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Climate change impact of relative humidity on water resources in Marathwada region Jalna District,Maharashtra, India

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Abstract: Climate change like relative humidity 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 ways 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, 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 predictand 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 such as relative humidity by considering the basic equation given by Wilby in (Inter-research). The study area selected for this research is jalna district Maharashtra State, India (Latitude: 19° .8347r, Longitude: 75° .8816r). 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 Statistical downscaling performed by using basic equation given by Wilby 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 were compared for future series. After study of these results, it is concluded that SDSM gives higher value of temperature changes in jalna district marathwada region.

Key Words: Climate change Impact, possible future series, SDSM, HadCM3, A2a, B2a, relative humidity

1. INTRODUCTION:

The escalating global climate crisis presents significant threats to water resources, ecological stability, and diverse environmental and societal systems, necessitating a detailed understanding of its local manifestations for effective mitigation and adaptation. While global climate models provide crucial insights into overarching climate trends, their inherent limitations in spatial resolution often impede direct applicability to regional planning. Consequently, downscaling techniques have become critical for translating coarse-resolution global climate projections into finer-scale predictions relevant to specific geographic areas, thereby enabling the refinement of broad climate predictions to elucidate localized changes in key variables such as temperature, precipitation, and humidity, among others.

2. LITERATURE SURVEY

Zin Moumen et.al.[2010][91], Statistical descriptive analysis of three climate variables Precipitation, temperature and the relative humidity. Study cases (Innocence watershed; Morocco) Understanding water-related data is essential for effective water management. This research used statistical analysis to examine rainfall, temperature, and humidity patterns at two locations within a specific watershed. The findings revealed that over several decades, temperatures have generally been increasing, while rainfall and humidity have been decreasing. Seasonal patterns were also evident, with winters being wetter and summers drier, while spring and autumn showed moderate conditions. Interestingly, there was a noticeable spatial difference, with rainfall slightly decreasing and temperatures slightly increasing as one moved from the central part of the watershed towards the lower areas. This can likely be attributed to the changing landscape, as higher elevations typically experience more rainfall and cooler temperatures compared to lower-lying regions. This study provides valuable insights into the changing climate patterns within the watershed, highlighting the importance of considering both temporal and spatial variations for effective water resource planning.

Castilloo et.al. [9] [2015], the effects of the relative humidity on drop wise condensation dynamics the humidity of the air. However, as the droplets grow larger and merge, the humidity becomes less influential. The overall rate of water condensation was also measured, showing that lower humidity not only slows down the process but also extends the time it takes for condensation to reach a stable rate. Essentially, the research highlights that humidity plays a critical role in the early stages of Understanding how water vapour in the air condenses into droplets is vital for many practical applications, especially those related to water collection and air dehumidification. This research aimed to explore how environmental conditions and surface properties influence this condensation process. The goal was to identify factors that could accelerate condensation and encourage water droplets to quickly roll off surfaces, leading to more efficient water harvesting. Experiments were conducted using a special setup that allowed researchers to observe water droplets forming on a water-repelling surface under controlled humidity and temperature conditions. The study revealed that in the initial stages of condensation, when many tiny droplets are forming, the rate of droplet growth is significantly affected by droplet formation, while the merging of droplets becomes the dominant factor in later stages.

Nikolas et.al [58] [2023], **Enhanced High-Resolution Daily Estimates of Relative Humidity Across Germany Using a high resolution of the Random Forest Approach**– The absence of accessible methods for estimating high-resolution near-surface relative humidity (RH), coupled with the limitations of weather stations in capturing detailed spatiotemporal patterns, can result in exposure misclassification in environmental epidemiological studies. To address this, the study aimed to predict daily mean RH across Germany at a 1 × 1 km resolution for the years 2000–2021. The Random Forest (RF) model incorporated various inputs, including RH observations, geographic coordinates (latitude and longitude), modelled air temperature, wind speed, precipitation, and remotely sensed data on elevation, vegetation cover, and a true colour band composite. Temporal variations were accounted for using date variables to capture dynamic relationships between predictors and the target variable. The model demonstrated excellent performance, achieving an R^2 of 0.99, a Root Mean Square Error (RMSE) of 5.07%, a Mean Absolute Percentage Error (MAPE) of 5.19%, and a Mean Percentage Error (MPE) of -0.53%, validated through ten-fold cross-validation. Validation against dense observational data from Augsburg, South Germany, confirmed its accuracy, with R^2 values ≥ 0.86, RMSE ≤ 5.45%, MAPE ≤ 5.59%, and MPE ≤ 3.11%. The model revealed a high average RH across Germany (22-year mean of 79.00%) with significant spatial variation, surpassing 12% in annual averages.

