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Statistical analysis of the relationship between rainfall and temperature in Gothalapani, Baitadi

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Abstract: This study delves into the intricate relationship between temperature and rainfall in Gothalapani, a climatically diverse region in Baitadi, Nepal. Utilizing three years of monthly meteorological data (2022–2024) provided by the Department of Hydrology and Meteorology, we employed a comprehensive suite of statistical techniques, including descriptive statistics, correlation analysis (Pearson, Kendall, and Spearman), and copula-based modelling to capture both linear and non-linear dependencies. Results consistently show a moderate to strong positive correlation between rainfall and temperature, with higher rainfall occurring during warmer months, especially during monsoon periods. Notably, Gaussian copula analysis confirmed this dependence structure, demonstrating the utility of copulas for capturing non-linear climatic dependencies. The insights presented in this work hold practical significance for regional climate adaptation, sustainable agriculture, and water resource planning. Importantly, the limited 3-year dataset constrains our ability to infer long-term climatic trends, which is acknowledged as a key limitation.

Keywords: Temperature • Rainfall • Correlation analysis • Gaussian copula • Climate variability

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I. Introduction

Understanding the dynamics between temperature and precipitation is crucial in a country like Nepal, where topographic complexity meets climatic variability [1]. Gothalapani, nestled in the rugged mid-hills of Baitadi, exemplifies this interplay. Agricultural productivity, water availability, and local biodiversity in this region are deeply intertwined with temperature and rainfall behaviour [2]. Global climate trends indicate rising surface temperatures driven by anthropogenic greenhouse gas emissions. According to the IPCC Sixth Assessment Report (2021), the global surface temperature has increased by approximately 1.09 °C between 1850 and 1900, and 2011 and 2020, with atmospheric CO_2 concentrations reaching 410 ppm in 2019. These findings highlight the urgency of localized studies such as this one in Gothalapani, which provide context-specific insights into regional climate dynamics [3]. While

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these trends offer a macroscopic perspective, regional and local assessments are essential to guide targeted climate responses [4]. This research explores whether rising temperatures in Gothalapani lead to increased rainfall and how consistently this pattern holds. Beyond traditional linear correlations, we incorporate copula modeling, a powerful statistical approach that captures nonlinear dependencies often missed by conventional techniques [5]. The Department of Hydrology and Meteorology provided monthly temperature and rainfall data for 2022–2024 [6]. Observations included maximum, minimum, and average temperatures, as well as recorded rainfall.

II. Methodology

This study utilized three years of monthly meteorological data (2022–2024) obtained from the Department of Hydrology and Meteorology (DHM), Nepal. For each month, maximum (Tmax), minimum (Tmin), and average (Tavg) temperatures, together with total rainfall, were recorded. Descriptive statistics, including the mean, standard deviation (SD), and coefficient of variation (CV), were employed to quantify central tendency and variability. To assess statistical associations between rainfall and temperature, correlation analyses were conducted using Pearson's correlation coefficient (linear dependence), Spearman's rank correlation coefficient (monotonic dependence), and Kendall's tau (rank-based concordance). All correlations were computed using pooled monthly data from 2022 to 2024 to capture the overall dependence structure. Furthermore, copula-based modelling was applied to investigate potential non-linear relationships. Specifically, a Gaussian copula was fitted to the joint distribution of temperature and rainfall using maximum likelihood estimation, and the adequacy of the fitted model was assessed through goodness-of-fit tests, including the Cramér–von Mises and Kolmogorov–Smirnov statistics. Nevertheless, the restricted temporal coverage of only three years is a key limitation. While the adopted statistical methods are suitable for exploring associations in the available dataset, the findings should be regarded as preliminary and not indicative of long-term climatic behavior. Extension of the dataset over a longer period is essential to confirm and generalize the observed patterns.

