this, basic equation of downscaling given by Wilby [1] which is the base for SDSM has been executed in the excel tool, and temperature values for future series have been found out. These results were compared with the SDSM results. For Indian region, various GCMs give better results in which one of the GCM is HadCM3 [7], because of this HadCM3 GCM has been selected for this study with A2a and B2a scenarios.

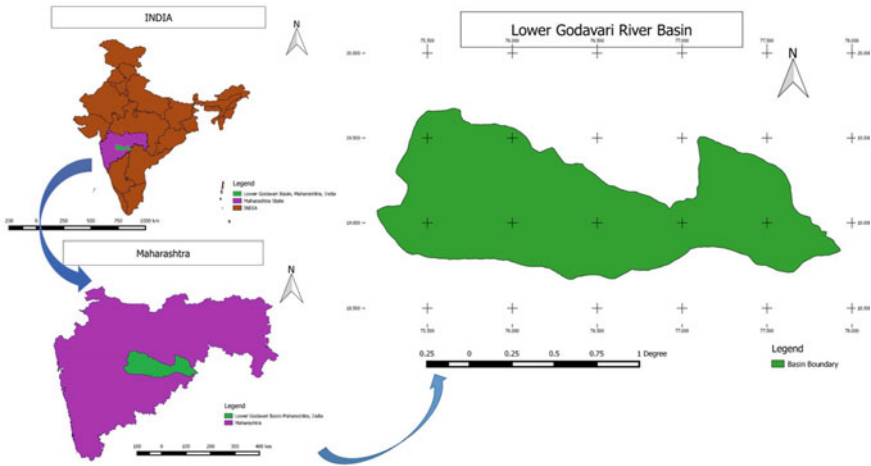


Fig. 1 Map of Lower Godavari Sub-basin

## 2 Materials and Method

### 2.1 Downscaling

Downscaling means converting high scale resolution data into finer scale resolution. In this study, statistical downscaling has been used to forecast the future series values of temperature parameter ( $T_{max}$ ,  $T_{min}$ ). In statistical downscaling, statistical relation developed between predictor and predictant. Such statistical relation helps to downscale the climatic variables for future series [2].

### 2.2 Study Area and Data Source

#### 2.2.1 Lower Godavari Sub-basin, Maharashtra State, India

The study area is Lower Godavari Sub-basin (area $\approx$ 17,850km<sup>2</sup>). Lower basin of Godavari river in Maharashtra lies between 18° 42' 49" N to 19° 40' 27" N and 75° 12' 12" E to 77° 55' 59" E. The mean monthly  $T_{max}$  changes from 29.63 to 38.50 °C over the basin. Map of study area is shown in Fig. 1

#### 2.2.2 Data Collection

For the execution of present study, daily temperature ( $T_{max}$  and  $T_{min}$ ) values have been obtained from Indian Meteorological Department (IMD), Pune for the period

