



Study of Climate Change Impact on Rainfall Erosivity Factor for Ratnagiri District

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Abstract: With the advent of erratic climate change, the problem of quantification of its effects needs a solution. This study attempted to identify, calculate and tabulate the effects and extent of future rainfall and its resultant erosivity on the study area of Ratnagiri district in Maharashtra. The past observed data used as a baseline was obtained from IMD, and the future predicted data utilised was of high-resolution Global Climate Models (FGOALS-g3 and MPI-ESM) for the duration of 2015 - 2100. Both these models had their own historic data and future predicted data, bias-corrected using Extreme Gradient Boosting machine learning algorithm. The results were compared to past observed data, and the correlation (r) of both models exceeded 0.9. MPI-ESM model was chosen for further analysis. Two Shared Socioeconomic Pathways (SSP 245 and 585) were chosen as climatic conditions for further analysis. The rainfall analysis of the future predicted data revealed a non-linear but increasing trend in overall annual rainfall amount and an equal growth in number of rainy days. Withdrawal dates shifted forwards by about a week by the end of the century. Rainfall erosivity factor calculation and analysis revealed the same non-linear positive growth. Overall, Rajapur taluka showed the greatest erosive potential, while Dapoli and Guhagar were among the least affected by this increase. Excessive precautions and conservation measures are suggested within the Rajapur and Mandangad talukas with complete priority to combat this increase in erosivity.

Index Terms – Erosivity factor, Rainfall trends, Python scripting, Bias Correction

I. INTRODUCTION

Soil and water are the most important natural resources that meet all human needs, and protect the environment and the civilization. Ever increasing demands for land and water resources due to burgeoning populations cause the degradation of these two precious natural resources. Land degradation is a serious problem in India and out of 329 million hectares of total geographical area, 146.8 Mha is reported as degraded by various factors (Manivannan et al., 2017). India is losing a huge amount of money in terms of loss of productivity from these degraded lands. Though India receives a good amount of annual rainfall (1190 mm), due to enhanced needs for domestic, agriculture and industrial development activities, over-exploitation and laxity of water resources, it becomes scarce. The declining trend of groundwater level in all parts of the country also indicates that the assured supply of good quality water will become a concern for the country's development. Hence, a holistic management approach of soil and water resources by linking social and economic development with protection of the natural ecosystem is the need of the hour.

A number of parametric models were developed to forecast soil erosion, yet Universal Soil Loss Equation (USLE) model was most widely used empirical formula for estimating annual soil loss from agricultural basins (Salunkhe et al., 2018). Along with the Revised Universal Soil Loss Equation (RUSLE), these two equations were preferred because of their simplicity (Ban et al., 2016). Rainfall erosivity (R factor) was a parameter that resided within these formulae. Among the various factors in the equations, rainfall erosivity was of high importance due to that fact that it was the major influencer of the detachment and transportation processes that took place as part of soil erosion (Nazuhan et al., 2018). With the availability of recorded data of the past rainfall events on a day-to-day basis, General Circulation Models (GCMs) became the most reliable and universally applicable way to assess climate change and predict climate scenes in long term studies (Shaikh et al., 2022). The usage of climate models allowed for quick and easy assessment of future climate (Dakhlaoui and Djebbi, 2021). The main issue that presented itself when using a GCM was the fact that the final output was far more coarse and comparatively inefficient in the diverse topography and climatic conditions of the Indian subcontinent (Jaiswal et al., 2021). To this end, there was a need for bias correction of any input data that was used in a regional climate model, and had been pursued in this particular study. These climate projections from these climate models emerged as critical inputs for many applications and decision support. To ensure that the data was as close to the ground reality as possible, statistical measures such as Pearson's Correlation Coefficient (r) (Mendez et al., 2020) and Coefficient of Determination (R^2) (Shiru and Chung, 2021) were also employed. To further bolster the scope of research, each and every step of the data extraction, calculation and trend analysis have been performed through the help of Python coding. All the aspects of the project were refined with the use of programming to enable a faster, smoother and vastly more superior and accurate final end product, whether that be the bias corrected output, or the trend analysis. To keep with the modern approach, all of the data was subject to strict quality checks all throughout the process through the help of machine learning algorithms. The choice of algorithm for bias correction was eXtreme Gradient Boost (XGB) for this study (Chen & Guestrin, 2016).

II. MATERIAL AND METHODOLOGY

Ratnagiri is a coastal district of Maharashtra, situated in the western coast of India. It has north-south length of about 180 km and average east-west extension of about 64 km. This district lies in between 16.30 to 18.04 °N and 73.02 to 73.53 °E as shown in Figure 2.2.1. The locations and data availability of the rain gauge stations is shown in Table 2.1.

