Long-Term Temperature Trends in the Upper Baitarani Basin, Odisha: Analyzing Regional Climate Variability

ABSTRACT

Aims: The Upper Baitarani Basin is highly susceptible to climate change, with significant consequences for local hydrology, agriculture, and ecosystems. However, the region lacks a detailed analysis of long-term temperature trends, which is crucial for understanding the extent of climate variability.

The objectives of this study are as follows:

(i) To analyze long-term trends in Tmin and Tmax over the past 70 years (1952-2022) using statistical methods such as the Mann-Kendall test and linear regression.

(ii) To evaluate the implications of observed temperature trends on the region's water resources, particularly the Upper Baitarani River Basin's hydrological patterns, considering the potential risks posed by climate change.

(iii) To assess the potential impact of temperature variability on agriculture and ecosystems, identifying vulnerable areas and proposing measures for climate adaptation and resilience in these sectors.

Study Design: This is a retrospective observational study utilizing historical climate data to assess temperature trends over a 70-year period from 1952 to 2022.

Place and Duration of Study: The study was conducted in the Upper Baitarani Basin, with data spanning the years 1952 to 2022.

Methodology: The study employs quantitative methods to analyze long-term temperature trends in the Upper Baitarani Basin. Specifically, the Mann-Kendall test was used to assess the statistical significance of temperature trends, while linear regression analysis was applied to quantify the rate of change over time.

Results: The analysis revealed a statistically significant warming trend in the Tmin during May for both locations, while Tmax displayed significant increases primarily in the latter half of the year (July through November) at both locations. The trends in Tmin were more variable and less statistically robust compared to Tmax, which showed consistent and significant increases, particularly in the late summer and early autumn months.

Conclusion: The findings indicate a significant warming trend in Tmax, especially from July to November, which could have critical implications for the local climate, agriculture, and water resources in the Upper Baitarani Basin. The observed trends underscore the need for adaptive strategies to mitigate the potential adverse effects of rising temperatures in this region. Further research incorporating additional climatic variables and longer time series data is recommended to enhance the understanding of regional climate dynamics.
patients.

Keywords:Linear Regression,Mann Kenall Test,Temperature trends, Tmin&Tmax,

1. INTRODUCTION

The Upper Baitarani River Basin, nestled in the Eastern Ghats of Odisha, India, is a region of significant ecological and economic importance. The basin is characterized by its mountainous terrain, which supports a variety of land uses, including extensive agricultural activities and substantial iron ore mining operations. The basin's socio-economic fabric is closely intertwined with its natural resources, making it particularly vulnerable to the impacts of climate change, especially shifts in temperature trends(1,2). Long-term temperature trend analysis in this region is essential for understanding how climate change might affect the region's agriculture, hydrology, and mining activities, all of which are crucial for the local population's livelihood(3,4,5).

Temperature is a critical climatic variable that influences various hydrological processes, including evapotranspiration, soil moisture retention, and river flow dynamics, all of which are vital for agricultural productivity(6,7,8). In regions like the Upper Baitarani Basin, where agriculture is the primary occupation, changes in temperature can have significant consequences for crop yield and food security(9,10,11,12). Furthermore, temperature trends are also crucial for the mining sector, particularly in the extraction and processing of iron ore, which can be sensitive to temperature fluctuations(13,14).

The analysis of long-term temperature trends is essential not only for predicting future climatic conditions but also for formulating adaptive strategies that can help mitigate the adverse impacts of climate change. Previous studies have highlighted the increasing trend of temperature in various river basins across India, often linked to broader global warming patterns(15,16,17).

The literature on temperature trend analysis in Indian river basins is extensive, with numerous studies employing statistical methods such as the Mann-Kendall test and Sen's slope estimator to assess long-term trends(12,18,19,20). These methods have been widely used to detect trends in temperature and precipitation data, providing valuable insights into regional climatic changes.

However, there is a notable gap in the literature regarding comprehensive temperature trend analyses specific to the Upper Baitarani River Basin. Most studies have focused on broader geographical areas, such as the Brahmani-Baitarani Basin, without delving into the micro-level impacts at the sub-basin scale, particularly in mountainous catchments like Upper Baitarani. Moreover, the interaction between temperature trends and land use changes, particularly the expansion of agriculture and mining activities in the region, has not been sufficiently explored. This presents an opportunity for focused research that examines how anthropogenic activities might be influencing local temperature trends and exacerbating climate change impacts .

Additionally, while some studies have considered the impacts of climate change on water resources in the region, few have specifically addressed how changing temperature patterns might alter hydrological cycles and, consequently, agricultural productivity(6,21,22). The interaction between temperature trends and land cover changes, such as deforestation for agricultural expansion and mining, is particularly under-researched, even though these factors are crucial for understanding the full scope of climate change impacts on the Upper Baitarani Basin(23,24).

The primary objective of this study is to conduct a comprehensive analysis of long-term temperature trends in the Upper Baitarani River Basin over the past 120 years. By examining historical temperature data, this research aims to identify significant trends and patterns that could have implications for the region's climate and socio-economic activities. This analysis will use established statistical methods, such as the Mann-Kendall test and Sen's slope estimator, to detect and quantify trends in temperature over the specified period. The findings from this study are expected to contribute valuable insights into how temperature trends have evolved in this mountainous catchment area, which is crucial for understanding potential impacts on agriculture, water resources, and the broader environment in the Upper Baitarani Basin

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2. MATERIAL AND METHODS

2.1 Study Area

The study area is a mountainous catchment located in the north-western part of the Baitarani basin, within the Keonjhar district of Odisha, and forms a part of the Eastern Ghats (Figure 1). The basin extends from 21° N to 22° 5' N in latitude and from 85° E to 86° E in longitude, covering an area of 1812.83 km^2. Elevations in this region range between 375 meters and 1116 meters above mean sea level, contributing to its diverse topography and climate.