Mean, standard deviation, and coefficient of variation

To analyse temperature and rainfall data for the years 2022–2024, the mean monthly temperature was calculated as the average of the daily maximum and minimum values provided by DHM. This approach provides an approximate central estimate, though we note, as a limitation, that more robust climatological studies typically use daily mean values over long periods [7]. Rainfall averages were computed from total monthly rainfall. The standard deviation (SD) was used to quantify absolute dispersion around the mean [8], while the coefficient of variation (CV = (SD/mean) $\times$ 100%) expressed relative variability. Higher CV values indicated greater relative dispersion, particularly during months with low baseline precipitation [9].

$$\mathrm{CV} = \frac{\mathrm{SD}}{\mathrm{Mean}} \times 100 \tag{1}$$

Pearson's correlation for linear dependence

The Pearson's correlation coefficient (r) measures the strength and direction of a linear relationship between two variables, such as temperature and rainfall [10]. It ranges from +1 (perfect positive correlation) to -1 (perfect negative correlation), with 0 indicating no linear relationship. Pearson's method for assessing correlation is based on several key assumptions. It requires that both variables under consideration follow a normal distribution [11], ensuring that the data are symmetrically distributed around their means. Additionally, it assumes a linear relationship between the variables, meaning that changes in one variable correspond proportionally to changes in the other. The observations must also be independent, ensuring that the value of one data point does not influence another. Lastly, the method presumes consistency in the relationship across the entire dataset [12], meaning the strength and direction of the correlation remain stable throughout. Based on the resulting correlation coefficient (r), the strength of the linear relationship is typically interpreted as follows: values between 0.8 and 1.0 indicate a highly linear relationship, 0.6 to 0.8 suggest a strong correlation, 0.4 to 0.6 denote a moderate correlation, and 0.2 to 0.4 reflect a weak correlation [13]. The Pearson correlation coefficient r is given by:

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 \cdot \sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \tag{2}$$

where X_i and Y_i are data values, and $\bar{X}$, $\bar{Y}$ are the means of X and Y respectively. The correlation coefficient ranges from -1 to +1.

Spearman's rank order correlation

Spearman's rank correlation coefficient is a non-parametric measure used to evaluate the strength and direction of a monotonic relationship between two ranked variables [14]. Unlike Pearson's correlation, it does not assume linearity or normal distribution, making it appropriate when these assumptions are violated [15]. While Pearson's method measures linear association, Spearman's correlation detects consistent increasing or decreasing trends, capturing monotonic but not necessarily linear relationships [16]. For data without ties, the Spearman correlation coefficient r_s is:

$$r_s = 1 - \frac{6\sum d_i^2}{n\,(n^2 - 1)} \tag{3}$$

where d_i is the difference between ranks and n is the number of observations. With tied ranks, the formula becomes:

$$r_s = \frac{\sum(R_{xi} - \bar{R}_x)(R_{yi} - \bar{R}_y)}{\sqrt{\sum(R_{xi} - \bar{R}_x)^2 \sum(R_{yi} - \bar{R}_y)^2}} \tag{4}$$

where R_{xi}, R_{yi} are the ranks and $\bar{R}_x$, $\bar{R}_y$ are their means.

Kendall's rank correlation coefficient

Kendall's Rank Correlation Coefficient, also known as Kendall's τ, is a nonparametric statistical measure used to evaluate the strength and direction of association between two variables based on their ranked data [17]. It focuses on measuring the similarity in the ordering of the two variables by comparing the number of concordant and discordant pairs. Introduced by Maurice Kendall in 1938 [18], with similar earlier concepts proposed by Gustav Fechner, Kendall's τ is calculated as the difference between the number of concordant and discordant pairs divided by the total number of possible pairs, with adjustments available to account for ties. The coefficient ranges from -1, indicating perfect disagreement, to 1, indicating perfect agreement, while a value of 0 signifies no association. Its advantages include robustness to outliers, no assumption of linearity [19], and suitability for ordinal data and small sample sizes. Kendall's τ is often preferred over Spearman's rank correlation, especially for smaller datasets or those with many tied ranks. Given these benefits, Kendall's τ tau will be incorporated into our study to provide a reliable measure of statistical dependence. Kendall's tau τ is computed as:

$$\tau = \frac{C - D}{\frac{n(n-1)}{2}} \tag{5}$$

where C is the number of concordant pairs and D is the number of discordant pairs.