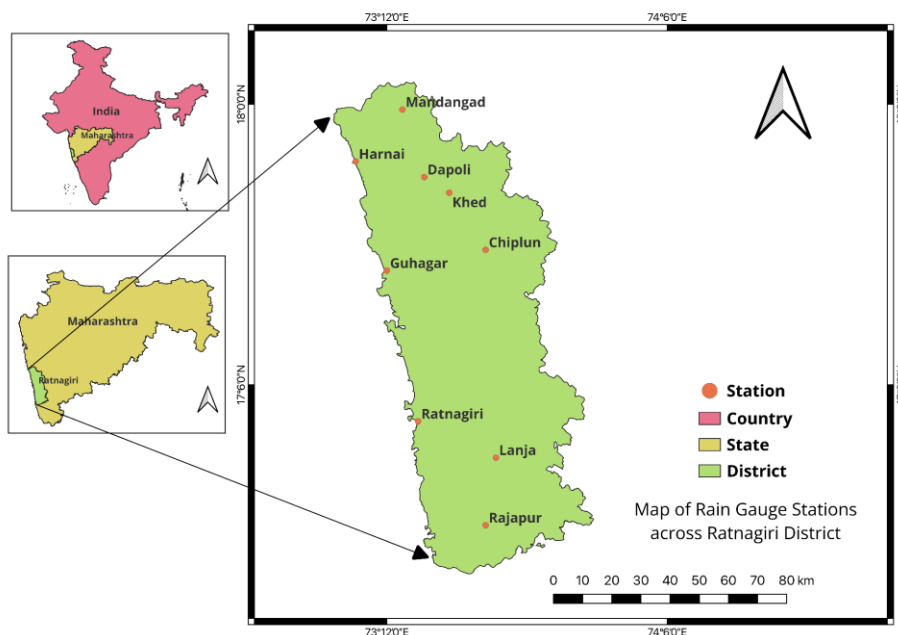


Figure 2.1 Map of rain gauge stations across study area of Ratnagiri district

Table 2.1 Location of different rain gauge stations in Ratnagiri district

Sr. No.	Name of location	Latitude (N) (degrees)	Longitude (E) (degrees)	Daily rainfall data availability
1.	Dapoli	17.767	73.200	1980-2023
2.	Chiplun	17.533	73.517	1980-2023
3.	Guhagar	17.467	73.200	1980-2023
4.	Harnai	17.817	73.100	1980-2023
5.	Khed	17.717	73.400	1980-2023
6.	Lanja	16.867	73.550	1980-2023
7.	Mandangad	17.983	73.250	1980-2023
8.	Rajapur	16.650	73.517	1980-2023
9.	Ratnagiri	16.9833	73.3000	1980-2023

Erosivity factor was closely related to the intensity of every storm and also with the depth of rainfall occurred in that storm. Several scientists estimated erosivity factor value of the day from daily precipitation (Vishwasrao and Jagtap, 2004) in other regions. These relations were tried out for the particular region where the intensity data was not available. In the present study, rainfall intensity data was not available for the stations. Daily rainfall data of ten stations viz., for 44 years (1980 - 2023) was available. For these stations the erosivity factor was estimated using empirical relationship. In the present study, due to the non-availability of sub-daily rainfall intensity data required for the computation of EI_{30} and $KE > 25$ indices, an empirical approach based on daily rainfall data was adopted. Daily rainfall data of 44 years for ten stations of Ratnagiri district were used for the analysis. Using the rainfall values as input, daily rainfall erosivity was calculated by the following formula as described by Salunkhe et al., (2018):

$$Y = 0.3339X^{1.5} \quad (1)$$

Where,

Y = daily erosivity factor, MJ-mm/ha-hr

X = daily rainfall depth, mm

Trend analysis of rainfall data is a statistical technique used to identify whether rainfall has increased, decreased or remained stable over the period under study. It shows patterns that evolve and change over time, allowing for better informed decisions and further course of action. Trend analysis is an essential part of any long-term study due to the fact that it allows for an easier visualization of the massive data condensed into easy-to-understand graphs and terms. In terms of the present study, once the annual erosivity was calculated, a trend analysis was conducted. The two main tests used were the non-parametric Modified Mann-Kendall Test (Hamed and Rao, 1998) and the Sen's Slope test (Sen, 1968). The main reason that the Modified Mann-Kendall Test was chosen over the standard test was because of the presence of cyclic trends in this study. Seasonal precipitation patterns meant that the standard test was susceptible to autocorrelation variance. According to Hamed and Rao (1998), positive autocorrelation will result in the increase of $V(S)$ and thus the variance of S will be underestimated by the original $var(S)$. Thus, if the original Mann-Kendall test was used for testing trends in positively autocorrelated data, it would have indicated significant trends, when actually no trends existed.

The Global Climate Models (GCMs) are valuable for the predicting of daily rainfall in India. These models are used for the simulation of precipitation patterns over time. The utilization of global climate model (GCM) simulations in hydrological climate-change impact studies, while increasingly prevalent, presented challenges due to the inherent risk of substantial biases within the simulated data. The models chosen for this study were shortlisted by studying various different research and review papers. Key to the choices was Deng et al., (2022), in which different CMIP6 models were ranked according to their performances in the Asian climatic region. The model of Flexible Global Ocean-Atmosphere-Land System Model - Grid-Point Version 3 (FGOALS-G3), developed by Chinese Academy of Sciences, China (Li et al., 2020) performed appreciably well under the parameters chosen by Deng et al., (2022), and hence was chosen for further study. Another model that was considered for this study was the Max Planck Institute - Earth System Model – High Resolution (MPI-ESM-HR) (Müller et al., 2018) model. This model was Germany based, created in the Max Planck Institute for Meteorology. Müller et al., (2018) was the introductory research paper that provided the latest information for the model. As evidence for its stellar performance within the subcontinent, the guidance of Bhatla et al., (2025) was considered when studying it.

With the two models chosen, it became imperative to identify which parameters would be necessary for the study. Currently, there are various different Shared Socioeconomic Pathways (SSPs) that are considered for climate modelling. For this, Gütschow et al., (2021) presented the necessary explanations. Two SSPs were chosen as described by Alizadeh et al., (2022): SSP 245 and SSP 585. SSP 245 is a combination of SSP 2 where climate conservation and its associated challenges are intermediate, and Representative Concentration Pathway (RCP) 4.5 gaseous concentration levels are moderate, with radiative forcing levels of 4.5 W/m^2 . SSP 585 being the combination of SSP 5 as the “worst-case” scenario under the extreme conditions where climate change mitigation challenges dominate the immediate need of addressing, and RCP 8.5 where atmospheric gaseous concentration is at an all-time high and with radiative forcing levels of 8.5 W/m^2 . The data for bias correction was gathered from the Climate Knowledge Portal (Eyring et al., 2016). Two datasets as discussed above were downloaded. For both the climate models chosen (FGOALS-g3 and MPI-ESM-HR), the daily data for historical period (1950 – 2014) and future prediction (2015 – 2100) were downloaded using python coding for automation and reduction of manual error. The data availability for the study period for all relevant data used within the study is given in Table **Error! Reference source not found.**

To verify if the bias-correction performed was accurate enough, several strategies were employed. The first of which being the comparison of observed data obtained from IMD with the bias-corrected historical data of the models. For this, the parameters considered were Correlation Coefficient (r) (Mendez et al., 2020; Zhu and Yang, 2020), Coefficient of Determination (R^2) (Shiru and Chung, 2021), Root Mean Square Error (RMSE) (Mendez et al., 2020; Daniel, 2023), and Mean Absolute Error (MAE) (Kim et al., 2020; Mendez et al., 2020). Once the correlation was verified, the statistical parameters were used to determine which of the two models would be used to pursue further analysis of the bias-corrected forecasted data. The choice was made by comparing all the calculated statistical parameters with the observed data obtained from IMD as the reference. The better performing model overall, across all chosen statistical parameters was chosen. The trend analysis was performed through the use of Python scripting. This approach was chosen to avoid the input and accuracy errors that plague manual calculation. With the use of Python scripting, it was possible to automate the process while also ensuring that the results were free of all inaccuracies.