The vegetation in the study area predominantly consists of dry deciduous forests and monsoon deciduous forests, which are typical of the Eastern Ghats. These forests are home to a variety of flora and fauna, with teak, sal, and bamboo being some of the common tree species. The undergrowth in these forests includes a mix of shrubs, grasses, and herbs that contribute to the region's biodiversity.

Agriculture is the primary livelihood for most of the population in this region, with rice being the staple crop. Other significant crops include millet, pulses, oilseeds, and vegetables, which are cultivated depending on the season. The fertile soils, nourished by the seasonal monsoon rains, make the region suitable for a variety of crops, although agricultural practices are largely dependent on the monsoon, leading to variability in crop yields.

In addition to agriculture, livestock production plays an essential role in the local economy. Cattle, goats, and poultry are commonly reared, providing supplementary income to farming households. Livestock also contributes to the agricultural system by providing manure and draft power, which are crucial for the sustenance of small-scale farming practices in this region.

Another significant economic activity in the study area is iron ore mining, particularly in the regions around Joda and Barbil. These areas are known for their rich mineral resources, and mining activities have a substantial impact on the local economy. However, mining also poses challenges, including environmental degradation and land-use conflicts, which intersect with the agricultural and forest-based livelihoods of the local population.

The climate of the region varies from tropical to subtropical, characterized by hot summers, heavy monsoon rains, and cold winters. The hottest month is May, with an average high temperature of 40.6°C, while the coldest month is January, with a mean low of 5°C. The region typically experiences monsoon rains beginning in June, which are vital for the success of the agricultural season.

2.2 Data Collection

This study involved collecting daily maximum (Tmax) and minimum (Tmin) temperature data from the Indian Meteorological Department (IMD) database, covering the period from 1952 to 2022(25). The 70-year data span is critical for capturing long-term temperature trends, essential for understanding the climatic changes in the Upper Baitarani River Basin. The data retrieval process was facilitated using the IMDLIB library within the PyCharm Python environment, which provided a robust framework for handling large climatological datasets.

Two strategically selected grid points were chosen for data collection, ensuring comprehensive coverage of the study area. These points were:

- Location 1: Latitude 21.69, Longitude 85.33
- Location 2: Latitude 22.01, Longitude 85.45

These grid points were selected to minimize spatial biases in temperature data and to capture the diverse climatic conditions across the basin.

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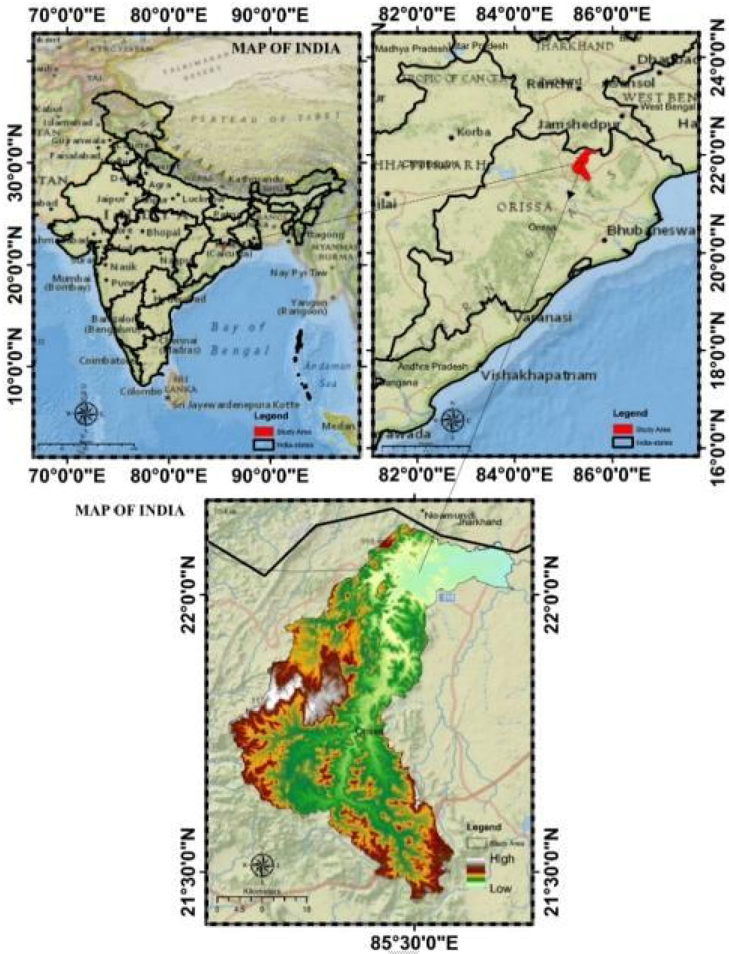

Figure 1. Location of the study area, Source: Created using ArcGIS by the Author[1]

2.3 Data Processing

The Python programming language was employed for data management and processing. Daily Tmax and Tmin readings were converted into mean monthly temperatures to reduce daily variability, allowing for a clearer analysis of long-term trends. The data was then structured chronologically to enable systematic examination of seasonal and annual temperature patterns over time.

2.4 Statistical Analysis

2.4.1Mann-Kendall Test

To detect and quantify trends in temperature data, the Mann-Kendall test was employed*(Mann, 1945, Kendal 1975)*. This nonparametric test is widely used in climate studies due to its ability to evaluate trend direction and strength without assuming data normality.

