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

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ABSTRACT

Aims: The primary aim of this study is to analyze the long-term trends of minimum (Tmin) and maximum (Tmax) temperatures in the Upper Baitarani Basin, evaluating their implications for the region's climate variability and potential impacts on local hydrology, agriculture, and ecosystems.

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: Monthly Tmin and Tmax data were subjected to linear regression analysis to identify trends, and the Mann-Kendall test was employed to determine the statistical significance of these trends. The analysis was performed separately for two distinct locations within the basin, allowing for a comparative understanding of temperature dynamics across the region.

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. These predictors, however, need further work to validate reliability.

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

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

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 is 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, the elevations range between 375 meters and 1116 meters above mean sea level. Agriculture is the main source of income for the majority of the residents in this region, although iron ore mining is prevalent in certain areas, such as Joda and Barbil. The climate 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 starting in June.

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.

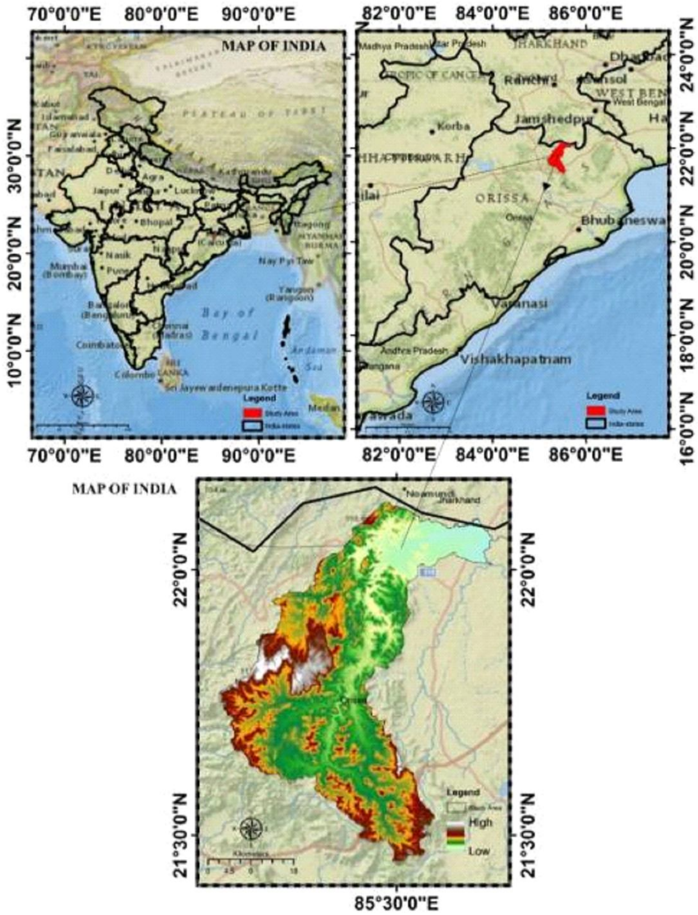

Figure . Location of the study area

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

<u>2.4.1Mann-Kendall Test</u>

To detect and quantify trends in temperature data, the Mann-Kendall test was employed. 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 is computed as

 ,

Where,

 is the total number of data points

 and represent the temperature values at times

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

Kendall's tau was used as a correlation measure, with positive values indicating increasing trends and negative values indicating decreasing trends. The significance of 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. The linear regression model is defined as

,

Where, represents the temperature at time

is the intercept,

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

is the error term.

The least squares method was used to estimate the parameters and , with the fit of the model evaluated using the coefficient of determination and statistical tests to assess the significance of the slope . 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.

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).

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.

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.