With the vast duration of the data (86 years), it was chosen to split it into decadal brackets upon reading about the present research approach to long-term data analysis (Dunstone et al., 2022; Devasthale and Karlsson, 2023; Jiang et al., 2024), starting from 2021-2030, and proceeding onwards till 2091-2100. Each of these decadal brackets contained the average erosivity for the duration for each of the rain gauge station locations under study, which allowed for easy visualization of change within the projected data. The decadal arranged data was transported into a vector layer within QGIS which contained the locations of the rain gauge stations. To generate maps from these points, Inverse Distance Weightage (IDW) method of interpolation was utilized (Angulo-Martinez et al., 2009; Fathizad et al., 2017; Sadeghi et al., 2017; Xie et al., 2025). The tool used within the QGIS environment was called “IDW interpolation”, which is a native tool of QGIS itself. The IDW method ignored any spatial relationships including effects of topography except the assumption that nearby points ought to be more closely related than distant points to the value at the interpolation location. It determined cell values using a linearly weighted combination of a set of sample points. The weight was therefore supposed as a function of inverse distance. The IDW interpolation allowed controlling the significance of known points upon the interpolated values, based on their distance from the reference point (Shamshad et al., 2008).

Each decade was used to create a map of the erosivity of the district, with an overlay of the talukas. The shapefiles for the map and taluka boundaries were obtained directly from the Survey of India website. Once the layers with the maps were prepared, a print layout was created, providing all the basic necessities of a map, including the north arrow, legend, scale and labels of all the rain gauge stations. The values for each threshold of erosivity were also detailed within the legend, being kept common for all the maps to provide an easy way to compare and understand the direction and magnitude of changes that occurred as time went by within the century according to the predicted data.

III. RESULTS

3.1 Observed rainfall data analysis

The greatest average annual rainfall was seen in the stations at Rajapur (3828.15 mm), Mandangad (3815 mm), Chiplun (3769.02 mm) and Khed (3735.01 mm). Conversely, the stations of Ratnagiri (2922.38 mm), Guhagar (2922.16 mm) and Harnai (2803.42 mm) recorded the lowest average annual rainfall. Lanja (3508.43 mm) was shown to be the middling station, with the overall average of the Ratnagiri district according to the data being 3438.56 mm. The obtained rainfall data from IMD of the timespan of 1980 – 2023 (44 years) were averaged and is displayed in Table 3.1.

Table 3.1 Observed Decadal Annual Mean for Rainfall (mm)

Sr. No.	Station	1981-1990	1991-2000	2001-2010	2011-2020
1.	Chiplun	3420.02	3558.48	3561.06	4054.32
2.	Dapoli	3100.89	3288.45	3079.85	3716.77
3.	Guhagar	2744.64	3181.04	2834.89	3510.60
4.	Harnai	2857.46	3037.86	2949.67	3765.64
5.	Khed	3381.90	3610.71	3600.76	3803.99
6.	Lanja	3483.59	3538.38	3146.10	3816.51
7.	Mandangad	3429.58	3710.43	3526.97	3873.81
8.	Rajapur	3812.70	4218.53	3525.33	3644.98
9.	Ratnagiri	3253.34	3291.45	3140.57	3527.55

3.2 Estimation of rainfall erosivity

The monthly and annual mean erosivity followed the same trends as the rainfall means, with Rajapur (9948.82 MJ-mm/ha-hr-yr), Mandangad (9477.57 MJ-mm/ha-hr-yr), Chiplun (9435.32 MJ-mm/ha-hr) and Khed (9494.15 MJ-mm/ha-hr-yr) showed the highest levels of rainfall erosivity. The stations that exhibited the least rainfall erosivity were Ratnagiri (8626.19 MJ-mm/ha-hr-yr), Guhagar (7878.31 MJ-mm/ha-hr-yr) and Harnai (8448.08 MJ-mm/ha-hr-yr). Lanja (9089.36 MJ-mm/ha-hr-yr) was observed to gravitate closest to the mean erosivity of the region (9000.56 MJ-mm/ha-hr-yr). All these values are illustrated in Table 3.2.

Table 3.2 Observed Decadal Annual Mean for Rainfall Erosivity (R) (MJ-mm/ha-hr-yr)

Sr. No.	Station	1981-1990	1991-2000	2001-2010	2011-2020
1.	Chiplun	8606.74	8786.28	9460.59	10628.33
2.	Dapoli	7900.55	8140.62	7804.72	9949.49
3.	Guhagar	6480.12	7678.32	7064.47	9050.10
4.	Harnai	7266.79	7598.50	7496.02	10637.67
5.	Khed	8690.37	9175.15	9677.53	9833.72
6.	Lanja	8927.55	9183.29	7874.88	9795.29
7.	Mandangad	8817.95	9630.54	9326.57	10156.88
8.	Rajapur	10404.96	11896.70	9510.76	8989.12
9.	Ratnagiri	8114.17	8382.96	8247.52	8936.76

3.3 Bias correction analysis of rainfall data

Bias correction of rainfall data involves a process that adjusted raw climate model outputs or estimates to closely match the local ground observations. This process was essential because raw data often misrepresents true rainfall totals, intensities and sequences. For the statistical analysis of both the models, the overlap time period between the observed historic data and the bias-corrected historical data was analyzed (1980 – 2014). All analysis was carried out on a daily scale. For the FGOALS model, the correlation (r) values were consistently high, ranging from 0.9668 (Harnai) to 0.9849 (Khed), indicating a strong linear positive relationship between the predicted and observed data. The R^2 values were also high, between 0.9347 and 0.9701, suggesting that the model explained an exceedingly large proportion of the variance in the data. The errors (RMSE and MAE) vary across locations, with Rajapur exhibiting the highest errors (RMSE: 128.62, MAE: 65.61) and Khed showing the lowest MAE (42.99). Since the MPI model performed better than the FGOALS model for 7 of the 9 stations, it was considered for further evaluation of trends.