The test statistic S is computed as

$S = \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} \text{sgn}\left(x_j - x_i\right)$,

Where,

n is the total number of data points

x_i and x_j represent the temperature values at times

i and j, respectively, and sgn is a sign function that indicates the direction of the difference between data points.

Kendall's tau (τ) was used as a correlation measure, with positive values indicating increasing trends and negative values indicating decreasing trends. The significance of τ was tested against a standard normal distribution to determine the statistical significance of the observed trends.

2.4.2 Linear Regression

In addition to the Mann-Kendall test, linear regression analysis was performed to further assess the rate of temperature change over the study period(Draper, N. R., & Smith, H. (1998)). The linear regression model is defined as

$T(t) = \alpha + \beta t + \epsilon$,

Where, $T(t)$ represents the temperature at time

t, α is the intercept,

β is the slope of the trend line, representing the rate of temperature change

ϵ is the error term.

The least squares method was used to estimate the parameters α and β, with the fit of the model evaluated using the coefficient of determination (R^2) and statistical tests to assess the significance of the slope (β). Consistency between the results of the Mann-Kendall test and linear regression was used to validate the identified trends, enhancing the robustness of the conclusions drawn about long-term temperature trends in the upper Baitarani basin.

2.5 Quality Assurance

Rigorous quality assurance protocols were followed to ensure data accuracy and reliability. These protocols included data validation checks, outlier detection, and sensitivity analysis, which tested the robustness of results under different scenarios. Ensuring data quality is crucial for deriving reliable conclusions from climatological studies.

3. RESULTS AND DISCUSSION

3.1 TMAX

3.1.1 Mann-Kendall Test

The Mann-Kendall trend test results for monthly maximum temperature (Tmax) data over the period from 1952 to 2022 provide a comprehensive insight into temperature changes for two locations within the Upper Baitarani River Basin. Both locations exhibit similar patterns in temperature trends, though with some variations in magnitude and significance(Table 1 & 2). For Location One, the analysis indicates that from January to April and June to December, no significant trends were detected in Tmax data, as the p-values exceeded the significance level (alpha = 0.05). This suggests that temperature changes during these months were not statistically significant, implying a relative stability in the temperature patterns over these periods. In contrast, significant increasing trends in Tmax were observed in May, July, August, September, October, and November. May showed a significant decrease in temperatures, with a p-value of 0.026, indicating a cooling trend which is contrary to the general warming trends observed globally. In July and August, marked increases in Tmax were detected with p-values of 0.030 and 0.001 respectively, suggesting significant warming during these months. From September to November, the significant warming trends continued with p-values ranging from 0.003 to 0.006, indicating a sustained increase in temperatures during the late monsoon and early post-monsoon seasons (Table 1).

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Table 1. Mann Kendall test results for TMAX

Month	**Kendall's Tau**		**S**		**Var(S)**		**P-value**	
	Location 1	**Location 2**	**Location 1**	**Location 2**	**Location 1**	**Location 2**	**Location 1**	**Location 2**
January	0.027	-0.023	67	-56	40,588.33	40587.33	0.743	0.785
February	0.104	0.037	259	93	40,588.33	40588.33	0.2	0.648
March	0.133	0.049	331	123	40,588.33	40588.33	0.101	0.545
April	0.076	-0.023	190	-57	40,587.33	40588.33	0.348	0.781
May	-0.024	-0.181	-59	-449	40,588.33	40588.33	0.773	0.026
June	0.01	-0.059	25	-147	40,588.33	40588.33	0.905	0.469
July	0.331	0.176	821	438	40,586.33	40587.33	<0.0001	0.03
August	0.362	0.27	899	671	40,588.33	40588.33	<0.0001	0.001
September	0.355	0.243	883	603	40,588.33	40588.33	<0.0001	0.003
October	0.273	0.18	679	447	40,588.33	40588.33	0.001	0.027
November	0.305	0.222	757	551	40,588.33	40588.33	0	0.006
December	0.108	0.044	269	109	40,588.33	40588.33	0.183	0.592

Similarly, for Location Two, the Mann-Kendall trend test results reveal that from January to April and June to December, no significant trends were detected in Tmax data, with p-values exceeding the 0.05 significance level. This indicates a lack of statistically significant temperature changes during these months, consistent with the findings from Location One. Significant increasing trends in Tmax were also observed in May, July, August, September, October, and November for Location Two. May exhibited a significant decrease in temperatures with a p-value of 0.026, similar to Location One. July and August showed substantial increases in Tmax, with p-values of 0.030 and 0.001 respectively. The warming trend persisted from September to November, with p-values ranging from 0.003 to 0.006, indicating significant warming during these months (Table 1).

When comparing the results at different significance levels (1%, 5%, and 10%), additional nuances in the trends emerge. For both locations, January through April and June through December generally showed no significant trends at the 5% level, indicating stable Tmax patterns during these months. Specifically, in both locations, January, April, June, and December had p-values well above the 0.10 threshold, suggesting no trend even at a less stringent level of significance. February and March exhibited slightly positive but statistically

insignificant trends at the 10% level, with p-values nearing this threshold but not crossing it, indicating minor but not statistically robust warming.
The months of July through November displayed significant warming trends across both locations. July and October showed increases at the 5% level, with p-values of 0.030 and 0.027, respectively, indicating notable warming that could impact agricultural cycles, particularly during critical growing and harvesting periods. August and September exhibited extremely strong warming trends with p-values of 0.001 and 0.003, respectively, surpassing even the stringent 1% significance level. This suggests a very robust warming trend during the late summer and early autumn, which could significantly increase evaporation rates and heat stress on both natural ecosystems and agricultural lands. November also showed a strong warming trend at the 5% significance level (p-value = 0.006), confirming significant late-autumn warming. This could extend the growing season but might also require adjustments in farming practices and water management strategies to accommodate the changing conditions.

