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Future Assessment of Precipitation and Temperature for Developing Urban Catchment Under Impact of Climate Change

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Abstract: ***In this study, the attempt is made to investigate the impact of future climate changes related to three weather parameter maximum temperature (Tmax), minimum temperature (Tmin) and precipitation for study area were projected for two future time slice (2017–2058), and (2059–2100) from the three Global Climate Models (GCMs), CanESM2, CGCM3 and HadCM3 under different representative concentration pathway (RCPs) scenarios (RCP2.5, RCP4.5, and RCP8.5) using statistical downscaling model (SDSM). The predictor variables are downloaded from National Center for Environmental Prediction/Atmospheric Research (NCEP/NCAR) and simulations from the three Global Climate Models (GCMs), Second Generation Canadian Earth System Model (CanESM2), Canadian Centre for Climate Modelling and Analysis (CGCM3) and Hadley Centre for Climate Prediction and Research/Met Office (HadCM3) variability and changes in Tmax, Tmin and precipitation under different (RCPs) scenarios have been presented for two future time slice. The performance for three models showed maximum/minimum temperature increases in future for almost all the (RCPs) scenarios. Also precipitation of the entire catchment was found to increasing trends for all scenarios. In case of HadCM3 model, under RCP8.5 scenarios for the period (2017-2058), changes in max temperature, min temperature, and precipitation are forecasted as 0.72 °C, 1.42 °C, and 2.82 mm and for the period (2059-2100) are 1.16 °C, 2.14 °C, and 6.85 mm.The results obtained from HadCM3 model is higher side as compared with CanESM2, CGCM3.These results can provide understanding of the hydrologic role of future climate change scenarios, which is essential for probable impacts of climate change for planning and management of appropriate choice for designing the storm water drainage system and infrastructure for newly growing urbanization under climate change are of great concern to hydrologists, water managers, and policymakers.***

Keywords: ***Downscaling, CanESM2, CGCM3, HadCM3, General Circulation model (GCM), Representative Concentration Pathway (RCPs), Temperature, Precipitation***

I. INTRODUCTION

The variation in climate parameter in relation to frequency, intensity, timing, changes in soil moisture, runoff and magnitude of precipitation will affect stormwater design capacity for developing urban catchment

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(Huber and Knutti, 2011, IPCC, 2014, IPCC, 2008, NCA, 2014a, NCA, 2014b). Global variation of weather temperature and hydrologic parameters precipitation, Evapotranspiration affect ethological as well universal systems (Bo, H., et al.2019).

As reported by Intergovernmental Panel on Climate variation (IPCC) Sixth Assessment Report cycle (2016-2022 (AR6). The Pollution (that heats up the Earth) and punishes of worldwide warming such as differen ces/different versions in rainfall (variation of uniformity in rainfall years), Maximum heat (2°C to 4°C), flood and drought, Groundwater, Sea level rise. Also as per (AR5) Report, global mean surface temperature forecasted as 0.3°C to 0.7°C in between the year 1986 and 2005. After every decade (10 years) the temperature rising rate of 0.13 °C recorded in the last 50 years, and the worldwide mean surface temperature in the 2100 is forecasted to rise by 3.7 - 4.8 °C compared to preindustrial level (IPCC 2014).

Assessment and simulations of urban drainage basin with regard to hydrology and hydraulics in case of historic as well as future time slice under climate variation summary on global and worldwide level, modern mechanism of GCMs are used. Climate change modeling is done by most reliable mechanism of General Circulation Models (GCMs) considering greenhouse gas concentration (GHGs) in the atmosphere (IPCC-TGCIA, 1999). General Circulation Models (GCMs) are establish to assess the feasible reply of the weather condition to the modification in the performance of universal and individual systems either independently or well-adjusted (Das, J., et al.2018). Using GCMs models it is easy to investigate and forecast the correlation among (**GHGs**) emission and the global climate also GCMs is a framework for climate model experiments, allowing scientists to analyze, validate (Gebremeskel et al. 2005).

(Wilby R.L et al.2002) have studied downscaling techniques of the weather parameters from GCMs i.e. statistical and dynamical, statistical downscaling techniques promote statistical correlation that convert coarse-scale observations and applying it to a specific area or region. Dynamical downscaling utilizes a finite region, only provides limited rectifiable of the data they can have higher resolution than GCMs and still run in a suitable time. Statistical downscaling (SD) method is divided into three major group (i) atmospheric classification, (ii) regression models and (iii) Weather generators. Atmospheric classification methods classify wide scale atmospheric parameters of GCMs into finite and number and describe them to catchment scale climate variation parameters. Regression is a statistical method to explore the correlation among a reliant parameter y and number of self reliant parameter x.

Weather generators form a synthetic sequence of weather data, during conserving statistical aspect in case of monitoring weather parameters (Saengsawang et al.2017).
The Bias Correction (BC) method can give model inputs proper for assessing hydrologic and hydraulic parameters under climate variation studies throughout the global (Wood et al., 2002; Payne et al. 2004). The projection of maximum weather/hydrologic parameters like Tmax, Tmin, PCP, and evaporation are calculated by using statistical downscaling approach (Huang et al.2011) and to classify the GCMs weather parameters for utilization in downscaling.