3.4 Trend analysis of rainfall data

Trend analysis of the observed rainfall data revealed that the majority of the increase was localized to the months of July and September. Even though there were trends detected in these months all throughout the study area and data duration, the values of Sen's Slope calculated were far too small to amount to much change over the duration of the available data (44 years). Mathematically significant trends were certainly present, but not practically applicable in any realistic sense. The trend analysis of the rainfall erosivity of the observed data revealed that the greatest increase of erosivity factor occurred within the months of July and September (Month 7 and 9). While the overall Sen's Slope values were minimal, the detection of a mathematically present and statistically significant trend within that period across all the stations showed that there was a change, or shift in erosivity patterns as opposed to the norm. This hinted at a greater presence of erosive potential of rainfall within these months in the past. The diverging trend at Rajapur was observed within the erosivity trends as well, once again decreasing in the months of August and October. As with observed rainfall, there were no trends detected for rainfall erosivity on the annual scale.

For the SSP245 scenario there were smaller trends detected, with a majority of them being statistically significant but negligible in a practical sense due to a minimal Sen's Slope value. This suggested that while there were statistical trends that are detectable, the magnitude of these trends was marginal at best. The main draw from the MMK and SS analysis was the fact that these tests detected very significant increasing trends detected for the month of October (Month 10) across all stations, while simultaneously showing a decrease of rainfall during August (Month 8) in some stations as well. The core finding across the data used in the decadal study of the MPI-ESM-HR model was a non-linear divergence, where the high-emissions scenario (SSP 585) led to exponentially greater changes and uncertainty in the second half of the century. The data revealed that, on average, the total seasonal change (May to October) by the end of the century (2091-2100) was projected to be four to five times greater under SSP585 than under SSP245 for highly sensitive stations like Dapoli, Lanja, and Rajapur. This stark separation began to materialize decisively

in the mid-century period (2041-2060) for most stations. Inference of the change in amount of total annual rainfall over the decades in the SSP 245 scenario showed that there was a small, but clear increase in amount. While it was not statistically significant, it was certainly numerically present. This was done through direct calculation of subtraction of initial and final values of the stations divided by the initial value to check for growth of annual rainfall over the study period of 86 years (2015 to 2100). The growth rate was around 6 to 7 % over the entire study duration, with all stations describing a similar pattern of growth. The data used for the calculation is presented in Table 3.3.

Table 3.3 Decadal Mean Annual Rainfall (mm) under SSP 245

Sr. No.	Station	2021-2030	2031-2040	2041-2050	2051-2060	2061-2070	2071-2080	2081-2090	2091-2100
1.	Chiplun	3178.3	3454.7	3381.0	3288.8	3353.8	3284.8	3268.5	3389.5
2.	Dapoli	2761.6	2915.7	2938.4	2806.9	2869.4	2807.2	2708.4	2944.7
3.	Guhagar	2629.1	2806.2	2787.1	2745.5	2789.6	2708.0	2670.9	2864.1
4.	Harnai	2554.8	2674.8	2666.7	2643.7	2739.3	2590.9	2577.4	2772.7
5.	Khed	3108.9	3332.0	3261.1	3212.6	3257.4	3176.6	3075.6	3289.2
6.	Lanja	2951.8	3241.3	3210.6	3223.4	3255.3	3195.7	3198.8	3280.1
7.	Mandangad	3143.1	3412.3	3405.2	3217.4	3369.9	3249.7	3148.6	3430.1
8.	Rajapur	3288.6	3614.7	3550.6	3576.0	3640.7	3556.3	3553.7	3682.3
9.	Ratnagiri	2900.7	3110.9	3041.4	3062.9	3230.0	3096.7	3074.6	3164.3

Decadal averages of average annual rainfall in the SSP 585 scenario were on average 8 to 10 % higher than the SSP 245 scenario for the same time frame, compared using the data presented in Tables 3.3 and 3.4. While this higher initial value influenced the final value at the end of the century also being higher, the overall rate of growth was found to be lesser than the SSP 245 scenario, at around 4 to 5 % by the end of the century. Monthly erosivity factor trends in the SSP245 scenario closely corroborated the trends seen in the monthly rainfall data, with a slight increasing trend detected at Lanja for the month of July (Month 7) rather than August (Month 8) as was expected. This was not detected in the rainfall trends, but its significance was rather marginal.

Table 3.4 Decadal Mean Annual Rainfall (mm) under SSP 585

Sr. No.	Station	2021-2030	2031-2040	2041-2050	2051-2060	2061-2070	2071-2080	2081-2090	2091-2100
1.	Chiplun	3422.6	3453.8	3627.2	3386.2	3663.1	3549.4	3734.1	3683.9
2.	Dapoli	3011.2	3048.5	3230.1	2962.0	3217.1	3158.3	3338.0	3227.9
3.	Guhagar	2770.1	2836.1	2988.6	2743.0	3017.5	2940.1	3106.9	3090.1
4.	Harnai	2736.0	2776.6	2946.7	2748.5	2934.0	2924.2	3124.2	3063.1
5.	Khed	3398.7	3442.9	3663.0	3355.7	3586.3	3498.9	3747.8	3651.9
6.	Lanja	3207.5	3224.4	3301.2	3074.4	3324.4	3314.8	3373.6	3365.8
7.	Mandangad	3352.3	3372.1	3633.5	3365.3	3540.8	3477.6	3725.6	3517.4
8.	Rajapur	3561.1	3565.1	3647.6	3397.8	3683.8	3705.0	3739.1	3760.0
9.	Ratnagiri	2926.9	3097.6	3226.8	2938.1	3205.0	3164.6	3354.4	3275.8

The decadal mean erosivity of the SSP 245 scenario (Table 3.5) revealed an increasing amount of erosivity throughout the decades, though the exact value between each decade was far too minimal to attest to any specific phenomenon or factor. In most locations, the rate of increase did not surpass 0.5 % per year, and as a result, was not statistically significant. The decadal means of the SSP 585 scenario erosivity revealed that while there was a slow increase in erosivity values all across the board, there were no deviations from the mold. There was an increase of about 6 to 10 % in values across the 86 years, resulting in an annual growth in erosivity of less than 0.1 %. Such growth could not be directly attributed to any real factor in the short term, but a long-term trend could be visualized owing to the timespan of data that was studied. Overall, the major point of note was that the values for the SSP 585 scenario were higher than those of the SSP 245 scenario all throughout the district and timespan of the study.