3.1.2 Linear Regression

The linear regression analysis of monthly maximum temperature (Tmax) data from 1952 to 2022 at the first location in the Upper Baitarani River Basin reveals varying trends throughout the year, with significant increases primarily in the latter half of the year(Figure 1 & 2).
In January, the trend for Tmax shows stability, with a high p-value of 0.7573, indicating no significant change. February exhibits a slight increasing trend, though not statistically significant (p-value: 0.1520). March shows a mild increase, nearing significance with a p-value of 0.0866. Similarly, April displays a slight increase in Tmax but is not statistically significant (p-value: 0.1876). May demonstrates stability in Tmax with a non-significant p-value of 0.5200, and June also indicates stability with a high p-value of 0.7666.
A statistically significant increasing trend is observed in July, with a very low p-value of 0.0002. August shows a notable increase ($y = 0.02 * x + 0.35$), indicating a strong warming trend. September presents a significant increasing trend ($y = 0.02 * x + -1.21$). October follows with a significant increase in Tmax, evidenced by a p-value of 0.0008. November shows a robust increasing trend with a p-value of 0.0003. December exhibits a mild increasing trend, although it is not statistically significant (p-value: 0.1416)(Figure 2 & 3).
For the second location, the linear regression analysis of Tmax data from 1952 to 2022 displays diverse trends, with significant trends more frequently observed in the latter half of the year.
In January, the trend for Tmax is stable, with a high p-value of 0.6938, indicating no significant change. February shows a mild increase, though not statistically significant (p-value: 0.4536). March exhibits no significant trend with a p-value of 0.5938, and April's trend is stable with a high p-value of 0.9109. May demonstrates a significant decreasing trend ($y = -0.02 * x + 75.98$) with a p-value of 0.0229, and June shows no significant trend with a p-value of 0.5936.
July reveals a slight but statistically significant increasing trend with a p-value of 0.0498. August shows a significant increasing trend ($y = 0.01 * x + 9.05$) with a very low p-value of 0.0007. September presents a significant increase ($y = 0.01 * x + 5.98$) with a p-value of 0.0025. October displays a significant increase in Tmax with a p-value of 0.0449. November continues with a significant increasing trend with a p-value of 0.0115. December shows no significant change with a p-value of 0.5684.

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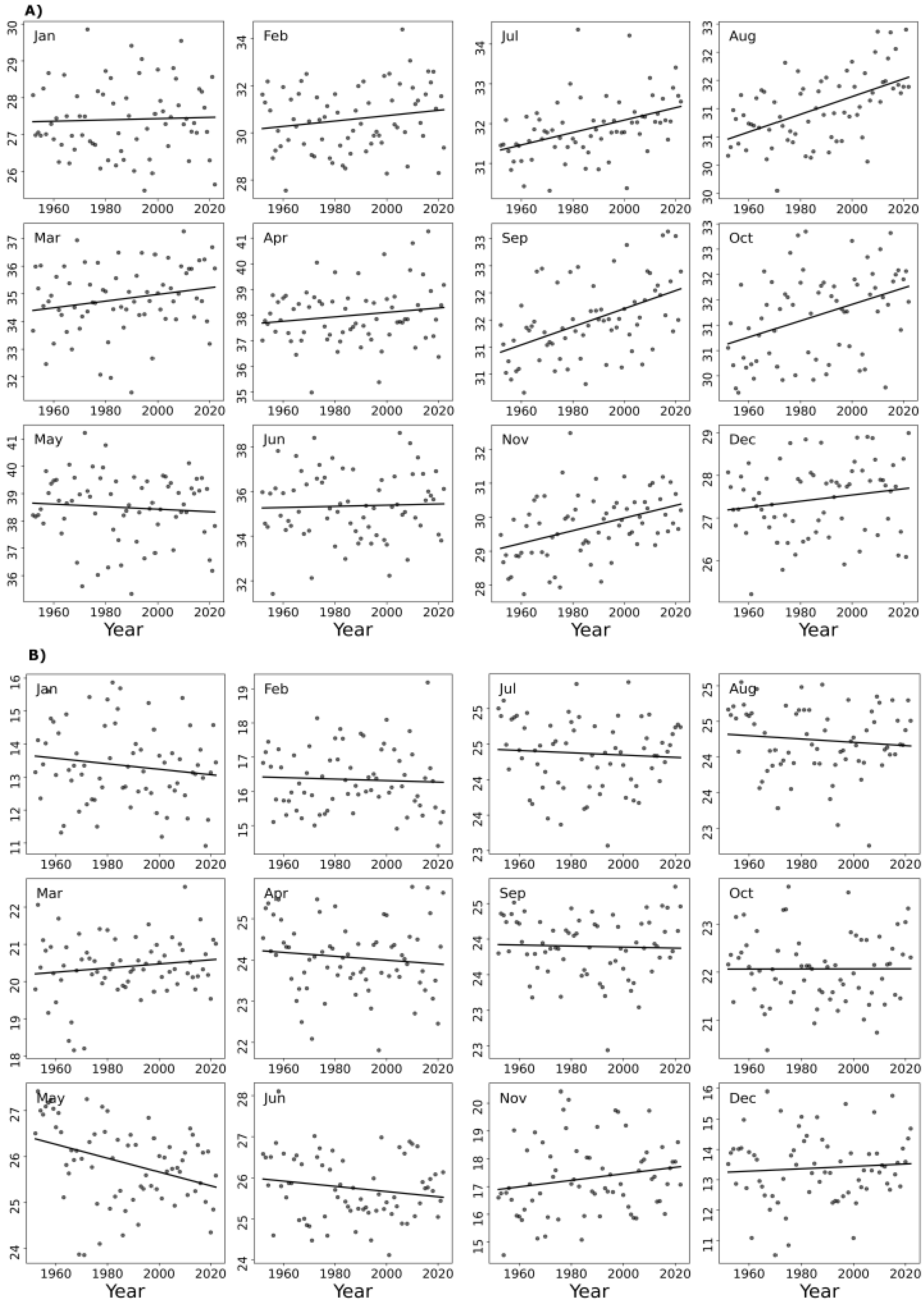