The aim of this research is future assessment of precipitation and temperatures for developing urban catchment under impact of climate change, SDSM are effectively used for downscaling. Next, statistical relation of observed and downscaled average yearly Tmax, Tmin and precipitation (PCP) through evaluation and verification periods was applied to project future changes in Tmax, Tmin and Precipitation (PCP) under different RCPs scenarios for two future time slice (2017-2058 and 2059-2100) are using the three GCMs Model of CMIP5 (i.e. CanESM2, CGCM3, HadCM3). This research provides a valuable datasets for decision makers and planners in good planning for the stormwater management (SWM) and storm drain design (SDD) for developing urban catchment.

II. STUDY REGION AND DATA REQUIREMENT

The study area named Bidkin Industrial Area (BIA) is located within the Paithan tehsil of Aurangabad district in the state of Maharashtra. The delineated region for BIA comprises of an area of 3179.1 hectares, spread over eight villages selected after excluding forest areas, large existing settlements and industries. Study area fall under Godavari basin. The proposed BIA has been planned as a mixed land use development, comprising of residential, commercial, social amenities and industrial land uses. The study area drains into Nath Sagar in the South. The area is dotted with small ponds and water bodies most of which are rain-fed. Site map of (MIP) as delineated in Figure.1.There are six major natural stream/nallah crossing the project site and one stream passing in close proximity to the project boundary on eastern side.

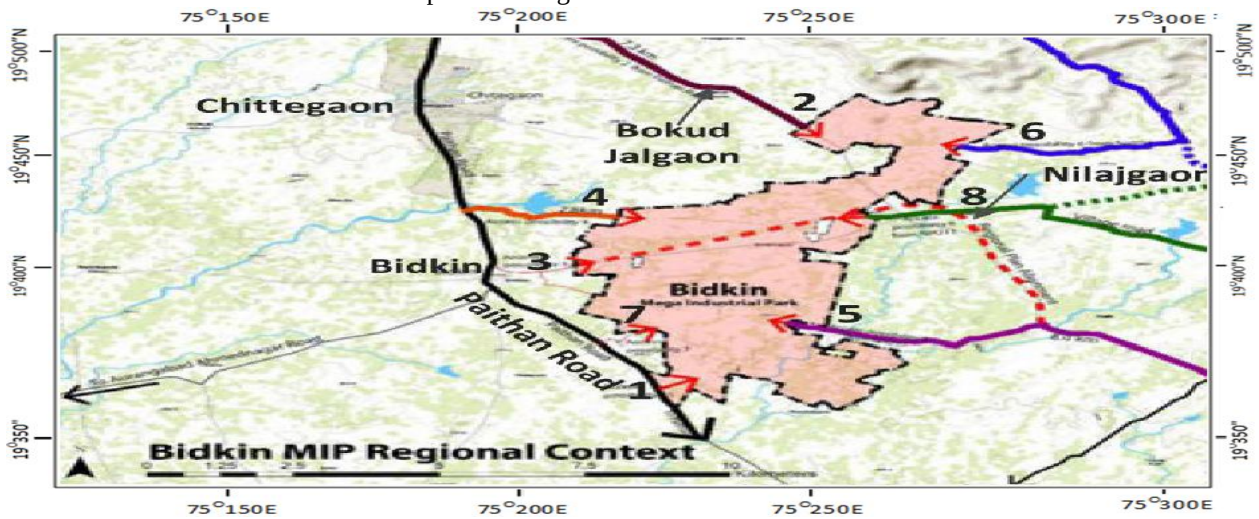

Fig.1. Site map of Mega Industrial Park (MIP) study area at Aurangabad (Akram. S.Pathan & Milind L.Waikar, 2018)

The mean yearly precipitation at the site (MIP) in the range around 571mm to 807 mm. The study of negative departures of the annual rainfall over normal reveals that areas around Paithan and Chikalthana experience moderate and severe drought conditions for more than 20 % of years. The ultimate and minimum temperature is 43^0C to 28.5^0C (summer), 35°C to 20°C (monsoon) and 26°C to 10.7°C (winter).

The screened predictor parameters of NCEP/NCAR, CGCM3 and HadCM3 in case of closest grid for (BIP) obtianed by using database of (DAI) (http://loki.qc.ec.gc.ca/DAI/predictors-e.html) and (CCIS) (http://www.cics.uvic.ca/scenarios/index.cgi). The yearly mean atmospheric parameters were obtained from the (NCEP/NCAR) for duration between (1961 to 2003).The gridded format observed data used in this study which is received from India Metrological Department (IMD), Ministry of Earth Science, Pune. The data consist of seventeen constant pressure levels in the vertical and horizontal resolution of 2.5˚ × 2.5˚. The CMIP5-ESMs climate model of the Canadian model for a largest emission (RCP8.5), an medium emission (RCP4.5), and minimum emission (RCP2.6) projections along grid resolution 2.8125° × 2.8125° obtianed by using database of (CCCma) (http://climate-scenarios.canada.ca/?page=pred-canesm2).
All the 26 predictors and reanalyzed predictors of the of NCEP/NCAR having network 2.5° × 2.5° using database(https://www.esrl.noaa.gov/psd/data/reanalysis/reanalysis.shtml). The simulation of all the predictors are carried out using past (GHG) and vaporizer absorption investigation (20C3M) and Emission Scenarios Special Report (ESSR) A2 for future assessment in case of CanESM2, CGCM3 and HadCM3 models.