Table 3.5 Decadal Mean Annual Erosivity (R) (MJ-mm/ha-hr-yr) for SSP 245

Sr. No.	Station	2021-2030	2031-2040	2041-2050	2051-2060	2061-2070	2071-2080	2081-2090	2091-2100
1.	Chiplun	5746.3	6306.0	6165.4	5967.5	6026.2	5937.5	5908.0	6101.8
2.	Dapoli	4769.0	5030.4	5122.8	4861.6	4906.9	4874.0	4676.0	5051.2
3.	Guhagar	4340.5	4664.0	4646.9	4605.4	4612.5	4486.3	4422.1	4764.3
4.	Harnai	4341.9	4534.6	4524.4	4493.8	4629.8	4367.1	4356.7	4698.8

5.	Khed	5602.7	6035.3	5860.2	5816.5	5858.1	5751.7	5531.1	5871.2
6.	Lanja	5186.8	5733.6	5743.4	5779.3	5780.3	5677.8	5670.0	5768.7
7.	Mandangad	5819.7	6356.2	6423.3	5964.6	6233.1	6104.4	5850.4	6371.7
8.	Rajapur	6120.7	6759.7	6678.9	6761.2	6847.7	6666.3	6642.5	6869.8
9.	Ratnagiri	5016.3	5401.0	5275.9	5346.5	5687.8	5415.7	5333.8	5450.8

The decadal means of the SSP 585 scenario erosivity revealed that while there was a slow increase in erosivity values all across the board, there were no deviations from the mold. There was an increase of about 6 to 10 % in values across the 86 years, resulting in an annual growth in erosivity of less than 0.1 %. Such growth could not be directly attributed to any real factor in the short term, but a long term trend could be visualized owing to the timespan of data that was studied. Overall, the major point of note was that the values for the SSP 585 scenario were higher than those of the SSP 245 scenario all throughout the district and timespan of the study. This is seen in Table 3.6. Erosivity trends for the months within SSP585 scenario were rather similar to the rainfall trends, though there were more months projecting increasing trends. In general, the months of June, September and October (Month 6, 9 and 10) exhibited the most trends. Most of these trends were increasing, but in some stations (Chiplun, Lanja and Rajapur), July (Month 7) represented a decreasing trend of erosivity, detailing the claim that there was a reduction in rainfall within that month.

Table 3.6 Decadal Mean Annual Erosivity (R) (MJ-mm/ha-hr-yr) for SSP 585

Sr. No.	Station	2021-2030	2031-2040	2041-2050	2051-2060	2061-2070	2071-2080	2081-2090	2091-2100
1.	Chiplun	6251.2	6308.2	6662.1	6209.5	6779.1	6441.3	6878.5	6738.3
2.	Dapoli	5236.9	5314.1	5633.1	5143.0	5651.3	5488.5	5852.9	5619.8
3.	Guhagar	4621.6	4737.0	5014.6	4581.6	5112.4	4909.3	5271.6	5216.7
4.	Harnai	4656.3	4717.1	5031.3	4711.3	4986.0	4988.4	5389.2	5234.8
5.	Khed	6158.3	6266.8	6735.5	6095.3	6578.1	6321.9	6918.3	6665.1
6.	Lanja	5718.8	5741.0	5858.2	5472.5	5976.8	5890.8	6015.8	5947.5
7.	Mandangad	6231.4	6259.9	6818.9	6299.8	6605.4	6496.7	7005.5	6516.0
8.	Rajapur	6697.5	6689.4	6801.3	6353.7	6972.7	6965.8	7030.9	7028.5
9.	Ratnagiri	5055.4	5414.2	5656.4	5129.1	5621.6	5477.6	5926.5	5700.6

4.5 Rainfall erosivity vulnerability map analysis

With the generation of the predicted rainfall erosivity, the necessary data to produce maps was ready. Upon creation of said maps, it was apparent that over the decades, the coastal areas surrounding the Harnai, Dapoli, Guhagar and Ratnagiri stations was less affected by erosion than the inland areas surrounding the Mandangad, Khed, Chiaplun and Rajapur stations. Lanja was observed to be the average in most cases. Of the inland stations, Rajapur station was identified as the most erosive across majority of the decades under analysis. The talukas of Mandangad, Khed, Chiaplun, Lanja, Sangameshwar and Rajapur, which were situated on the eastern side of the district were found to be more susceptible to rainfall erosivity, especially so towards the end of the century. All the rivers within the district were westward-flowing, which would result in the rivers carrying the eroded soil towards the western coastal talukas. This would present its own problems should the rainfall erosivity of these highly susceptible talukas not be arrested and remedied.

Throughout the course of SSP 245 scenario (the initial and final decadal data shown in Figures 3.1 and 3.2), the trend was in the general positive direction, with the exception of the 2051-2060 and 2081-2090 decades. The station that showed the greatest increase in erosivity was Rajapur. The least erosive stations were also consistently Harnai and Guhagar. This was attributed to their coastal location, as well as lower relief as compared to the inland areas. Mandangad and Chiaplun were hotspots of erosive activities as well, and Lanja was seen as an intermediate average all throughout the decades.

Within the SSP 585 scenario (the initial and final decadal data shown in Figure 3.3 and Figure 3.4), the pattern of increase was similar to the SSP 245, with greater increase in erosivity as the decades progressed. A dip in erosivity was observed within the 2051-2060 and 2071-2080 decades, and the growth in erosivity resumed with the following decades. The overall growth at the end of the study duration was far greater than the initial value, indicating that there was most certainly a pressing concern for conservation efforts, especially in Rajapur taluka. Across the entire century, it was evident that the SSP 585 scenario had a greater impact on the rainfall erosivity factor of the region, not only starting off higher, but also growing in intensity as the century progressed and maintaining that trajectory right till the end of the study period. Each and every taluka saw a growth that pushed it into the higher category of severity, especially so with Rajapur taluka.