Figure 2. Location One A) Tmax B) Tmin. Source: Created using Python by the Author[1]

3.1.3 Discussion

The implications of the observed warming trends are substantial for both locations in the Upper Baitarani Basin. The significant increase in temperatures during the critical cropping months from July to November can severely impact agricultural productivity. Higher temperatures during these months lead to heat stress on crops, reduce yields, and increase water demand for irrigation. This aligns with the findings of Lal et al. (2011), who observed that rising temperatures in tropical regions negatively affect crop growth and overall food security. Rice, which is the primary crop of the region, is highly sensitive to temperature fluctuations, with Jagadish et al. (2012) reporting similar adverse effects on rice production in other Indian regions under rising temperatures.

The increased temperatures also heighten evaporation rates, which exacerbate water scarcity during the dry months. This finding is consistent with the results of Dey and Adhikary (2018), who analyzed evaporation trends in eastern India and found that rising temperatures were leading to increased water loss, complicating water management strategies in agricultural areas. This poses a challenge for both domestic water usage and irrigation needs, placing significant stress on local water resources.

Additionally, the warming trends can disrupt the phenology of both plant and animal species, potentially leading to mismatches in ecosystem interactions, which may reduce biodiversity. This observation is supported by Parmesan (2006), who reported similar disruptions in phenological events due to climate change across various ecosystems globally. Such disruptions could undermine the stability of local ecosystems, particularly in biodiverse regions like the Eastern Ghats, as indicated by Root et al. (2003) in their studies of phenological changes under warming conditions.

Given these challenges, it is essential to promote adaptive agricultural practices such as the adoption of drought-resistant crops, improved irrigation techniques, and crop diversification. Studies by Rao et al. (2010) suggest that such practices have proven successful in increasing climate resilience in similar agrarian landscapes. Furthermore, effective water resource management strategies—including the construction of water storage facilities, the development of rainwater harvesting systems, and the implementation of water conservation practices—are critical to managing the increasing water demands in the basin. Aggarwal et al. (2019) emphasizes the importance of water management in adapting to the effects of climate change, particularly in water-scarce regions like Odisha.

Lastly, increasing awareness about climate change impacts and building local capacity for adaptive responses are crucial for enhancing community resilience. Singh et al. (2015) stress that community-level interventions and policy support are vital for ensuring long-term sustainability in vulnerable regions such as the Upper Baitarani Basin.

3.2 TMIN

3.2.1 Mann-Kendall Test

The Mann-Kendall trend test results for monthly minimum temperature (Tmin) data over the period from 1952 to 2022 provide a comprehensive insight into temperature changes for two locations within the Upper Baitarani River Basin. Both locations exhibit similar patterns in temperature trends, though with some variations in magnitude and significance.

For Location One, the analysis indicates that from January to April and June to December, no significant trends were detected in Tmin data, as the p-values exceeded the significance level (alpha = 0.05). This suggests that temperature changes during these months were not statistically significant, implying a relative stability in the temperature patterns over these periods. In contrast, a significant decreasing trend in Tmin was observed in May, with a p-value of 0.001, indicating a cooling trend which is contrary to the general warming trends observed globally (Table 2). For Location Two, the Mann-Kendall trend test results reveal that from January to April and June to December, no significant trends were detected in Tmin data, with p-values exceeding the 0.05 significance level. This indicates a lack of

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statistically significant temperature changes during these months, consistent with the findings from Location One. A significant decreasing trend in Tmin was also observed in May, with a p-value of 0.002.

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Table 2. Mann-Kendall Test results for TMIN

	Kendall's Tau		P-Value		Alpha		S	
Month	**Location 1**	**Location 2**	**Location 1**	**Location 2**	**Location 1**	**Location 2**	**Location 1**	**Location 2**
January	-0.102	-0.084	0.211	0.302	0.05	0.05	-253	-209
February	-0.023	-0.049	0.781	0.551	0.05	0.05	-57	-121
March	0.078	0.046	0.341	0.571	0.05	0.05	193	115
April	-0.107	-0.107	0.19	0.19	0.05	0.05	-265	-265
May	-0.257	-0.264	0.002	0.001	0.05	0.05	-639	-657
June	-0.152	-0.096	0.062	0.237	0.05	0.05	-377	-239
July	-0.004	-0.048	0.96	0.558	0.05	0.05	-11	-119
August	-0.025	-0.041	0.766	0.62	0.05	0.05	-61	-101
September	0.002	-0.027	0.984	0.743	0.05	0.05	5	-67
October	-0.021	0.004	0.796	0.968	0.05	0.05	-53	9
November	0.136	0.133	0.095	0.101	0.05	0.05	337	331
December	0.041	0.028	0.62	0.736	0.05	0.05	101	69