Michael Geruso et.al [53] [2018], The relationship between heat, humidity, and infant mortality in developing countries was examined. Our results show that the Random Forest (RF) model is effective for estimating relative humidity (RH) at high resolution across an entire country, offering a reliable RH dataset that can be used for epidemiological studies and various environmental research applications. Understanding how severe weather affects infant survival in developing countries is crucial, but often hindered by a lack of official birth records. To overcome this, researchers examined data from household surveys across numerous countries in Africa, Asia, and Latin America. Their findings revealed that extreme heat significantly increases infant mortality in these regions, with the impact being much greater than previously observed in wealthier nations. Humidity was also identified as a key factor in these outcomes. The scale of this issue, and where it's most prevalent, has significant implications for how we address climate change and its potential impact on vulnerable populations. This research highlights the urgent need to consider the disproportionate effects of climate change on infant survival in developing countries when formulating global climate policies.

Roy et.al.[2004] Well-built for wellbeing controlling relative humidity in the workplace matters for our health. This study investigates the impact of relative humidity (RH) on office worker health and wellbeing, addressing a gap in research on the topic. The study involved 134 diverse office workers from four federal buildings who wore heart rate variability monitors for three days, while RH and temperature were measured in their workplaces. Results indicated that workers exposed to RH levels between 30% and 60% experienced 25% less stress than those in drier environments. Additionally, the study suggests that optimal RH levels for stress reduction may fall within a narrower range around 45%. The influence of humidity on the health and comfort of office workers is often overlooked, with current building standards downplaying its importance due to limited research. This study aimed to provide a clearer understanding by examining how humidity levels affect stress, physical activity, and sleep quality in a diverse group of office workers. By monitoring heart rate variability, a measure of stress, alongside workplace humidity and temperature, the researchers found that workers exposed to moderate humidity levels experienced significantly less stress compared to those in drier environments. Specifically, the findings suggest that humidity within a certain range might be optimal for minimizing stress. Additionally, the study indicates that even more precise humidity levels might be ideal. This research offers a fresh look at the impact of humidity on workplace wellbeing, suggesting that maintaining appropriate humidity levels could be a crucial factor in creating healthier and more comfortable office spaces.

Sheeba Valsson et.al [70] [2001] Impact of the Air Temperature on to the Relative Humidity - A study Understanding how temperature and moisture interact in urban environments is crucial for creating comfortable and healthy spaces. This research focused on exploring the connection between air temperature, its ability to hold

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moisture, and the resulting relative humidity. Through statistical analysis, the study confirmed that warmer air can hold more moisture. Consequently, as temperature rises, the relative humidity decreases, assuming no additional moisture is introduced into the air. This insight sheds light on the interplay between temperature and moisture, providing a clearer picture of how these factors influence the perceived comfort of our surroundings.

Fig -1: **Figure**

3. RESEARCH METHODOLOGY

Downscaling means converting high scale resolution data into finer scale resolution for the purpose of the statically downscaling .In this study, statistical downscaling has been used to forecast the future series values of temperature parameter (**Relative humidity**). In statistical downscaling, statistical relation developed between predictor and predictand. Such statistical relation helps to downscale the climatic variables for future series.