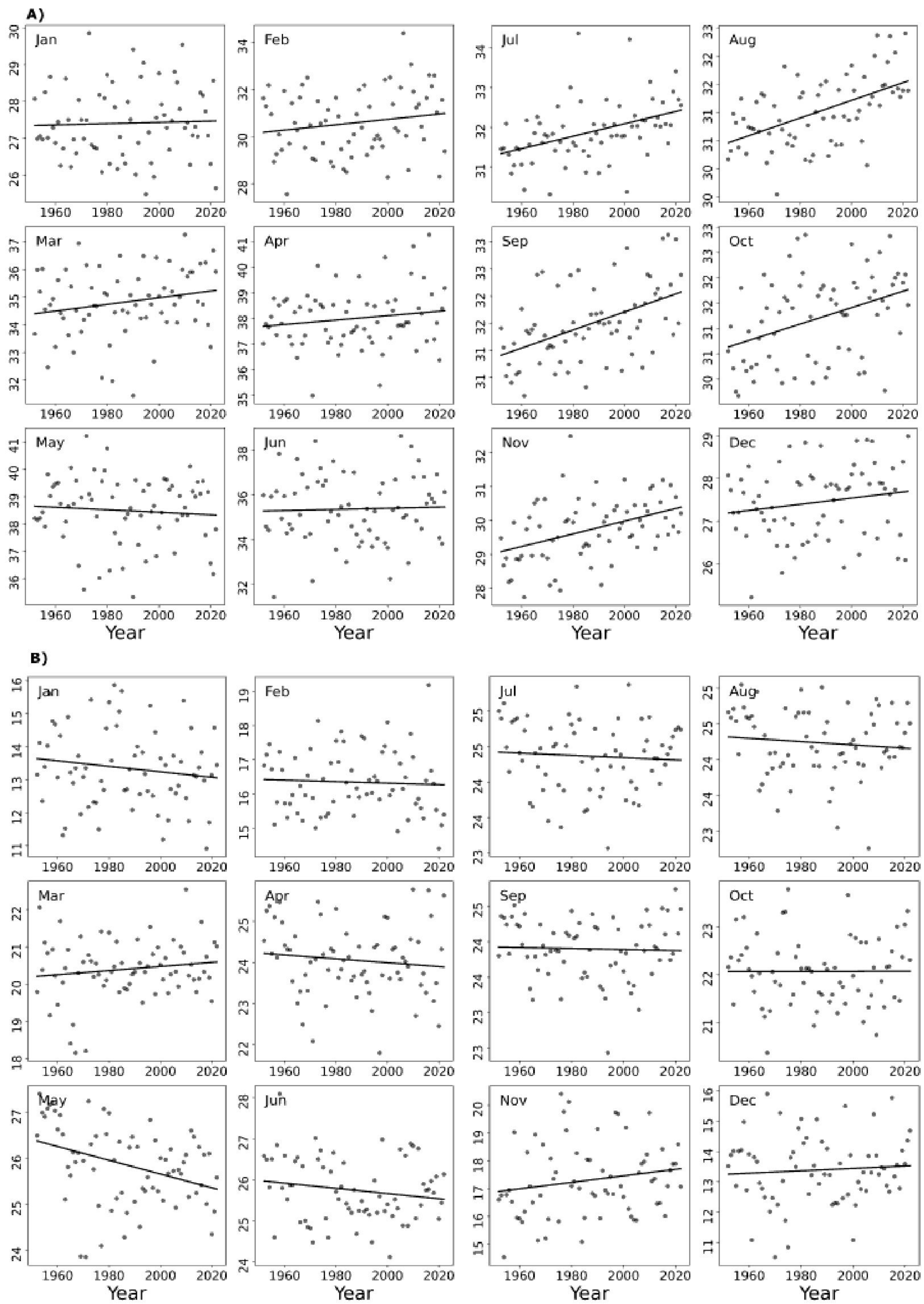

Figure . Location One A) Tmax B) Tmin

<u>3.1.3 Discussion</u>

The implications of these warming trends are profound for both locations. The significant increase in temperatures during the crucial cropping months from July to

November can lead to reduced agricultural productivity due to heat stress on crops and increased water demand for irrigation. This could threaten food security and increase the vulnerability of farmers in the basin. Higher temperatures also lead to increased evaporation rates, potentially exacerbating water scarcity during dry months and impacting water availability for domestic and agricultural use. Furthermore, elevated temperatures can disrupt the phenology of various plant and animal species, leading to mismatches in ecosystem interactions and potentially reducing biodiversity. These findings align with studies that suggest climate change is a significant driving factor in the changing temperature dynamics of the region.