Copula analysis

Copulas are statistical tools that model and analyse the dependence structure between random variables, allowing the construction of multivariate distributions by combining univariate marginal distributions [20]. They are particularly useful in capturing complex dependencies that are not adequately described by traditional correlation measures. In this study, copulas are employed to understand the relationships between variables, providing a more nuanced view of their interdependencies [21]. Copulas allow the modeling of dependence between variables with different marginal distributions [22]. To apply copulas, empirical CDFs are first computed:

$$F_X(x) = \frac{\text{Number of data points } \leq x}{\text{Total number of data points}}, \quad F_Y(y) = \frac{\text{Number of data points } \leq y}{\text{Total number of data points}} \tag{6}$$

The data is transformed into pseudo-observations:

$$(U_i, V_i) = (F_X(x_i), F_Y(y_i)) \in [0,1]^2 \tag{7}$$

Various copula families (Gaussian, Clayton, Gumbel) are then fitted [23]. Parameter estimation uses maximum likelihood or the method of moments, with model selection guided by criteria such as the

Akaike Information Criterion (AIC) [24]. Goodness-of-fit tests such as the Cramér–von Mises and Kolmogorov–Smirnov are applied. Copulas help simulate joint distributions and assess extreme dependencies, which are useful in climate and risk modelling [25].

Estimating copulas involves determining the parameters that best describe the dependence structure between variables, using methods such as maximum likelihood estimation and the method of moments, with the choice depending on the data and copula model used. Various copula families, such as the Gaussian, Clayton, and Gumbel, offer different ways to model dependencies, and selecting the appropriate family is critical; this selection is often guided by criteria such as the Akaike Information Criterion (AIC). After estimation, goodness-of-fit tests such as the Cramér-von Mises and Kolmogorov-Smirnov tests are applied to evaluate how well the copula fits the observed data. Copulas also enable the simulation of multivariate distributions that reflect the specified dependence structure, which is valuable in applications like risk assessment and financial modelling. In risk management [26], copulas model the joint distribution of risks, allowing for a comprehensive assessment of simultaneous adverse events beyond traditional methods. However, copula models have limitations, including reliance on correctly specified marginal distributions and potential inadequacy in capturing certain dependencies, such as tail dependence, if the copula family is not well chosen. Interpreting copula parameters, such as tail dependence coefficients, provides insights into the strength of extreme dependencies [27], which is especially important in finance and insurance. Comparing different copula models based on goodness-of-fit and predictive accuracy helps identify the most suitable model. Copula-based forecasting extends these models to predict future dependencies among variables by incorporating temporal dynamics. Additionally, copulas play a key role in multivariate extreme value theory by modelling the joint behaviour of rare but impactful extreme events, such as natural disasters or financial crises [28]. To determine the statistical significance of observed dependencies, hypothesis testing is performed, with the null hypothesis assuming independence and the alternative hypothesis suggesting dependence between variables. Finally, interpreting copula results involves analysing estimated parameters and model fit, which aids in drawing meaningful conclusions about variable dependencies and informs decision-making across various fields.

III. Results and Discussion

The statistical analysis evaluated the relationship between temperature and rainfall in Gothalapani from 2022 to 2024 using descriptive statistics, correlation coefficients, and copula modelling.

Fig. 1 illustrates the monthly variation of Tmax, Tmin, Tavg, and rainfall in Gothalapani during 2022. The plot highlights the onset of monsoon in June, peak rainfall in July, and declining precipitation by October, with temperature trends stabilizing during peak rainfall.