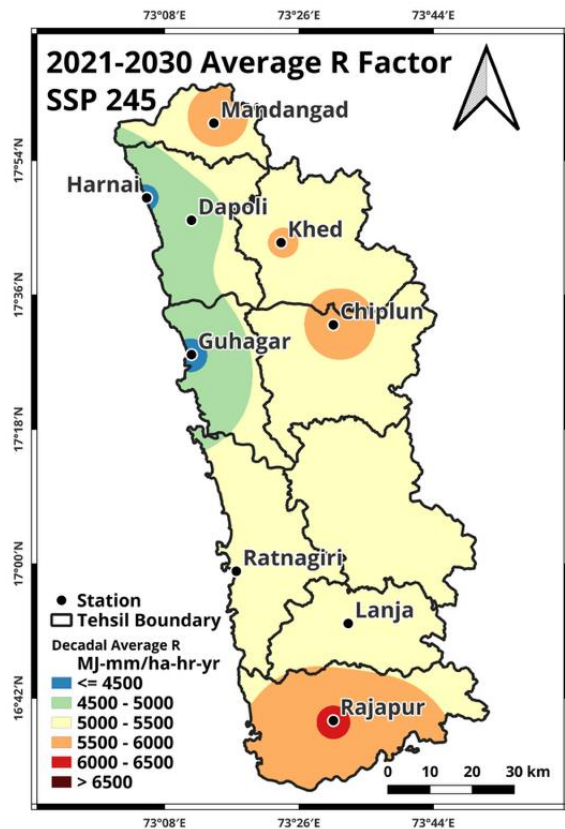


Figure 3.1
Average R Factor During 2021 – 2030
Under SSP 245

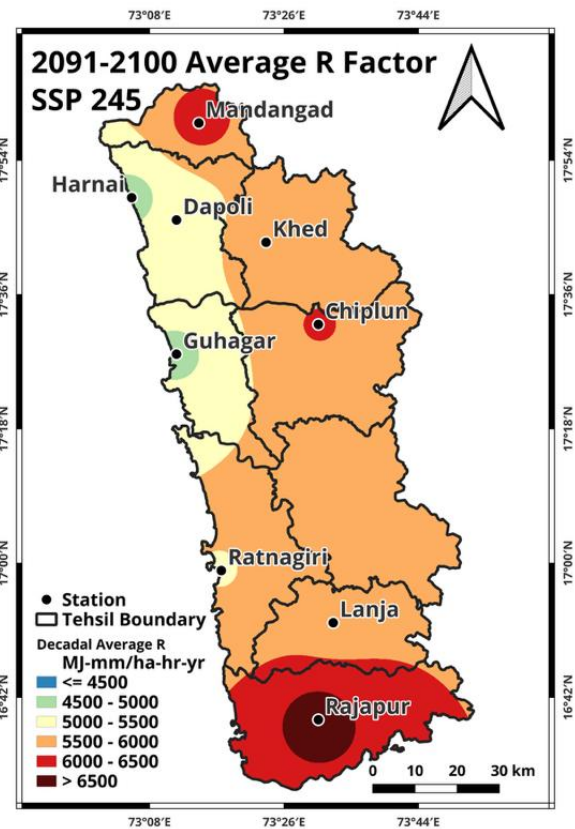


Figure 3.2
Average R Factor During 2091 – 2100
Under Ssp 245

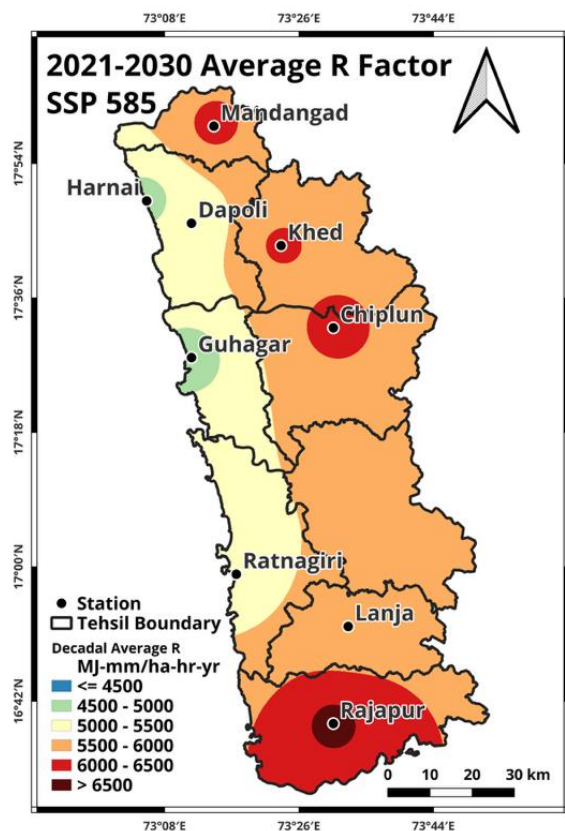


Figure 3.3
Average R factor during 2021 – 2030
under SSP 585

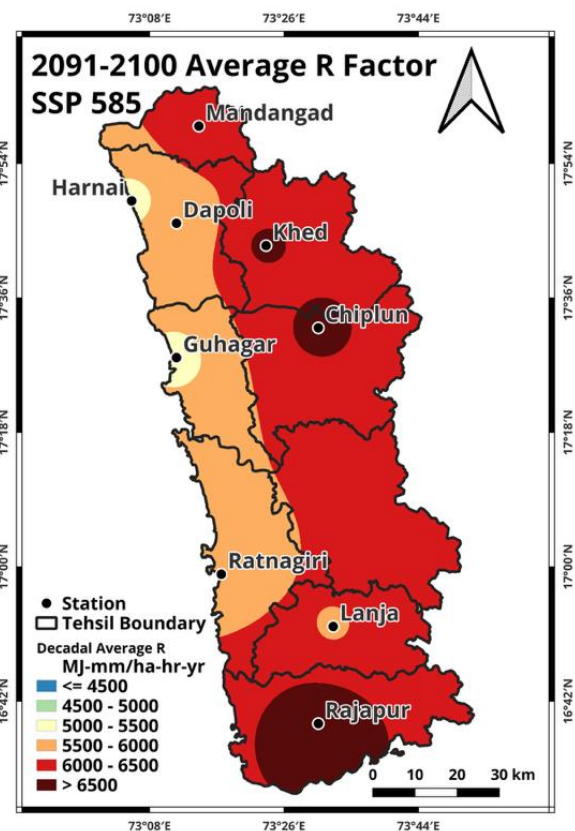


Figure 3.4
Average R factor during 2091 – 2100
under SSP 585

IV. CONCLUSIONS

The study revealed that over the course of the rest of the century, two major decades were visible where there would be a prominent decline in rainfall (2021–2030 and 2051–2060). These two decades potentially indicated the strong presence of droughts, along with reduced monsoonal rainfall patterns, which directly influence the amount of erosivity that would be generated during