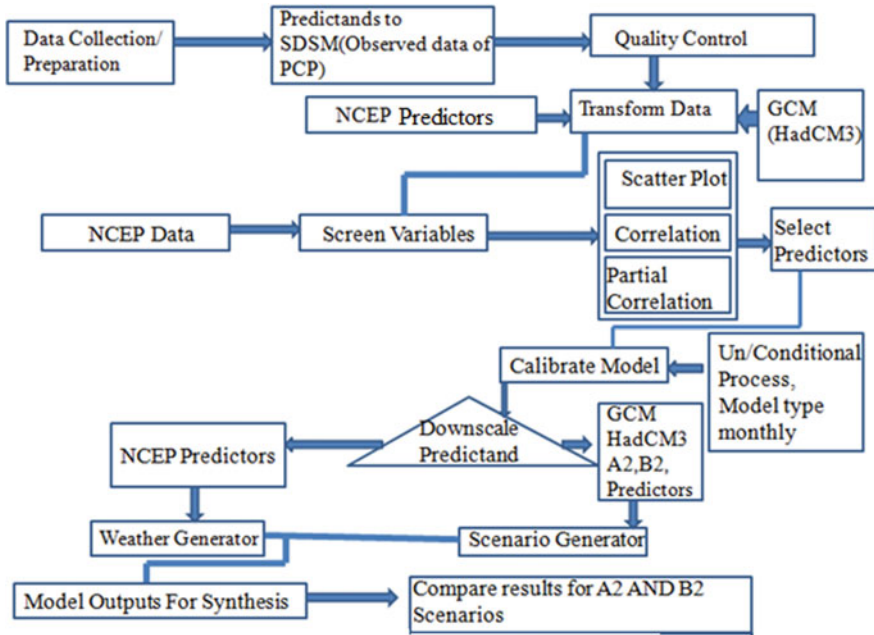


Fig. 2 Flowchart for statistical downscaling method given by Wilby

1961–2000. GCM data of HadCM3 under A2a and B2a scenarios have been obtained from Canadian Climate Impact Scenarios (CCIS) site for the area Lower Godavari Sub-basin, Maharashtra State, India (Latitude: 19° 11', Longitude: 76° 33').

**Selection of Input Parameters**

The flowchart and basic equation for downscaling given by Wilby [5] is as shown in Fig. 2.

Working of statistical downscaling model (SDSM) which is developed by Wilby [5] and Dawson is divided into below steps:

- (a) Quality Control, (b) Transforming Predictor data, (c) Screen Variables, (d) Model Calibration, (e) Weather Generator, (f) Finding statistics of the data, and (g) Compare results.

Quality control helps to detect the missing values in our observed data, whereas in Transform data we can apply suitable transformation to the data so that it will be well distributed. Screen variables helps to decide the suitable predictors over the selected region. Model Calibration and Weather Generator helps to develop statistical model and compare it with the observed data. In last step, we can find different statistical values and compare the results.

The basic equation for finding amount of temperature by Wilby [5] is as given below.

Amount of total Temp. (*t*) downscaled on day “*i*” is given by

**Table 1** List of NCEP predictors

Sr. no	Predictor name	Sr. no	Predictor name
1	p_f-Airflow strength at surface	14	p8_z-850 hPa vorticity
2	p_u-Zonal velocity at surface	15	p8th-850 hPa wind direction
3	p_v-Meridional velocity at surface	16	p8zh-divergence of 850 hPa
4	p_z-Surface velocity	17	r850-Relative humidity of 850 hPa
5	p_th-Surface wind direction	18	p500-00 hPa geopotential height
6	p_zh-Divergence at surface	19	p5_v-500 hPa meridional velocity
7	rhum-Relative humidity at surface	20	p5_z-500 hPa vorticity
8	p5_f-500 hPa airflow strength	21	p5th-500 hPa wind direction
9	p5_u-500 hPa velocity of zonal	22	p5zh-500 hPa divergence
10	r500-relative humidity of 500 hPa	23	r850-Relative humidity 850 hPa
11	p8_f-850 hPa airflow strength	24	Temp-Mean temperature at a height of 2 m
12	p8_u-Zonal velocity of 850 hPa	25	Shum-Surface-specific humidity
13	p8_v-meridional velocity of 850 hPa	26	mslp Pressure at Mean Sea Level

$$U_i = \gamma_0 + \sum_{i=1}^n \gamma_j X_{ij} + e_i \quad (1)$$

where  $\gamma_0$  = Intercept between predictor and predictant,

$X_{ij}$  = Predictor values for selected predictors.

$e_i$  = Bias correction value.

The list of NCEP predictors used for downscaling purpose is given in Table 1.

### 3 Results and Discussions

Results for this study are as given below for the downscaling of temperature ( $T_{\max}$  and  $T_{\min}$ ) over Lower Godavari Sub-basin for future series.