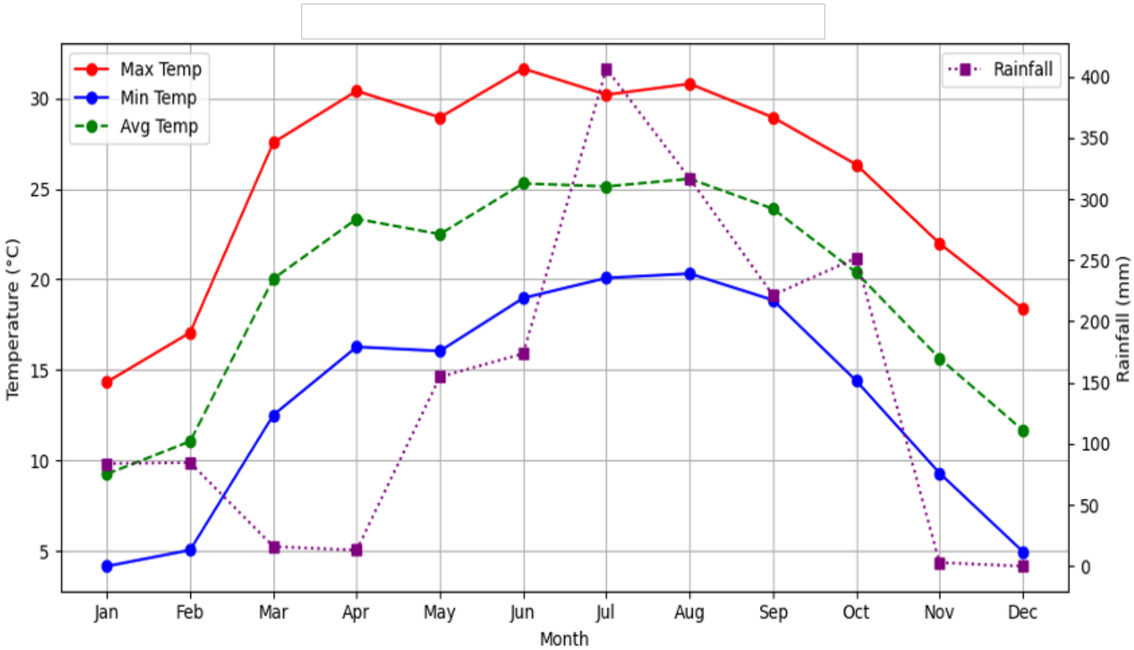

Figure 1. Monthly variation of maximum, minimum, and average temperatures along with rainfall for Gothalapani in 2022.

Table 1 presents monthly climatic statistics for 2022. Rainfall variability (CVR) was highest in January, February, March, and April, reflecting low baseline precipitation and high relative variation. Conversely, monsoon months (July–September) exhibited low CVR values (40%-61%), indicating consistent rainfall.

Table 1. Monthly climate summary for Gothalapani in 2022, showing maximum, minimum, and average temperatures alongside standard deviations (SD) and coefficients of variation (CV) for both temperature and rainfall.

Month	Tmax	Tmin	Tavg	SDT	CVT	Rainfall	SDR	CVR
January	14.34	4.17	9.25	7.18	77.6%	83.84	135.83	163%
February	17.07	5.06	11.06	8.48	76.6%	54.52	141.2	258%
March	27.56	12.52	20.04	10.65	53.1%	16.02	145.32	907%
April	30.41	16.28	23.34	9.99	42.8%	13.14	145.08	1104%
May	28.94	16.05	22.50	9.12	40.5%	154.69	141.566	91%
June	31.63	18.96	25.80	8.97	35.4%	173.67	152.08	87%
July	30.19	20.08	25.13	7.15	28.4%	406.45	166.24	40%
August	30.80	20.32	25.56	7.42	29.0%	316.74	147.47	46%
September	28.94	18.86	23.90	7.13	29.8%	221.35	136.29	61%
October	26.35	14.41	20.38	8.43	41.4%	251.82	144.52	57%
November	22.03	9.31	15.65	8.97	57.3%	3.00	2.10	70%
December	18.38	4.98	11.68	9.47	81.0%	0.02	0.00	0%

According to the tabulated data, monthly maximum temperatures ranged from 14.34 °C in January to 31.63 °C in June, while minimum temperatures ranged from 4.17 °C to 20.85 °C. The average temperature peaked at 25.80 °C in June and dipped to 9.25 °C in January, showing a typical pre-monsoon warming and winter cooling pattern. Standard deviation (SD) and coefficient of variation (CV) of temperature indicate the extent of variability across months. Notably, temperature variability (CVT) was highest in the winter months (above 75%), suggesting a significant diurnal temperature range driven by clear skies and radiative cooling. In contrast, CV values during monsoon months (July–September) dropped below 30%, indicating more stable temperature patterns under consistent cloud cover and rainfall. Overall, the data and visualizations depict a classic subtropical climate pattern: hot, wet summers with stabilized temperatures, and cooler, dry winters with greater temperature fluctuations and sparse rainfall.