those said decades. Analysis of the number of rainy days showed that there was a growth that corresponded to the non-linear increase in rainfall, following the same pattern. The onset dates did not variate throughout both SSPs within the entire study period, but there was evidence noting the shifting of withdrawal dates forwards, into early October. The total amount of annual rainfall and erosivity saw a small but notable increase in value of around 8 to 10 % of the observed value baseline. The erosivity analysis described the same patterns as the rainfall analysis of the study area, and the generation of vulnerability maps using the decadal averages was conducted to provide a much better visual representation of changes throughout the decades. While the pattern of increase echoed the same sentiment throughout both SSP scenarios, the SSP 585 scenario boasted much larger values of annual erosivity as compared to the SSP 245 scenario, a clear indicator of the disastrous impact of climate change on future erosivity, should it remain unmitigated.

Based on the findings of the study, the following conclusions were drawn:

- 1) No significant annual trends were detected in the past observed data or future predicted rainfall despite the fact that there was shift in monthly precipitation values. This indicated that while total rainfall was relatively constant, its distribution from month to month was changing. Similar trends were observed in rainfall erosivity as well.
- 2) Bias corrected Global Climate Model (GCM) rainfall data of models MPI-ESM-HR and FGOALS-g3 showed very high correlation with ground truth data for the study area. Both of these models can be recommended to be used in future similar studies within the study area.
- 3) Mapping of future predicted rainfall erosivity revealed Rajapur, Mandangad, Chiplun and Khed as highly susceptible regions for rainfall erosivity in lieu of climate change.

REFERENCES

- [1] Alizadeh, M. R., Adamowski, J., & Inam, A. (2022). *Integrated assessment of localized SSP–RCP narratives for climate change adaptation in coupled human–water systems*. *Science of The Total Environment*, 823, 153660. <https://doi.org/10.1016/j.scitotenv.2022.153660>
- [2] Angulo-Martinez, M., Lopez-Vicente, M., Vicente-Serrano, S. M., & Begueria, S. (2009). *Mapping rainfall erosivity at a regional scale: A comparison of interpolation methods in the Ebro Basin (NE Spain)*. *Hydrol. Earth Syst. Sci.*
- [3] Ban, J. K., Yu, I., & Jeong, S. (2016). *Estimation of Soil Erosion Using RUSLE Model and GIS Techniques for Conservation Planning from Kulekhani Reservoir Catchment, Nepal*. *Journal of Korean Society of Hazard Mitigation*, 16(3), 323–330. <https://doi.org/10.9798/KOSHAM.2016.16.3.323>
- [4] Bhatla, R., Verma, A., Vishwakarma, A., & Mall, R. K. (2025). *India's Drought Challenge: Insights From CMIP6 Models on Historical and Future Climate Scenarios*. *International Journal of Climatology*, 45(13), e70075. <https://doi.org/10.1002/joc.70075>
- [5] Chen, T. & Guestrin, C. (2016). *XGBoost: A Scalable Tree Boosting System*. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 785–794. <https://doi.org/10.1145/2939672.2939785>
- [6] Dakhlaoui, H. & Djebbi, K. (2021). *Evaluating the impact of rainfall–runoff model structural uncertainty on the hydrological rating of regional climate model simulations*. *Journal of Water and Climate Change*, 12(8), 3820–3838. <https://doi.org/10.2166/wcc.2021.004>
- [7] Daniel, H. (2023). *Performance assessment of bias correction methods using observed and regional climate model data in different watersheds, Ethiopia*. *Journal of Water and Climate Change*, 14(6), 2007–2028. <https://doi.org/10.2166/wcc.2023.115>
- [8] Deng, X., Ye, A., Zhong, J., Xu, D., Yang, W., Song, Z., Zhang, Z., Guo, J., Wang, T., Tian, Y., Pan, H., Zhang, Z., Wang, H., Wu, C., Shao, J., & Chen, X. (2022). *Bagging–XGBoost algorithm based extreme weather identification and short-term load forecasting model*. *Energy Reports*, 8, 8661–8674. <https://doi.org/10.1016/j.egyr.2022.06.072>
- [9] Devasthale, A. & Karlsson, K.-G. (2023). *Decadal Stability and Trends in the Global Cloud Amount and Cloud Top Temperature in the Satellite-Based Climate Data Records*. *Remote Sensing*, 15(15), 3819. <https://doi.org/10.3390/rs15153819>
- [10] Dunstone, N., Lockwood, J., Solaraju-Murali, B., Reinhardt, K., Tsartsali, E. E., Athanasiadis, P. J., Bellucci, A., Brookshaw, A., Caron, L.-P., Doblas-Reyes, F. J., Früh, B., González-Reviriego, N., Gualdi, S., Hermanson, L., Materia, S., Nicodemou, A., Nicolì, D., Pankatz, K., Paxian, A., et al. (2022). *Towards Useful Decadal Climate Services*. *Bulletin of the American Meteorological Society*, 103(7), E1705–E1719. <https://doi.org/10.1175/BAMS-D-21-0190.1>
- [11] Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., & Taylor, K. E. (2016). *Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization*. *Geoscientific Model Development*, 9(5), 1937–1958. <https://doi.org/10.5194/gmd-9-1937-2016>
- [12] Fathizad, H., Hakimzadeh, M. A., Fallah Shamsi, S. R., & Yaghoobi, S. (2017). *Watershed-level Rainfall Erosivity Mapping Using GIS-based Geostatistical Modeling*. *Journal of Earth Science Research*, 5(1), 13–22. <https://doi.org/10.18005/JESR0501002>
- [13] Gütschow, J., Jeffery, M. L., Günther, A., & Meinshausen, M. (2021). *Country-resolved combined emission and socio-economic pathways based on the Representative Concentration Pathway (RCP) and Shared Socio-Economic Pathway (SSP) scenarios*.
- [14] Hamed, K. H. & Rao, R. A. (1998). *A modified Mann-Kendall trend test for autocorrelated data*. *Journal of Hydrology*, 204(1–4), 182–196. [https://doi.org/10.1016/S0022-1694\(97\)00125-X](https://doi.org/10.1016/S0022-1694(97)00125-X)