III. METHODOLOGY

SDSM consist of software package designed to contribute statistical downscaling methods. The link for downloading mode https://sdsm.org.uk/software.html.established by (Wilby et al. 2002) to crop largest-resolution daily climate data from minimum-resolution climate model (GCM) simulations. The SDSM is handy software for assessing and simulating climate change parameters at regional/local scale. Many researcher have used SDSM for climate variation impact assessment (Bastin, J., et al., 2019; Bettolli, M. L., 2018; Zhu, Zhang et al., 2019; Feyissa, G et al., 2018).The most widely used two downscaling methods suggested by Canadian Climate Impact Scenarios (CICS) are regression based and stochastic weather generator (SWG) (Smid, M., et al 2017). In order to create statistical or empirical linkages among course and local-scale parameters (i.e. predictands and predictors) Multivariate Multiple Linear Regression (MMLR) utilized. In regression based downscaling represents linear and non-linear relationship by developing a quantitative relationship between atmospheric predictor variables and regional surface (predictands). The common equation of downscaling is:

$$R_t = F\ (XT) for\ T\ \leq t$$
(1)

Where, R_t - indicates the regional-scale predictands at separate or various locations at time t, XT- predictor set (e.g. a assembling of present and historic values of course-scale weather parameters) for time t, F - indicates the procedure applied to evaluate the correlation among two dissimilar structural range.

The general equation for a linear regression is given as

$$y_i = \beta_0 1 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \varepsilon_i, \qquad i = 1, \ldots, n,$$
(2)

Where, y denotes the dependent variable (rainfall) and xi where i=1, 2,.., n, denotes the explanatory or independent variables and is called the intercept.

In SDSM, arrangement of station scale climate variables is linearly modified by observed high scale predictors of weather *(j = 1, 2,…, n)*. The technique of downscaled is like conditional or unconditional. The downscaling of daily precipitation under conditional technique were depends on an central parameter such as existence of a rainy season. The existence of wet day (W_i) on day i is linearly reliant on predictors X_{ij} (Equation 3)

$$W_i = \alpha_0 + \sum_{j-1}^{n} \alpha_j X_{ij}$$
(3)

Subjected to constraint $0 \leq Wi \leq 1$. According to climate conditions (denoted by the predictor parameters) the value of wet day Wi varies as per prevailing high scale and found 0 and 1. If reliable irregular number $r \leq Wi$ then it will lead to precipitation. The values of Wet day is not a Boolean (0 or 1) number but is a regular parameters among 0 and 1. For a particular day with large pressure, wet day perhaps equivalent to 0.2. Next, r value indicates whether a precipitation will actually take place and it is subjected to conditions of whether $r \leq 0.2$. The magnitude of total precipitation (Pi) downscaled on day i with return period of Wi is calculated by Equation (4)

$$P_i^k = \beta_0 + \sum_{j-1}^{n} \beta_j X_{ij} + \varepsilon_i$$
(4)

Where, k is a conversion (logarithmic, reverse normal or fourth root) used, as precipitation data. Weather parameter like definite system of regular temperature (Tmax and Tmin), a direct linear correlation is formed among the predictands Ui and preferred NCEP/NCAR predictors Xij on particular location catchment indicated by Equation (5).

$$U_i = \gamma_0 + \sum_{j-1}^{n} \gamma_j X_{ij} + \varepsilon_i$$
(5)

Where, U_i is temperature on day i and X_{ij} is selected NCEP/NCAR predictors on day i. α_j, β_j and γ_j are regression coefficients projected for every month under multiple linear regression, and ε_i is quantifying the efficiency of the model. It is developed theoretical applying an arrangement of successively unconstrained Gaussian numbers. Flow chart display procedure elaborated in scenario formation and downscaling is presented in Figure 2.

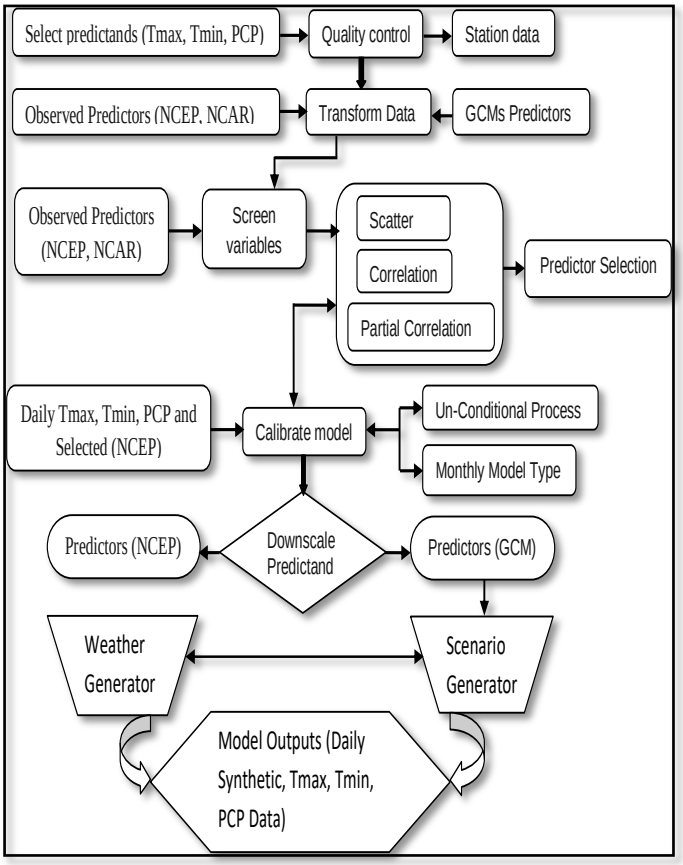

Fig.2. Diagram indicates procedure elaborate in scenario formation and downscaling (Wilby and Dawson, 2012).