#### 3.1 Calibration and Validation of the Model

In this study, calibration has been done over a period of 1960 to 1980. Observed monthly mean daily temperature data ( $T_{\max}$  and  $T_{\min}$ ) and downscaled monthly mean daily temperature data ( $T_{\max}$  and  $T_{\min}$ ) over this selected period have been compared graphically. Graphical comparison for  $T_{\max}$  and  $T_{\min}$  is as given in Figs. 3 and 4.

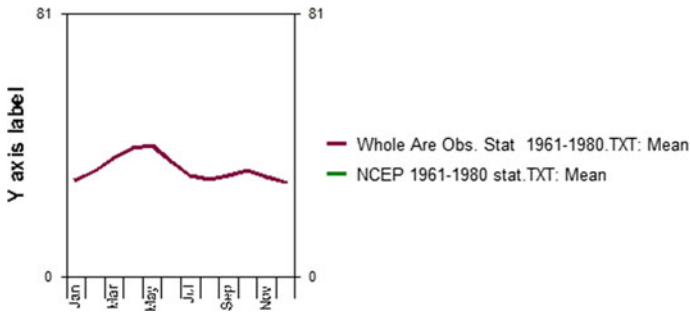


Fig. 3 Graphical representation for calibrated model of *T*max

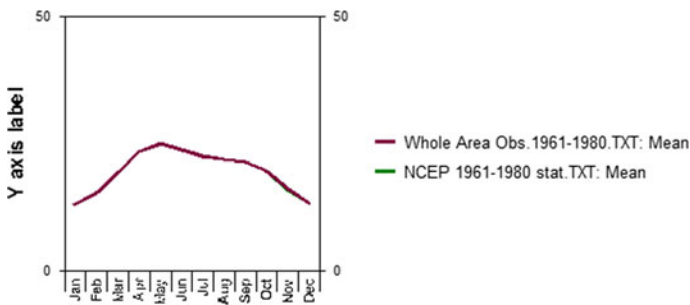


Fig. 4 Graphical representation for calibrated model of *T*min

Graphical results indicate that observed and downscaled values of *T*max and *T*min over a selected period are matching with each other it means our model calibrated successfully.

After successful calibration of the model, we tested this model over next time period. For this, the time period of 1981–2000 have been selected. Observed monthly mean daily temperature data of *T*max and *T*min were compared with downscaled monthly mean daily temperature data of *T*max and *T*min over this period. For this statistical comparison, the coefficient of determination has been used. Results are as shown below (Tables 2).

Table 2 Coefficient of determination between observed and downscaled data over a period of 1981–2000

Model name	GCM	Temperature parameter	$R^2$ value between observed and downscaled parameter over 1981–2000
SDSM	HadCM3	<i>T</i> max	0.99
	HadCM3	<i>T</i> min	0.99

The statistical results indicate the downscaled values of monthly mean daily temperature ( $T_{max}$  and  $T_{min}$ ) are matching with observed monthly mean daily temperature ( $T_{max}$  and  $T_{min}$ ). So with the help of this selected model, we tried to find out future series values of mean daily temperature ( $T_{max}$  and  $T_{min}$ ). With the help of this model, temperature values have been downscaled up to 2099 with the help of SDSM under A2a and B2a scenarios. These downscaling results of monthly mean daily temperatures ( $T_{max}$  and  $T_{min}$ ) have been compared with observed monthly mean daily temperature ( $T_{max}$  and  $T_{min}$ ) over a base line period of 1961–2000. Statistical comparison has been studied with the help of coefficient of determination as shown (Table 3).

In this statistical comparison, coefficient of determination gives better values over the base line period under both the scenarios.

The same predictors we have selected to perform downscaling with the help of basic equations given by Wilby [5] in Excel. Downscaled temperature values have been compared with the observed temperature values over a base line period (1961–2000) (Table 4).

The above result indicates the good correlation between observed monthly mean daily temperature and downscaled monthly mean daily temperature.