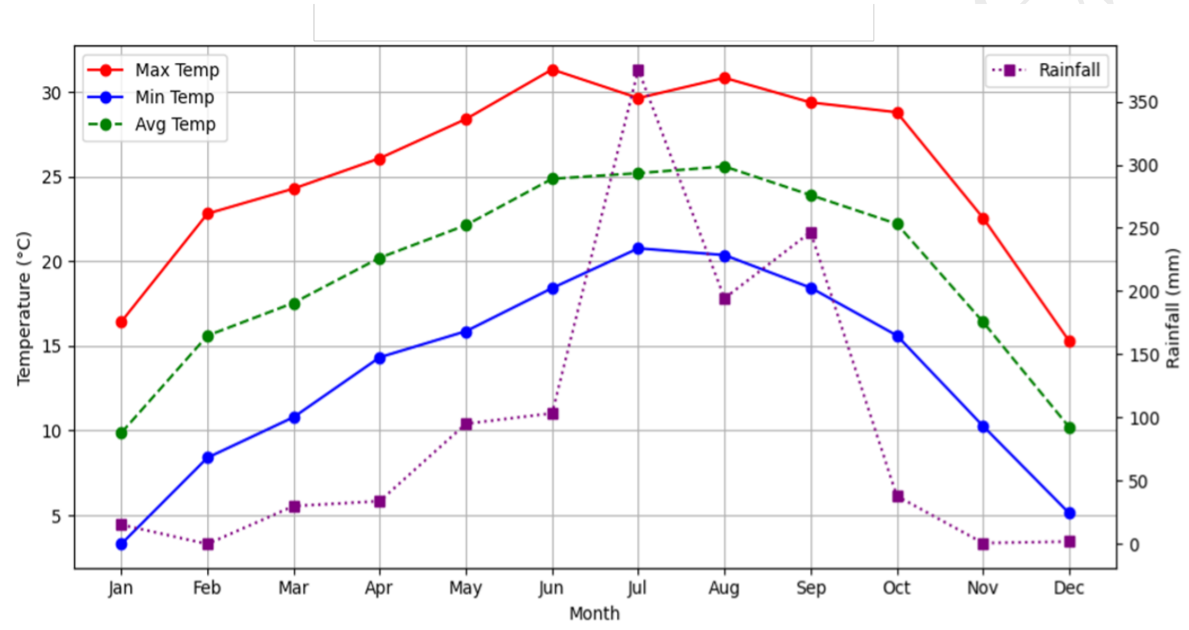

Figure 2. Monthly variation of maximum, minimum, and average temperatures alongside rainfall in Gothalapani during 2023.

Fig. 2 illustrates the monthly variation of Tmax, Tmin, Tavg, and rainfall in Gothalapani during 2023. Tmax peaked in June, Tmin in July, and Tavg in August, while the lowest values occurred in January and December. Rainfall was highly seasonal, rising in June, peaking in July, and remaining elevated through September before declining.

Table 2 presents monthly climatic statistics for 2023. The coefficient of variation for temperature (CVT) was highest in January, reflecting large daily fluctuations in winter, and lowest in the monsoon months. Rainfall variability (CVR) was greatest in March and April, when precipitation was low and unevenly distributed, while CVR values during July–September remained below (40%-61%), showing consistent monsoonal rainfall.

The coefficient of variation for temperature (CVT) is highest in January (94.2%), indicating substantial daily temperature fluctuations during winter. In contrast, during the peak summer and monsoon

Table 2. Monthly climate statistics for Gothalapani in 2023, showing maximum, minimum, and average temperatures, standard deviation and coefficient of variation of temperature, total rainfall (mm), and variability of rainfall.