IV. DESCRIPTIONS OF GENERAL CIRCULATION MODELS (GCMS) AND SCREENING OF PROBABLE PREDICTORS

Climate change modeling is done by most reliable mechanism of General Circulation Models (GCMs) considering greenhouse gas concentration (GHGs) in the atmosphere, it deal with changes in the behavior of universal and individual systems either independently or well-adjusted. Downscaling is performed to estimate (GCM) variables of higher resolution climatic projections to local range is useful for superior delineation of local weather (Her, Y., Yoo, S.-H, 2019 and Chandra Rupa R., Mujumdar P.P (2018). To find out most important predictors on predictands process termed as screening of predictors in statistical downscaling (Hewitson and Crane 1996).Therefore, in this research, coefficient of determination (R2), Normalized Root Mean Square Deviation (NRMSD), Mean Absolute Relative Deviation (MARD), Mean (μ), Standard Deviation (SD), Mean of Standard Deviation (RE_μ) and mean absolute deviation (MAD) are useful to distinguish observed data with downscaled data among evaluation and verification duration for getting the accurate series of predictors among NCEP/NCAR data (Wilby, R.L. and Dawson, C.W. 2012). Table 1 show descriptions of three GCMs Model of CMIP5 included in present study and Table 2 show predictors used in downscaling process.

Table I. Descriptions of Three GCMs Model of CMIP5 included in present study

Model name	Modeling centre	Grid resolution
CanESM2	Second Generation Earth System Model, Canada	2.7906° × 2.
CGCM3	Third Generation Coupled Global Climate Model, Canadian	3.75° × 3.7
HadCM3	coupled climate model of Hadley Centre, version 3, UK	2.50° × 3.7

Table II. Following list of predictors of NCEP/NCAR utilized in the process of screening

Sr. No	Predictors	Predictor summary	Sr. No	Predictors	Predictor summary
1	ncepmslpgl	Mean sea level pressure	14	ncepp8-zhgl	850-hpa diverge
2	ncepp1-vgl	1_hpa meridional velocity	15	ceshp5_upgl	ncepp1-zhgl- u
3	ncepp1-fgl	1_hpa airflow strength	16	nceppcpgl	precipitation
4	ncepp500-gl	500_hpa geopotential height	17	ncepshumgl	surface-specific hu
5	ncepp1-ugl	1_hpa zonal velocity	18	ncepp5-zhg	500-hpa diverge
6	nceps500-gl	specific humidity at 500 hpa	19	nceptempgl	Mean_ temperature _ (2
7	nceptempgl	mean temperature at 2 m	20	ncepp5-thgl	500_hpa wind dire
8	ncepp1-thgl	1_hpa wind direction	21	ncepp5-fgl	500_hpa airflow st
9	ncepp8-zgl	850_hpa vorticity	22	nceppv	Surface meridional v
10	nceps850-gl	specific humidity at 850 hpa	23	ncepp8-thgl	850_ hPa wind dire
11	ncepp8-fgl	850_hpa airflow strength	24	nceppr850	850_ hPa relative hu
12	ncepp8-ugl	850_hpa zonal velocity	25	ncepp850-gl	850_hpa geopotential
13	ncepp8-vg	850_hpa meridional velocity	26	nceppth	Surface wind direc

A. SDSM Evaluation and Verification

The evaluation and verification of SDSM 4.2 is done for the data from 1970 to 1990 and 1991 to 2010, for this period screening of NCEP/NCAR predictors is evaluated with the yearly sub-models, for the relevant predictands. Using (Gebremeskel S, Liu YB, de Smedt F, Hoffmann L,et.al 2005) observed station parameter (Tmax, Tmin and precipitation) and arranged all the observed NCEP/NCAR predictor evaluation of SDSM model is done. Statistical Downscaling Model is established with prefer Centers for Environmental Prediction pred monthly, seasonal and yearly sub-model downscaling of predictands (Tmax, Tmin and catchment location. The monthly, seasonal an model computes different regression equatio yearly sub model, multiple linear (MLR) formulated in case of twelve months cons model variables.

The methodology preferred for downscaling are classified as unconditional for temperature (e.g., Tmax, Tmin) or conditional fourth root transformation for precipitation (e.g., PCP).The outputs obtained by SDSM are aligned with observed inputs by estimating seven indicators like square of the correlation (R2), square root of the variance (RMSD), mean (μ), amount of variation (σ), relative average deviation (RE_μ), and average absolute deviation (RE_σ) for Tmax and PCP for the durations of evaluation and verification. R2 and RMSD indicate the correctness of the model in predicting data. Steps to be performed in SDSM: i) Quality control and data transform ii) Predictor parameters screening iii) Evaluation of model iv) Weather generator v) Statistical analysis iv) Graphing model output vii) Generation Scenario.

B. Screening of probable sets of predictors for Tmax, Tmin and Precipitation (PCP) under CanESM2, CGCM3 and HadCM3 models.

The screening of predictors means of selection of most effective predictors on predictands (Hewitson and Crane 1996).The most efficient-correlated predictor parameters were preferred based on the statistics of qualitative such as scatter plots along with quantitative such as value of interpreted variance under particular days, correlation, partial correlation (r) and P values) (Gebrechorkos and Hulsmann 2019) are take up for getting the better relevant predictors receive under the NCEP/NCAR predictors for the study area. As for model CanESM2, CGCM3 and HadCM3 the most effective parameters on temperature are nceps850-gl, ncepp500-gl, nceptempgl and ncepshumgl of the study area.