We can find the range of  $R^2$  between observed monthly mean daily temperature and downscaled monthly mean daily temperature ( $T_{max}$  and  $T_{min}$ ) by using SDSM is in between 0.97 and 0.99 and by using Excel Model it is in between 0.63 and 0.80. Downscaling results with the help of SDSM model and Excel Model are found

**Table 3** Coefficient of determination between observed and downscaled data over period 1961–2000

Model name	GCM	Temperature parameter	$R^2$ value between observed and downscaled parameter over 1961–2000
SDSM	HadCM3 A2a	$T_{max}$	0.97
	HadCM3 A2a	$T_{min}$	0.99
	HadCM3 B2a	$T_{max}$	0.96
	HadCM3 B2a	$T_{min}$	0.99

**Table 4** Coefficient of determination between observed and downscaled data over period 1961–2000

Model name	GCM	Temperature parameter	$R^2$ value between observed and downscaled parameter over 1916–2000
Excel model	HadCM3 A2a	$T_{max}$	0.80
	HadCM3 A2a	$T_{min}$	0.63
	HadCM3 B2a	$T_{max}$	0.78
	HadCM3 B2a	$T_{min}$	0.63

**Table 5** Future change in monthly mean daily  $T_{max}$  and  $T_{min}$  under different scenarios with respect to base line period 1961–2000

Model	GCM	Series	$T_{max}$ (°C)	$T_{min}$ (°C)
SDSM	HadCM3 A2a	2020s (2011–2040)	0.92	0.26
		2050s (2041–2070)	1.96	0.82
		2080s (2071–2099)	3.17	1.56
	HadCM3 B2a	2020s (2011–2040)	0.97	0.33
		2050s (2041–2070)	1.6	0.64
		2080s (2071–2099)	2.39	1.07
Excel model	HadCM3 A2a	2020s (2011–2040)	0.16	0.86
		2050s (2041–2070)	0.42	0.86
		2080s (2071–2099)	0.72	0.91
	HadCM3 B2a	2020s (2011–2040)	0.18	0.83
		2050s (2041–2070)	0.33	1.04
		2080s (2071–2099)	0.52	1.07

out for three future series (2020s, 2050s, and 2080s) as given below. The results are shown in terms of future change in monthly mean daily  $T_{max}$  and  $T_{min}$  under different scenarios with respect to base line period 1961–2000 (Table 5).

In prediction for these three future series, we identified that SDSM model is giving more change in monthly mean daily temperature values ( $T_{max}$  and  $T_{min}$ ) in 2080s (2071–2099) under A2a and B2a scenarios. According to the results, there will also be increase in monthly mean daily temperature values ( $T_{max}$  and  $T_{min}$ ) for the series 2020s (2011–2040) and 2050s (2041–2070), but it will be less in amount compared to 2080s series. The same reflection we identified in the results of Excel model just the change is whatever predicted values are given by Excel model are smaller in amount compared to SDSM results, but the pattern of results with excel is also says that there will be more change in temperature values ( $T_{max}$  and  $T_{min}$ ) over the series 2080s (2071–2099) compared to the series 2020s (2011–2040) and 2050s (2041–2070).

## 4 Conclusions

The following conclusions are derived from the foregoing study:

1. In calibration and validation, both the models (SDSM and Excel) give satisfactory results; SDSM is giving more appropriate results compared to excel. It may be because of the bias correction which we apply in SDSM at the start of execution. It means if we change bias correction value in excel, then we may get some more accurate results and also we can predict future climatic values for our region in a better way.



2. SDSM and Excel Model both give increasing trends in the value of  $T_{\max}$  and  $T_{\min}$  in the near future with respect to the baseline period 1961–2000. According to IPCC reports, the amount of greenhouse gases may increase in the future which will lead to an increase in temperature, so these results satisfy the prediction of IPCC.

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