For both locations, January through April and June through December generally showed no significant trends at the 5% level, indicating stable Tmin patterns during these months. Specifically, in both locations, January, April, June, and December had p-values well above the 0.10 threshold, suggesting no trend even at a less stringent level of significance. February and March exhibited slightly negative but statistically insignificant trends at the 10% level, with p-values nearing this threshold but not crossing it, indicating minor but not statistically robust cooling.The month of May displayed significant decreasing trends across both locations. This significant cooling trend in May, with p-values of 0.001 and 0.002 for Location One and Location Two, respectively, suggests a very robust cooling trend during late spring, which could impact agricultural cycles, particularly during critical growing and harvesting periods. This cooling trend in May is noteworthy and contrasts sharply with the generally warming global temperature trends.

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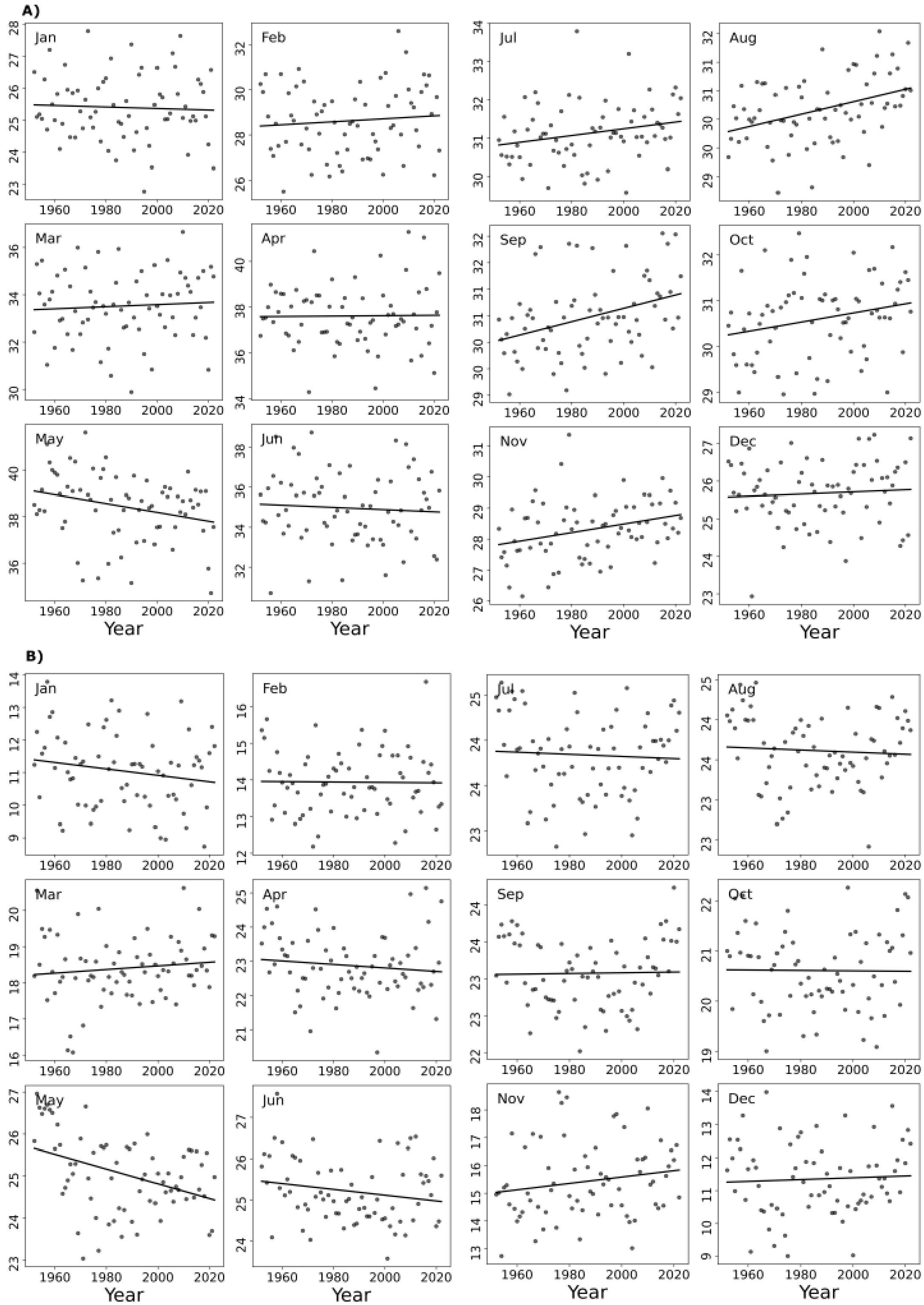

Figure 3. Location Two A) Tmax B) Tmin. Source: Created using Python by the Author[1]

3.2.2 Linear Regression

The linear regression analysis of monthly minimum temperature (Tmin) data from 1952 to 2022 at the first location in the Upper Baitarani River Basin reveals varying trends throughout the year, with significant changes primarily observed in late spring.

In January, the trend for Tmin shows a slight decrease, with the equation $Y = -0.01x + 29.83$, but this trend is not statistically significant (p-value: 0.2299). February exhibits a stable trend with a non-significant p-value of 0.6829. March indicates a slight increase in Tmin ($Y = 0.01*x + 9.38$), but this trend is also not statistically significant (p-value: 0.2314).A notable and statistically significant decreasing trend is observed in May ($Y = -0.02x + 55.70$), with a p-value of 0.0020, indicating a cooling trend during this month. For the other months, including June, July, and August, the trends indicate stability or slight changes without statistical significance. October shows no significant change in Tmin ($Y = 0.00x + 21.90$), with a very high p-value of 0.9839, indicating stable temperature patterns (Figure 2 & 3).