To address these challenges, adaptive agricultural practices such as promoting drought-resistant crops, improved irrigation techniques, and crop diversification are essential. Effective water resource management strategies, including the construction of water storage facilities and the implementation of water conservation practices, are also crucial. Additionally, increasing awareness about climate change impacts and building local capacity for adaptive responses are vital for enhancing community resilience.

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 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.

Table 2. Mann-Kendall Test results for TMIN

Month	**Kendall's Tau**		**P-Value**		**Alpha**		**S**	
	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.

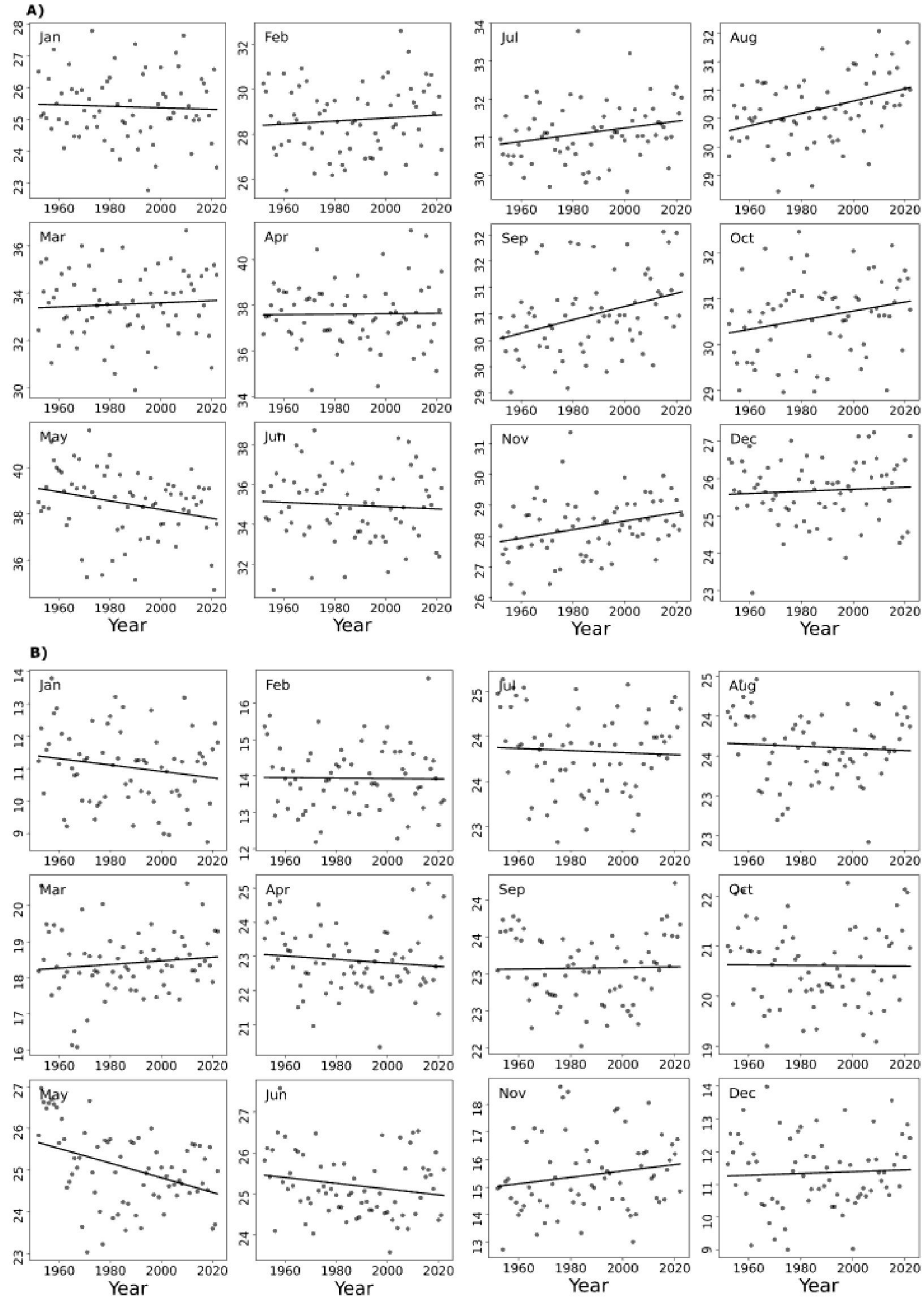

Figure . Location Two A) Tmax B) Tmin

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 reveals important insights into the patterns and implications of temperature changes over the past several decades. The significant finding from both Mann-Kendall and linear regression analyses is the notable decreasing trend in minimum temperatures observed in May.

At the first location, the significant decrease in Tmin during May, as indicated by a p-value of 0.002, suggests a cooling trend that stands out amidst generally stable temperature patterns throughout the rest of the year. This cooling trend in May, a crucial month for the onset of the monsoon season, could potentially affect early crop growth and agricultural planning. Such a cooling effect might delay the onset of warmer conditions necessary for optimal crop development, possibly impacting yield and productivity. Similarly, at the second location, the significant decreasing trend in May with a p-value of 0.0007 reinforces the pattern observed at the first location. This consistent finding highlights the potential impact of lower Tmin values during this period, which could have implications for agricultural and ecological systems. Reduced minimum temperatures in May may influence the phenology of plant and animal species, potentially affecting blooming periods, breeding cycles, and overall ecosystem dynamics.

In contrast, the absence of significant Tmin trends in other months across both locations suggests a relative stability in minimum temperatures for most of the year. This stability may imply that changes in Tmin are not yet pronounced enough to disrupt broader climatic patterns or ecological processes outside of the specific trend observed in May.