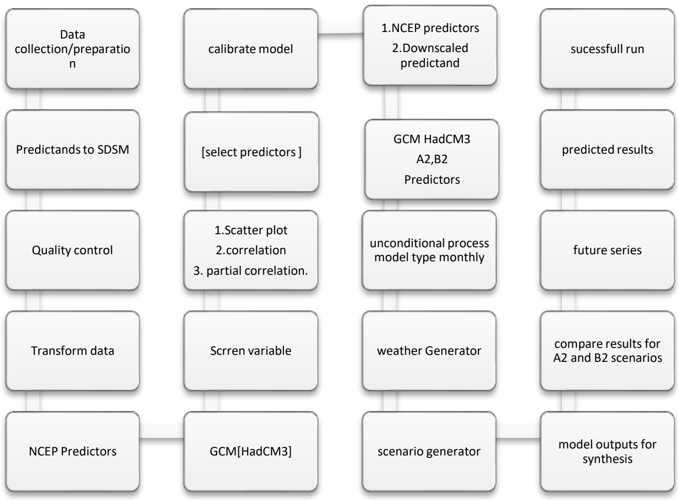
3.1 STUDY AREA AND SOURCES OF DATA

Jalna District Marathwada region, Maharashtra State, India**.**

The study area is Jalna district in Maharashtra (area≈7687.39km^2).between 18° 42^{r} 49^{rr} N to 19° 40^{r} 27^{rr} N and 75° 12^{r} 12^{rr} E to 77° 55^{r} 59^{rr} E.

3.2 DATA COLLECTION

For the execution of present study, daily temperature (*relative humidity*) values have been obtained from NASA power dot Indian Meteorological Department (IMD), Pune for the period 1961–2000. GCM data of HadCM3 under A2a and B2a scenarios have been obtained from Canadian Climate Impact Scenarios (CCIS) site for the area of Jalna Marathwada region Maharashtra State, India (Latitude: 19° .8347^{r}, Longitude: 75° .8816^{r}). The methodology section outlines the plan and method that how the study and the SDSM software are running successfully is shown. This includes methodology and steps of the study to be followed for the future series.



3.3 SELECTION OF INPUT PARAMETERS

The flowchart and basic equation for downscaling given by is as shown in Fig. 2.Working of statistical downscaling model (SDSM) which is developed by Wilby And Dawson is divided into below steps: (a) Home (b) Quality Control, (c) Transforming Predictor data, (d) Screen Variables, (e) Model Calibration, (f) Weather Generator, (g) Finding statistics of the data, and (h) 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 in a proper manner. Screen variables help to decide the suitable predictors over the selected region with both options scattering and correlation parameters. Model Calibration suggests whether selected NCEP predictors are correct or not for 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 is as given below.

Amount of total Temperature (t) Downscaled on day "i" is given by

$$U_i = \gamma_0 + \sum_{i=1}^{n} \gamma\, jX_{ij} + e_i \qquad (1)$$

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Where γ_0 = Intercept between predictor and predictand,

X_{ij} = Predictor values for selected predictors.

e_i = Bias correction value.