For Location Two, the linear regression analysis of Tmin data from 1952 to 2022 also reveals varying trends across different months, with most trends not reaching statistical significance. January shows a slight decreasing trend ($Y = -0.01x + 30.70$), although it is not statistically significant (p-value: 0.1414). February's trend is stable ($Y = -0.00x + 15.03$) with a high p-value of 0.9137, indicating no significant change.

A clear and statistically significant decreasing trend is observed in May ($Y = -0.02x + 59.87$), with a very low p-value of 0.0007. June's trend ($Y = -0.01x + 39.20$) suggests a decrease, though it is not statistically significant (p-value: 0.1156). The months from July to September exhibit very little change with high p-values, indicating stability in Tmin during these months.

In summary, significant trends in Tmin are primarily observed in May for both locations, indicating a cooling trend during this month. Other months show stable or slightly varying trends without statistical significance, suggesting general stability in Tmin throughout most of the year at both locations.

3.2.3 Discussion

The analysis of Tmin trends for both locations in the Upper Baitarani River Basin provides important insights into the region's climate variability. The results of the Mann-Kendall test and linear regression analysis revealed significant changes, particularly during the month of May. A notable decrease in Tmin was observed at both locations during this month, with p-values of 0.002 and 0.0007, respectively, indicating statistically significant cooling trends. These findings are particularly important as they coincide with the onset of the monsoon season, a critical period for agricultural activities. The cooling trend in May suggests that the onset of warmer conditions necessary for early crop growth may be delayed, potentially disrupting agricultural cycles and impacting crop yields.

From an agricultural perspective, this shift in Tmin may also affect water demand for irrigation, as cooler temperatures could reduce evapotranspiration, thereby altering the timing and volume of water required during the early stages of crop development. In addition to agricultural productivity, this cooling trend could have broader implications for ecosystems. Lower Tmin values in May may disrupt the phenology of plant and animal species, potentially affecting blooming periods, breeding cycles, and other seasonal behaviors. Such disruptions could lead to mismatches in ecosystem interactions, ultimately reducing biodiversity and affecting the overall health of the ecosystem.

While no significant Tmin trends were observed in other months, the stability of temperatures throughout the year suggests that broader climatic patterns in the region remain relatively unchanged. However, the cooling trend in May warrants further investigation into potential drivers, such as shifts in atmospheric circulation or regional climate variability, to better understand the forces behind this anomaly.

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The implications of these findings highlight the need for adaptive strategies that address the observed temperature changes. Adjustments to planting dates, enhanced frost protection measures, and close monitoring of climate patterns could help mitigate the potential adverse effects on crop growth and productivity. Additionally, understanding the broader climatic context and potential drivers of this cooling trend is crucial for developing effective adaptation strategies for both agricultural practices and ecosystem management. Continuous monitoring and analysis of Tmin trends will be essential for maintaining resilience and sustainability in the face of evolving climatic conditions in the Upper Baitarani Basin.

4. CONCLUSION

The long-term analysis of minimum temperature trends in the Upper Baitarani Basin has provided valuable insights into the region's climate variability, particularly concerning the trends in Tmin. The study's use of both the Mann-Kendall trend test and linear regression analysis revealed significant findings, notably the decreasing trend in minimum temperatures during May. This cooling trend could have profound implications for the region's agricultural productivity by delaying the onset of warmer conditions crucial for early crop growth. The cooling trend during this key period may also affect water demand for irrigation, disrupt planting schedules, and influence overall crop yields. Additionally, the findings suggest potential disruptions in the phenology of plant and animal species, which could affect blooming periods, breeding cycles, and broader ecosystem stability.While the study did not detect significant trends in Tmin during other months of the year, the observed cooling trend in May highlights a specific area of concern that warrants further investigation. The stability of Tmin in other months suggests that, for now, broader climatic patterns remain relatively unchanged, but the cooling anomaly in May could have targeted impacts on both agriculture and ecosystems.This research underscores the importance of adaptive strategies, such as adjusting planting dates, enhancing frost protection measures, and improving climate monitoring efforts, to mitigate the potential adverse effects of these observed trends. Furthermore, the study emphasizes the need to understand the broader climatic drivers behind this cooling trend to develop more effective climate adaptation strategies.

Given the limitations of this dataset, future research should aim to extend the time series and incorporate additional climatic variables like precipitation and maximum temperature to develop a more comprehensive understanding of the region's climate dynamics. Integrating these climatic trends with socio-economic data could further assist in formulating targeted adaptation strategies for local communities. This study contributes to the growing body of literature on regional climate change impacts and highlights the critical need for localized climate action to address the specific challenges posed by changing temperature patterns in the Upper Baitarani Basin.
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ETHICAL APPROVAL

Not Applicable

Disclaimer (Artificial intelligence)

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REFERENCES

1. Sabbaghi MA, Nazari M, Araghinejad S, Soufizadeh S. Economic impacts of climate change on water resources and agriculture in Zayandehroud river basin in Iran. Agric Water Manag. 2020;241:106323.

2. Whitehead PG, Barbour E, Futter MN, Sarkar S, Rodda H, Caesar J, et al. Impacts of climate change and socio-economic scenarios on flow and water quality of the Ganges, Brahmaputra and Meghna (GBM) river systems: low flow and flood statistics. Environ Sci Process Impacts. 2015;17(6):1057–69.