Table III. Significant sets of predictors from CanESM2, CGCM3 and HadCM3 model for precipitation

Model	Predictors	Tmax	Tmin	Precipitation (PCP)
CanESM2	ncepmslpgl	Mean sea level pressure (mslp)	Mean sea level pressure (mslp)	1000 hPa divergence (pzh)
	ncepp1-fgl	1-hpa airflow strength	----	----
	ncepp1-ugl	----	1-hpa_Zv	----
	ncepp1-thgl	1-hpa Va	----	----
CGCM3	ncepp500-gl	Hus at 850 hpa	----	Hus at 850 hpa
	ncepp850-gl	----	Hus at 850 hpa	----
	nceps500-gl	----	Hus at 500 hpa	----
	ncepmslpgl	Mean sea level pressure (mslp)	Mean sea level pressure (mslp)	1000 hPa divergence (pzh)
	ncepp850	850 hPa Hus (s850)	Lagged Hus (shum_ lag)	----
HadCM3	ncepp500-gl	500 hPa _Gh (p500)	Lagged Hus (shum_ lag)	500 hPa Hus (s500)
	ncepp8-thgl	850 hPa Va	850 hPa Va	----
	ncepp5-thgl	500-hpa Va	500-hpa Va	----
	ncepp8-vg	----	----	850-hpa _Mv

The following are steps for screening of probable sets of predictors for Tmax, Tmin and Precipitation (PCP) under CanESM2, CGCM3 and HadCM3 models.

(1) In this research, correlation matrix is formed among 26 NCEP predictors shown in (Table 2) and the predictands then those predictors are having maximum correlation coefficient are preferred.

The predictors having the maximum correlation coefficient are given first rank between whole predictors, is preferred and known super predictor (SP). **(2)** Find out all historical predictors and then correlated with the past observed Tmax, Tmin and Precipitation (PCP) in the past. **(3)** Then all those correlations are having ($p < 0.05$) were preferred.

The coefficient of correlation up to 0.8 among two predictors is desirable (Pallant 2007). **(4)** In this research to downscaling of precipitation (mslp) is prove to be the supporting ideal relevant predictor at study area. In similar fashion, all screened predictors are shown in (Table 3).

V. ASSESSMENT OF SDSM PERFORMANCE AND BIAS CORRECTION

To assess the SDSM attainment in case of observed Tmax, Tmin, and (PCP) data, various statistical measures are adopted to correlate observed data along downscaled data such as Coefficient of Determination (R^2), Mean Absolute Percentage Deviation (MAPD), mean (μ), Standard Deviation (SD), Mean of Standard Deviation (SE μ) and Mean Absolute Deviation (MAD).

1. Coefficient of determination (R^2)

The coefficient of determination is a statistical parameter utilized to calculate the fluctuation of data (observed) that the model calculate (Krause et al. 2005).

$$R^2 = \frac{(\sum[X_i - X_{av}][Y_i - Y_{av}])^2}{\sum(X_i - X_{av})^2 \sum(Y_i - Y_{av})^2}$$
(6)

Here, X_i is counted value, Xav is mean counted value, Yi is forecasted value, and Yav is mean forecasted value.

2. Mean Absolute Relative Deviation (MARD)

The Mean Absolute Relative Deviation (MARD) is a way of measuring the closeness of forecast and can be calculated as the average absolute percent deviation for all time duration minus actual values divided by actual values.

$$MARE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{X_i - Y_i}{Y_i}\right)$$
(7)

Here Xi - actual value and Y_i - forecast value

3. Mean (μ)

$$\mu = \text{mean} = \frac{1}{n}\sum x_i$$
(8)

4. Standard Deviation (SD)

$$SD = \sqrt{\frac{\sum(X_i - \bar{X})^2}{n-1}}$$
(9)

5. Root Mean Square Deviation

To calculate deviation index type of model assessment dimensional statistics a root mean square deviation (RMSD) is used. To check superior model attainment the (RMSD) value should closer to zero (Singh et al. 2004).

$$SD = \sqrt{\frac{\sum_{i=1}^{n}(X_i - Y_i)^2}{n}}$$
(10)

Where *n* is the total number count.

The bias correction is adapted to remove the biases among the routine duration sequence of downscaled data (Sunyer M. A., et.al 2015 and Li, X., et.al.2019). The difference among observed and forecasted weather parameters is create and it is defined as bias (Sunyer M. A., et.al 2015) recommends removing biases among the routine duration sequence of downscaled data. To eliminate biases in the time series, the approach of) (Gebrechorkos and Hulsmann 2019) is used. The long span observed yearly average data (1971–1990, 20 years) is used to estimate biases by subtracting temperature or dividing precipitation also biases from mean yearly simulated downscaled data by SDSM for the same duration. As per future downscaled daily duration, the biases are then modified in line with their relevant months. Following equations are implemented to de-bias daily Tmax, Tmin and PCP data.

$$T_{deb} = T_{SCEN} - (\bar{T}_{CONT} - \bar{T}_{OBS})$$
(11)

$$T_{deb} = T_{SCEN} \times \left(\frac{\bar{T}_{OBS}}{\bar{T}_{CONT}}\right)$$
(12)

Where T_{deb} and P_{deb} are the de-biased (reformed) daily duration sequence of Tmax and (PCP) for future durations. T_{CONT} and P_{CONT} are the long span average yearly values for Tmax and (PCP) in case of restraint duration calculated by SDSM. T_{OBS} and P_{OBS} indicate the long-term observed average yearly values for Tmax and (PCP) (Hassan et.al.2013). The long-span average values of all observed and simulated data shown by bar on T and P.