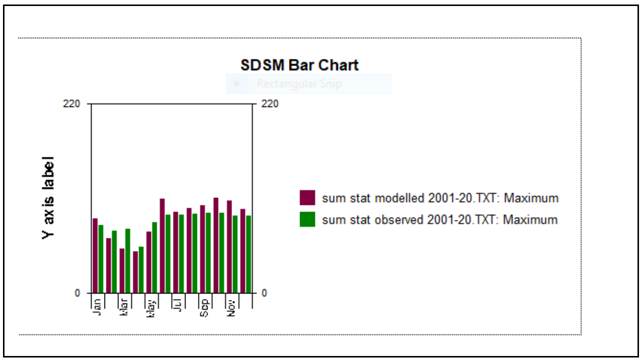
i =1

Table -1: Predictor Variables in the analysis Data Set

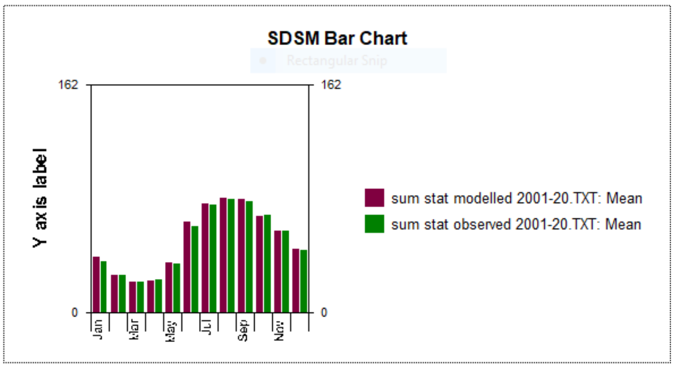
Sr.no	Predictor Name
1	p_f-airfloe strength at surface
2	p_u-zonal velocity at surface
3	p_meridional velocity at surface
4	p_z- surface velocity
5	p_th_surface wind direction
6	p_zh divergence at surface
7	rhum- relative humidity at surface
8	p5_f-500hPa airflow strength
9	r500-relative humidity of 500hPa
10	p8_f-850hPa airflow strength
11	p8_u-zonal velocity of 850 hPa
12	8_v-meridional velocity of 850hPa
13	P8_z850hPa vorticity
14	p8th-850hPa wind direction
15	p850-relative humidity of 850 hPa
16	r850-relative humidity of 850hPa
17	p5_u-500hPa velocity of zonal
18	p5_v-500hPa meridional velocity
19	p5_z-500hPa vorticity
20	p5zh-500hPa wind direction
21	5zh-500hPa divergence
22	p500-00hPa Geopotential height
23	r850-Relative humidity 850hPa
24	Temp-Mean temperature at a height of 2m
25	Shum-surface –specific humidity
26	mslp pressure at mean sea level

4. SYSTEM DEVELOPMENT

1981 to 2000. Observed monthly mean daily temperature data (*relative humidity*) and downscaled monthly mean daily temperature data (*relative humidity*) over this selected period have been compared graphically. Graphical comparison for relative humidity is as given in Graph 1 and 2.



Graph 1: Graphical representations for calculated results of relative humidity maximum by bar graph method.



Graph 2: Graphical representations for calculated results of relative humidity mean by bar graph method.

Graphical results indicate that observed and downscaled values of *relative humidity* 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 has been selected. Observed monthly mean daily temperature data of relative humidity were compared with downscaled monthly mean daily temperature data relative humidity over this period. For this statistical comparison, the coefficient of determination has been used. Results are as shown below Tables

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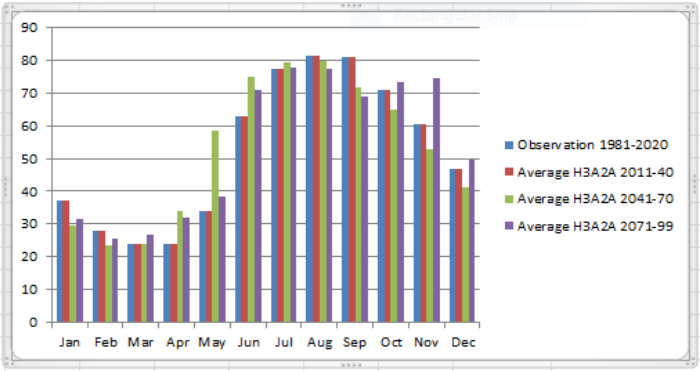
Model name	GCM	Temperature parameter	R^2 value between observed and downscaled parameter over 1981–2000
SDSM	HadCM3	Relative humidity	0.99

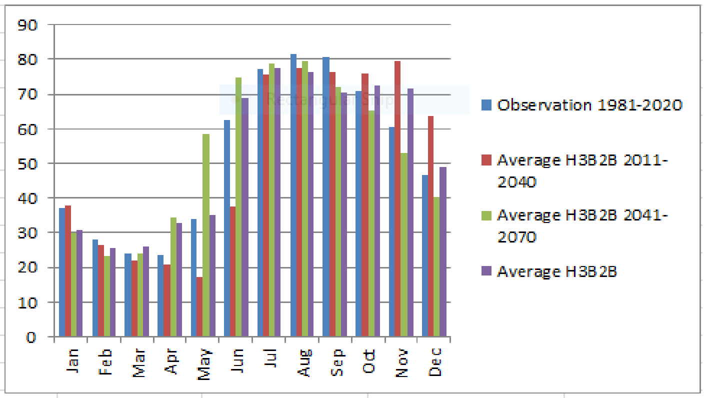
This section highlights the generation of future time series generation for the downscaled GCM dataset for future relative humidity. In this study, HadCM3 models were utilized due to their robust performance and high resolution in representing regional climate dynamics. With the SDSM model calibrated and validated, future climate scenarios from the selected GCMs are used to generate future time series for the predictand. This involves applying the statistical relationships established during calibration to the future predictor variables provided by the GCMs. The future predictor data in this study covers multiple emission scenarios and time horizons, such as the early- 21st century (2011-2040) mid-21st century (2041-2070) and the late 21st century (2071- 2099).