3. Chen Y, Li Z, Fan Y, Wang H, Deng H. Progress and prospects of climate change impacts on hydrology in the arid region of northwest China. Environ Res. 2015;139:11–9.

4. Kukal M, Irmak S. Long-term patterns of air temperatures, daily temperature range, precipitation, grass-reference evapotranspiration and aridity index in the USA Great Plains: Part II. Temporal trends. J Hydrol. 2016;542:978–1001.

5. Leng G, Tang Q, Rayburg S. Climate change impacts on meteorological, agricultural and hydrological droughts in China. Glob Planet Change. 2015;126:23–34.

6. Aliyari F, Bailey RT, Arabi M. Appraising climate change impacts on future water resources and agricultural productivity in agro-urban river basins. Sci Total Environ. 2021;788:147717.

7. Mehan S, Kannan N, Neupane RP, McDaniel R, Kumar S. Climate change impacts on the hydrological processes of a small agricultural watershed. Climate. 2016;4(4):56.

8. Xue J, Huo Z, Kisekka I. Assessing impacts of climate variability and changing cropping patterns on regional evapotranspiration, yield and water productivity in California's San Joaquin watershed. Agric Water Manag. 2021;250:106852.

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9. Ali S, Liu Y, Ishaq M, Shah T, Abdullah, Ilyas A, et al. Climate change and its impact on the yield of major food crops: Evidence from Pakistan. Foods. 2017;6(6):39.

10. Knox J, Hess T, Daccache A, Wheeler T. Climate change impacts on crop productivity in Africa and South Asia. Environ Res Lett. 2012;7(3):034032.

11. Mishra A, Singh R, Raghuwanshi NS, Chatterjee C, Froebrich J. Spatial variability of climate change impacts on yield of rice and wheat in the Indian Ganga Basin. Sci Total Environ. 2013;468:S132–8.

12. Singh P, Kumar V, Thomas T, Arora M. Basin-wide assessment of temperature trends in northwest and central India / Estimation par bassin versant de tendances de température au nord-ouest et au centre de l'Inde. Hydrol Sci J. 2008 Apr;53(2):421–33.

13. Hodgkinson JH, Smith MH. Climate change and sustainability as drivers for the next mining and metals boom: The need for climate-smart mining and recycling. Resour Policy. 2021;74:101205.

14. Peiffer JJ, Abbiss CR. Thermal stress in North Western Australian iron ore mining staff. Ann OccupHyg. 2013;57(4):519–27.

15. Jhajharia D, Dinpashoh Y, Kahya E, Choudhary RR, Singh VP. Trends in temperature over Godavari River basin in Southern Peninsular India. Int J Climatol [Internet]. 2014 [cited 2024 Aug 13];34(5). Available from: https://deepakjhajharia.com/wp-content/uploads/2021/05/2014Godavari-Temperature-trends_joc.3761.pdf

16. Rao PG. Climatic changes and trends over a major river basin in India. Clim Res. 1993;2(3):215–23.

17. Singh D, Glupta RD, Jain SK. Statistical analysis of long term spatial and temporal trends of temperature parameters over Sutlej river basin, India. J Earth Syst Sci. 2015 Feb;124(1):17–35.

18. Bisht DS, Chatterjee C, Raghuwanshi NS, Sridhar V. Spatio-temporal trends of rainfall across Indian river basins. Theor Appl Climatol. 2018 Apr;132(1–2):419–36.

19. Chandole V, Joshi GS, Rana SC. Spatio-temporal trend detection of hydro-meteorological parameters for climate change assessment in Lower Tapi river basin of Gujarat state, India. J Atmospheric Sol-Terr Phys. 2019;195:105130.

20. Joshi S, Kumar K, Joshi V, Pande B. Rainfall variability and indices of extreme rainfall-analysis and perception study for two stations over Central Himalaya, India. Nat Hazards. 2014;72:361–74.

21. Ding Z, Ali EF, Elmahdy AM, Ragab KE, Seleiman MF, Kheir AM. Modeling the combined impacts of deficit irrigation, rising temperature and compost application on wheat yield and water productivity. Agric Water Manag. 2021;244:106626.

22. Liu M, Xu X, Jiang Y, Huang Q, Huo Z, Liu L, et al. Responses of crop growth and water productivity to climate change and agricultural water-saving in arid region. Sci Total Environ. 2020;703:134621.

UNDER PEER REVIEW

23. de Oliveira RG, Júnior LCGV, da Silva JB, Espíndola DA, Lopes RD, Nogueira JS, et al. Temporal trend changes in reference evapotranspiration contrasting different land uses in southern Amazon basin. Agric Water Manag. 2021;250:106815.

24. Feddema JJ, Oleson KW, Bonan GB, Mearns LO, Buja LE, Meehl GA, et al. The Importance of Land-Cover Change in Simulating Future Climates. Science. 2005 Dec 9;310(5754):1674–8.

25. Srivastava AK, Rajeevan M, Kshirsagar SR. Development of a high resolution daily gridded temperature data set (1969–2005) for the Indian region. Atmospheric Sci Lett. 2009 Oct;10(4):249–54.

26. Hussain, M., & Mahmud, I. (2019). pyMannKendall: a python package for non parametricMann Kendall family of trend tests. *Journal of open source software*, *4*(39), 1556.

27. Mann HB. Nonparametric tests against trend. Econometrica: Journal of the econometric society. 1945 Jul 1:245-59.

28. Kendall MG. Rank correlation methods, Griffin, London (1975)

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