VI. RESULT AND DISCUSSION

The SDSM developed for screening of relevant predictors for downscaling predictands. As per the calculated values of correlation and scatter plots, the appropriate predictors are chosen for downscaling the Tmax and routine precipitation are shown in Table 3.Table 4 and Table 5 indicate difference among analytical magnitude of observed and downscaled NCEP / NCAR for mean yearly Tmax, Tmin and PCP during evaluation duration. The statistical values of entire downscaled data are very nearest to the analytics of observed data Tmax, Tmin and PCP. Likewise, results of difference among observed and downscaled average yearly Tmax, Tmin and PCP in junction with analytical magnitude for evaluation and verification duration are shown in Table 4 and Table 5. As per as NCEP/NCAR data is concern, for evaluation period (1970-1990) the values of R^2 and root mean square deviation (RMSD) estimated as 0.96, 0.96, 0.98 and 1.45, 1.45, 1.50 C for Tmax and estimated as of 0.71, 0.73, 0.75 and 1.52, 1.55, 1.62 C for Tmin respectively. For precipitation (PCP) values of R^2 are found in order of 0.87, 0.87, 0.92 and RMSD range is 10.42, 10.82, 10.88. Similarly for verification period (1991-2010) the values of R^2 and RMSD are found in the range of 0.83, 0.86, 0.88 and 1.23, 1.24, 1.30 C for Tmax and found estimated as 0.48, 0.55, 0.62 and 1.62, 1.87, 1.98 C for Tmin. For precipitation values of R^2 are estimated as 0.56, 0.68, 0.76 and RMSD range is 19.88, 19.96, 20.93. In this research, bias correction (BC), which is indicated above, is also adopted to the downscaled data received

from the SDSMs using CanESM2, CGCM3 and HadCM3 predictors, in sequence to receive a sufficient reasonable and unbiased data of future weather. Before adopting in case of future downscaled data, the average yearly biases are received from the duration of 1971-1990 and validated for the duration of 1991-2010. Using three global circulation model (GCM), bias correction of future downscaled data (Tmax, Tmin, and precipitation) done after complete verification of data.

Table IV.Statistical comparisons of observed and downscaled mean yearly Tmax, Tmin and PCP among evaluation (1970–1990) period.

Model	Parameter	Data type	μ (˚C)	SD (˚C)	SE-μ (˚C)	MAD (˚C)	R^2	RMSD (˚C)	MAPE
CanESM2	Tmax	OBS	37.66	4.14	0.96	2.78	–	–	–
		NCEP	38.89	4.26	1.10	3.12	0.96	1.40	3.10
	Tmin	OBS	24.40	3.85	0.88	2.30	–	–	–
		NCEP	25.18	3.62	0.84	2.20	0.73	1.50	4.96
	PCP (mm)	OBS	39.84	31.26	9.50	28.10	–	–	–
		NCEP	32.88	26.33	7.88	21.60	0.87	10.40	16.82
CGCM3	Tmax	OBS	37.66	4.14	0.96	2.78	–	–	–
		NCEP	38.96	4.26	1.10	3.15	0.96	1.45	3.25
	Tmin	OBS	24.40	3.85	0.88	2.30	–	–	–
		NCEP	25.18	3.71	0.84	2.30	0.71	1.55	4.98
	PCP (mm)	OBS	39.84	31.26	9.50	28.10	–	–	–
		NCEP	32.60	26.64	7.96	21.88	0.87	10.82	20.82
HadCM3	Tmax	OBS	36.93	4.18	0.98	2.78	–	–	–
		NCEP	37.98	4.36	1.15	3.19	0.98	1.50	3.36
	Tmin	OBS	23.50	3.86	0.91	2.32	–	–	–
		NCEP	25.52	3.79	0.84	2.33	0.75	1.62	5.01
	PCP (mm)	OBS	39.84	31.26	9.50	28.10	–	–	–
		NCEP	33.14	26.70	7.98	21.88	0.92	10.88	24.85

Table V. Statistical comparisons of observed and downscaled mean yearly Tmax, Tmin and PCP during verification (1991-2010).

Model	Parameter	Data type	μ (˚C)	SD (˚C)	SE-μ (˚C)	MAD (˚C)	R^2	RMSD (˚C)	MAPE
CanESM2	Tmax	OBS	37.98	4.22	1.06	2.96	–	–	–
		NCEP	38.93	4.28	1.14	3.16	0.86	1.30	2.93
	Tmin	OBS	24.58	3.82	0.85	2.33	–	–	–
		NCEP	25.33	3.74	0.86	2.28	0.62	1.62	5.86
	PCP (mm)	OBS	43.92	38.52	12.06	33.28	–	–	–
		NCEP	32.96	27.36	7.98	23.96	0.76	19.88	33.52
CGCM3	Tmax	OBS	37.98	4.22	1.06	2.96	–	–	–
		NCEP	39.69	4.93	1.18	3.16	0.83	1.23	2.76
	Tmin	OBS	24.58	3.82	0.85	2.33	–	–	–
		NCEP	25.68	3.78	0.88	2.36	0.55	1.87	6.85
	PCP (mm)	OBS	43.92	38.52	12.06	33.28	–	–	–
		NCEP	33.84	27.92	8.03	25.39	0.68	19.96	32.42
HadCM3	Tmax	OBS	37.98	4.22	1.06	2.96	–	–	–
		NCEP	40.32	5.14	1.25	3.18	0.88	1.24	2.86
	Tmin	OBS	24.58	3.82	0.85	2.33	–	–	–
		NCEP	25.89	4.10	0.89	2.56	0.48	1.98	7.20
	PCP (mm)	OBS	43.92	38.52	12.06	33.28	–	–	–
		NCEP	35.45	28.72	8.58	26.23	0.56	20.93	31.76