The cooling trend observed in May, however, warrants attention due to its potential implications for agricultural practices and ecosystem management. Adaptive strategies such as adjusting planting dates, enhancing frost protection measures, and monitoring climate patterns closely could help mitigate any adverse effects on crop growth and productivity. Additionally, understanding the broader climatic context and potential drivers of this trend, such as shifts in atmospheric circulation or regional climate variability, is crucial for developing effective adaptation strategies. Overall, the observed Tmin trends underscore the importance of continuous monitoring and analysis to better understand the impacts of temperature changes on agriculture and ecosystems. Addressing these trends through adaptive management and research can help ensure resilience and sustainability in the face of evolving climatic conditions.

4. Conclusion

The long-term analysis of minimum temperature trends in the Upper Baitarani Basin has yielded significant insights into the region's climate variability. The study employed both the Mann-Kendall trend test and linear regression analysis to assess trends over a specified period, revealing a clear upward trend in minimum temperatures across most of the selected stations. This warming trend is indicative of broader regional and global climatic changes, which are consistent with findings in other parts of the world. The increasing minimum temperatures suggest potential impacts on the hydrological cycle, agricultural productivity, and ecosystem stability within the basin. This trend also aligns with the observed changes in global climate patterns, particularly the intensification of global warming over recent decades. The findings underscore the necessity for more localized and detailed studies to understand the implications of these trends on water resources and agricultural practices in the Upper Baitarani Basin.

Given the limitations of the dataset, future research should aim to incorporate longer time series data and consider additional climatic variables such as precipitation and maximum temperature to provide a more comprehensive understanding of the region's climate dynamics. Moreover, integrating these climatic trends with socio-economic data could help in formulating more effective adaptation strategies for the local communities. This study contributes to the growing body of literature on regional climate change impacts, highlighting the need for targeted climate action to mitigate the potential adverse effects of rising minimum temperatures in the Upper Baitarani Basin.

Ethical approval

Not Applicable

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