- [15] Jaiswal, R., Mall, R. K., Singh, N., Lakshmi Kumar, T. V., & Niyogi, D. (2021). *Evaluation of Bias Correction Methods for Regional Climate Models: Downscaled Rainfall Analysis Over Diverse Agroclimatic Zones of India*. *Earth and Space Science*, 9(2), e2021EA001981. <https://doi.org/10.1029/2021EA001981>
- [16] Jiang, F., Seager, R., & Cane, M. A. (2024). A climate change signal in the tropical Pacific emerges from decadal variability. *Nature Communications*, 15(1), 8291. <https://doi.org/10.1038/s41467-024-52731-6>
- [17] Kim, Y.-H., Min, S.-K., Zhang, X., Sillmann, J., & Sandstad, M. (2020). *Evaluation of the CMIP6 multi-model ensemble for climate extreme indices*. *Weather and Climate Extremes*, 29, 100269. <https://doi.org/10.1016/j.wace.2020.100269>
- [18] Li, L., Yu, Y., Tang, Y., Lin, P., Xie, J., Song, M., Dong, L., Zhou, T., Liu, L., Wang, L., Pu, Y., Chen, X., Chen, L., Xie, Z., Liu, H., Zhang, L., Huang, X., Feng, T., Zheng, W., et al. (2020). *The Flexible Global Ocean-Atmosphere-Land System Model Grid-Point Version 3 (FGOALS-g3): Description and Evaluation*. *Journal of Advances in Modeling Earth Systems*, 12(9), e2019MS002012. <https://doi.org/10.1029/2019MS002012>
- [19] Manivannan, S., Thilagam, V. K., & Khola, O. P. S. (2017). *Soil and water conservation in India: Strategies and research challenges*. *Journal of Soil and Water Conservation*, 16(4), 312. <https://doi.org/10.5958/2455-7145.2017.00046.7>
- [20] Mendez, M., Maathuis, B., Hein-Griggs, D., & Alvarado-Gamboa, L.-F. (2020). *Performance Evaluation of Bias Correction Methods for Climate Change Monthly Precipitation Projections over Costa Rica*. *Water*, 12(2), 482. <https://doi.org/10.3390/w12020482>
- [21] Müller, W. A., Jungclaus, J. H., Mauritsen, T., Baehr, J., Bittner, M., Budich, R., Bunzel, F., Esch, M., Ghosh, R., Haak, H., Ilyina, T., Kleins, T., Kornblueh, L., Li, H., Modali, K., Notz, D., Pohlmann, H., Roeckner, E., Stemmler, I., et al. (2018). *A Higher-resolution Version of the Max Planck Institute Earth System Model (MPI-ESM1.2-HR)*. *Journal of Advances in Modeling Earth Systems*, 10(7), 1383–1413. <https://doi.org/10.1029/2017MS001217>
- [22] Nazuhan, M., Rahaman, Z. A., & Othman, Z. (2018). *A Review on Rainfall Erosivity (R factor) in Universal Soil Loss Equation*. *International Journal of Academic Research in Business and Social Sciences*, 8(2), Pages 816-822. <https://doi.org/10.6007/IJARBS/v8-i2/3988>
- [23] Sadeghi, S. H., Zabihi, M., Vafakhah, M., & Hazbavi, Z. (2017). *Spatiotemporal mapping of rainfall erosivity index for different return periods in Iran*. *Natural Hazards*, 87(1), 35–56. <https://doi.org/10.1007/s11069-017-2752-3>
- [24] Salunkhe, S. S., Nandgude, S. B., Mahale, D. M., Bhambure, T. V., Bhattacharya, T., & Wandre, S. S. (2018). *Estimation of Soil Erosion and Nutrient Loss by USLE Model for Ratnagiri District*. (1).
- [25] Sen, P. K. (1968). *Estimates of the Regression Coefficient Based on Kendall's Tau*.
- [26] Shaikh, M. M., Lodha, P., Lalwani, P., & Mehta, D. (2022). *Climatic projections of Western India using global and regional climate models*. *Water Practice and Technology*, 17(9), 1818–1825. <https://doi.org/10.2166/wpt.2022.090>
- [27] Shamshad, A., Azhari, M. N., Isa, M. H., Hussin, W. M. A. W., & Parida, B. P. (2008). *Development of an appropriate procedure for estimation of RUSLE EI30 index and preparation of erosivity maps for Pulau Penang in Peninsular Malaysia*. *CATENA*, 72(3), 423–432. <https://doi.org/10.1016/j.catena.2007.08.002>
- [28] Shiru, M. S. & Chung, E.-S. (2021). *Performance evaluation of CMIP6 global climate models for selecting models for climate projection over Nigeria*. *Theoretical and Applied Climatology*, 146(1–2), 599–615. <https://doi.org/10.1007/s00704-021-03746-2>
- [29] Vishwasrao SR, and Jagtap SK (2004) Synthesis of rainfall characteristics for predicting the erosivity pattern of Dapoli region. Unpublished B.Tech. Thesis submitted to Department of Soil and Water Conservation Engineering, Dr.B.S.K.K.V. Dapoli.
- [30] Xie, J., Ding, L., Wang, X., Qin, W., Xu, H., & Zhang, M. (2025). *Comparison of spatial interpolation methods for rainfall erosivity in a typical basin in the Hengduan Mountain region, Southwest China*. *Ecological Indicators*, 174, 113451. <https://doi.org/10.1016/j.ecolind.2025.113451>
- [31] Zhu, Y.-Y. & Yang, S. (2020). *Evaluation of CMIP6 for historical temperature and precipitation over the Tibetan Plateau and its comparison with CMIP5*. *Advances in Climate Change Research*, 11(3), 239–251. <https://doi.org/10.1016/j.accr.2020.08.001>