C. Future variation in Tmax, Tmin and Precipitation (PCP) under different RCP scenarios

The (SDSM) used to forecast future Tmax, Tmin and Precipitation (PCP) in the urban catchment (Bidkin DMIC) for the two future time slice of 2017–2058 and 2059–2100 under minimum (RCP2.6), intermediate (RCP4.5), and maximum (RCP8.5) emission projections developed by using models of CanESM2, CGCM3 and HadCM3 as highlighted in Figures 4, 5, and 6 for Tmax, Tmin, and (PCP) forecasted using SDSM model for two future time slice. Table 6 presents the changes values of Tmax, Tmin, and precipitation (PCP), estimated using SDSM model for two future time slice. The increase in Tmax and Tmin is forecasted in future in case of scenarios all the models. As it can be noticed, as compared with CanESM2 and CGCM3 in case of HadCM3 model for Tmax, there is decline in first time slice (2017-2058) of 0.01˚C belong RCP2.5 and increase of 0.12˚C belong RCP8.5 scenarios. In case of second time slice (2059-2100) decrease of 0.01˚C belong RCP2.5 and increase of 0.06˚C belong RCP8.5 scenario as compared in case of CGCM3 and HadCM3 models. It is identified that the difference in Tmin in case of CanESM2 and CGCM3 model under RCP4.5 is 0.08˚C and under RCP8.5 shows increase of 0.34 in first time slice (2017-2058). Similarly for second time slice (2059-2100), difference in Tmin in case of CanESM2 and CGCM3 model under RCP4.5 is 0.66˚C and under RCP8.5 shows increase of 0.65˚C. Figure 5 show forecasted ultimate increase in Tmin in case of CanESM2 and HadCM3 model under RCP2.6 is 0.84˚C in second time slice (2059-2100).

Table 6 presents the variation in yearly mean precipitation (PCP) of two future time slice (2017-2058 and 2059-2100) the outcome of downscaled (PCP) indicate rise in average yearly (PCP) in study area (Bidkin DMIC) belong all RCPs emission projections regards to all models (Figure 6). Belong to CanESM2 and HadCM3 model considerable difference increase in precipitation (PCP) observed belong to RCP2.6, RCP4.5 and RCP8.5 is 0.08, 0.05 and 0.62 mm in first time slice (2017-2058). Similarly for second time slice (2059-2100) difference with respect to precipitation (PCP), in case of CanESM2 and HadCM3 model under RCP2.6, RCP4.5 and RCP8.5 is 0.38, 1.86 and 2.95 mm. The ultimate increase in yearly precipitation (PCP) in case of HadCM3 under RCP8.5 is 6.85mm was observed in between 2059-2100 future time slices. The minimum yearly precipitation in case of CGCM3 under RCP2.6 is 0.99mm was observed in between 2017-2058 time slices.

Table VI Future variation in Tmax, Tmin and Precipitation (PCP) under various RCP scenarios for two future time slice (2017-2058 and 2059-2100).

Model	Variable	2017 - 2058			2059 - 2100		
		RCP2.6	RCP4.5	RCP8.5	RCP2.6	RCP4.5	RCP8.5
CanESM2	Tmax	0.004	0.005	0.105	0.89	0.89	0.98
	Tmin	0.44	0.85	1.06	0.48	0.94	1.47
	PCP (mm)	1.07	2.00	2.20	2.80	3.00	3.90
CGCM3	Tmax	0.06	0.47	0.60	0.94	0.99	1.10
	Tmin	0.48	0.93	1.40	1.30	1.60	2.12
	PCP (mm)	0.99	1.88	2.22	2.26	2.27	3.56
HadCM3	Tmax	0.05	0.53	0.72	0.93	1.05	1.16
	Tmin	0.53	0.95	1.42	1.32	1.39	2.14
	PCP (mm)	1.15	1.95	2.82	3.18	4.86	6.85

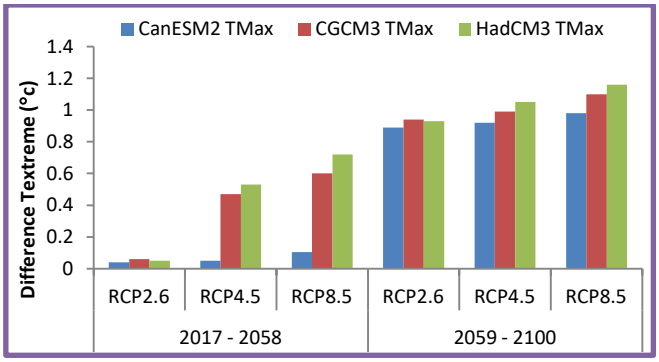

Fig. 4.Variation in mean yearly ultimate temperature in the future belongs to Model CanESM2, CGCM3 and HadCM3 with RCP2.6, RCP4.5 & RCP8.5 emission projection.