Future changes in monthly means daily relative humidity under different scenario with respect to base line period 1981-2020

Model	GCM	Series	Relative Humidity
SDSM	HadCM3 A2a	2020s(2011-2040)	0.07
SDSM	HadCM3 A2a	2050s(2041-2070)	0.06
SDSM	HadCM3 A2a	2080s(2071-2099)	0.03
SDSM	HadCM3 B2a	2020s(2011-2040)	0.05
SDSM	HadCM3 B2a	2050s(2041-2070)	0.012
SDSM	HadCM3 B2a	2080s(2071-2099)	0.25



Future mean monthly time series for HADCM3 model under A2 and A1B scenarios.



Future mean monthly time series for HADCM3 model under A2 and A1B scenarios.

5. CONCLUSIONS

The following conclusions are derived from the for the study in calibration and validation, both the models (SDSM) give satisfactory results; SDSM is giving more appropriate results. It means that calibration and validation are done in proper manner and then we have get some more accurate results and also we can predict future climatic values for Jalna District in Marathwada region in an appropriate way. SDSM gives increasing trends in the value of relative humidity in the near future with respect to the baseline period 1981–2020. 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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REFERENCES

[1] Revadekar, J.V., Kothawale, D.R.,Patwardhan, S.K.,Pant, G.B.,Kumar, K.R.,2012. About the observed and future changes in temperature extremes over India. Nat. Hazards 60(3),1133–1155. http://dx.doi.org/10.1007/s11069-011-9895-4.

[2]Chu,J.,Xia,J.,Xu,C.Y.,Singh,V.,2010.Statistical downscaling of daily mean temperature ,pan evaporation and precipitation for climate change scenarios in Haihe River, China. Theory .Application Climatol. 99(1),149–161. http://dx.doi.org/ 10.1007/s00704-009-0129-6

[3] Goyal, M.K., Ojha, C.S.P. and Burn, D.H. (2012) Nonparametric Statistical Downscaling of Temperature, Precipitation and Evaporation in Semiarid Region in India. *Journal of Hydrologic Engineering ASCE*, **17**, 615-627

[4]CCCSN.2012 .Statistical Downscaling Input:HadCM3 PredictorsA2 and B2 Experiments.⟨http://www.cccsn.ec.gc.ca/?page=pred-hadcm3. 2013⟩.

[5] Intergovernmental Panel on Climate Change (IPCC) (2001) Climate Change 2001— The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change.

[6] Wilby RL, Dawson CW, Barrow EM (2002) SDSM—a decision support tool for the assessment of regional climate change impacts. Environ Model Software 17:147–159

[7]Castillo, J. E.; Weibel, J. A.; and Garimella, S V., "The Effect of Relative Humidity on Dropwise Condensation Dynamics" (2015). CTRC Research Publications. Paper 244. http://dx.doi.org/http://dx.doi.org/10.1016/j.ijheatmasstransfer.2014.09.080.

[8] Michael Geruso and Dean Spears NBER Working Paper No. 24870 July 2018 JEL No. H23, I1, J1, O1, Q5, Q54, Q56.

[9] Nikolaos Nikolaou, Laurens M. Bouwer, Marco Dallavalle, Mahyar Valizadeh, Massimo Stogie, Annette Peters, Kathrin Wolf, and Alexandra Schneide Effects of cold weather on mortality: results from15 European cities within the PHEWE project. Am. J. Epidemiol. 168 (12), 1397–140https://doi.org/10.1093/aje/kwn266.

[10] Sanchez,E., Gallardo,C. ,Gaertner,M.A. ,Arribas,A. ,Castro,M.,2004. Future climate extreme events in the Mediterranean simulated by a regional climate model: a first approach. Global Planet Change44 (1–4), 163–180. http://dx.doi.org/ 10.1016/j.gloplacha.2004.06.010.