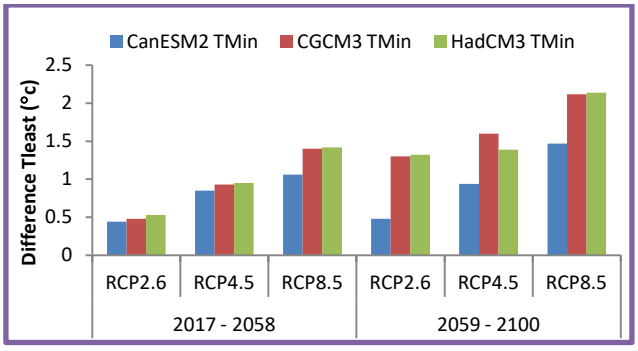

Fig. 5. Variation in mean yearly minimum temperature in the future belongs Model CanESM2, CGCM3 and HadCM3 with RCP2.6, RCP4.5 & RCP8.5 emission projection.

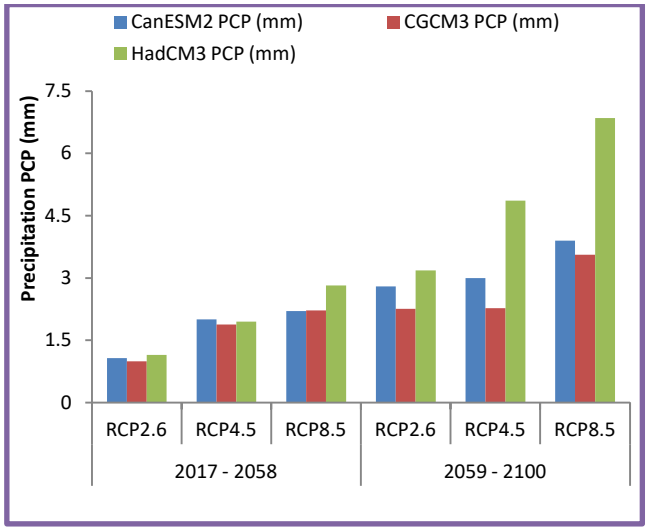

Fig. 6. Mean yearly variation in forecasted precipitation under
Model CanESM2, CGCM3 and HadCM3 with RCP2.6, RCP4.5 & RCP8.5 emission scenario.

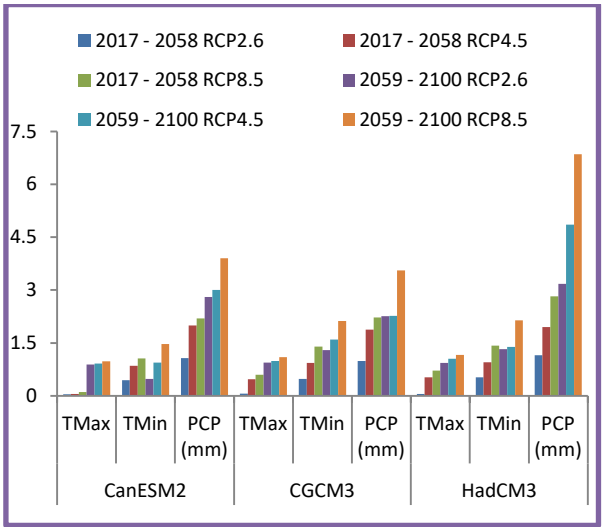

Fig. 7.Variation in average yearly consolidated Tmax, Tmin and PCP (mm) in the future under Model CanESM2, CGCM3 and HadCM3 with RCP2.6, RCP4.5 & RCP8.5 emission scenario.

VII. CONCLUSIONS

This research identified the future projection weather variation impacts on Tmax, Tmin and precipitation (PCP) in the study area Bidkin Delhi–Mumbai Industrial Corridor (BDMIC) Aurangabad (MS), India. SDSM is used to downscale and develop two future times slice (2017-2058 and 2059-2100) scenarios of climate parameters of Tmax and (PCP) belong predictors of CanESM2, CGCM3 and HadCM3 models. The CMIP5- CanESM2, CGCM3 and HadCM3 models outputs with RCP2.6, RCP4.5 and RCP8.5 emission projections is utilized to generate the future changes. The performance of SDSM is good in downscaling of Tmax, Tmin and (PCP). The estimated rise in ultimate Tmax is larger in HadCM3 model as correlate with CanESM2 and CGCM3 model. In case of forecasting the Tmin in case of HadCM3 model indicate drop and CGCM3 model indicate rise for future time slice of (2059-2100) under all RCPs scenarios. Similarly CanESM2 model indicate higher increase in precipitation comparative with CGCM3 model. However, from research it is clear that downscaled outputs of the GCMs depend on verification SDSM indicates increase in mean yearly Tmax and (PCP) for the future two time slice (2017-2058 and 2059-2100) under three models concerned with emission scenarios. It is also seen that in case of variation in average yearly consolidated parameter the rise in Tmax is higher than the rise in Tmin under all emission scenarios. All three models indicate different arrangement in forecasting future Tmax, Tmin and (PCP) belong distinct RCPs emission projections. The ambiguity in forecasted Tmax, Tmin and (PCP) caused by ambiguity correlate with CanESM2, CGCM3 and HadCM3 models and constraint based on SDSM in downscaling. The output of this research can provide insight into the hydrologic performance of climate variation which is essential for planning and management of appropriate choice for designing storm water drainage and infrastructure under climate change for newly growing urbanization.

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