Month	Tmax	Tmin	Tavg	SDT	CVT	Rainfall	SDR	CVR
January	16.43	3.29	9.87	9.30	94.2%	15.33	24.82	162%
February	22.82	8.40	15.62	10.19	65.2%	0.03	0.08	267%
March	24.30	10.79	17.55	9.57	54.5%	30.06	272.38	906%
April	26.10	14.33	20.21	8.33	41.2%	33.97	374.92	1104%
May	28.41	15.87	22.14	8.85	39.9%	95.15	87.07	91%
June	31.35	18.42	24.88	9.12	36.6%	103.45	89.99	87%
July	29.65	20.77	25.21	6.26	24.8%	375.35	150.34	40%
August	30.85	20.37	25.61	7.43	29.0%	194.36	89.86	46%
September	29.40	18.44	23.92	7.77	32.4%	246.74	150.52	61%
October	28.81	15.62	22.22	9.33	42.0%	38.01	21.67	57%
November	22.57	10.27	16.42	8.71	53.0%	0.81	0.57	70%
December	15.29	5.11	10.20	7.20	70.6%	2.00	0.00	0%

months (June–August), temperature variability is relatively low, indicating stable warm conditions. On the other hand, the coefficient of variation for rainfall (CVR) is highest in April (1104%), reflecting inconsistency in rainfall patterns when precipitation is generally low. Overall, the data reflect a typical monsoon-influenced subtropical climate, characterized by hot, wet summers and cool, dry winters. The transition periods in spring (April–May) and autumn (October–November) exhibit moderate temperatures and rainfall, serving as climatic buffers between the extremes.

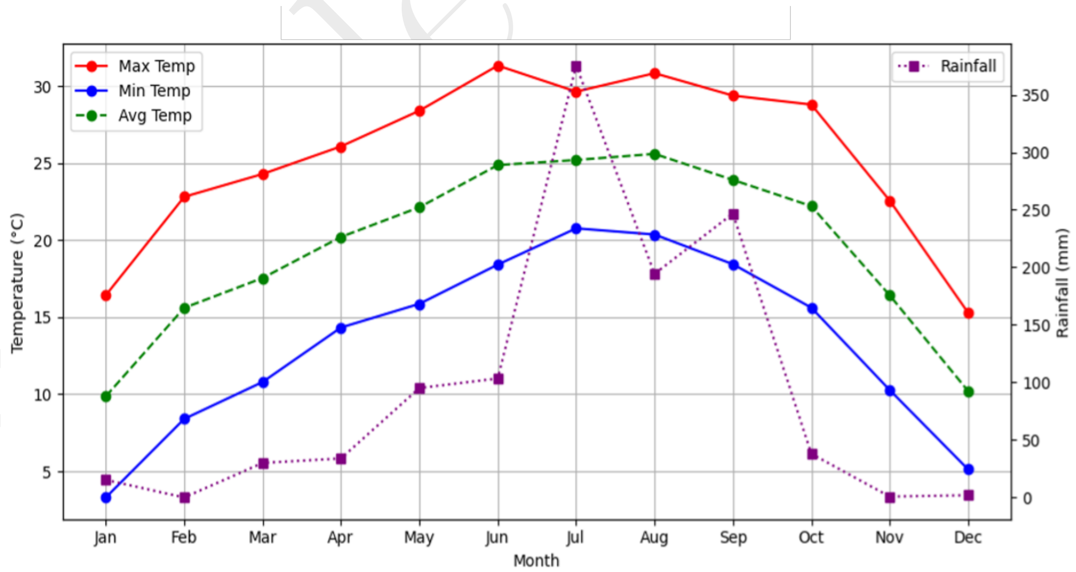

Figure 3. Monthly variation of maximum, minimum, and average temperatures along with rainfall in Gothalapani during 2024.

Fig. 3 illustrates the monthly variation of Tmax, Tmin, Tavg, and rainfall in Gothalapani during 2024. Tmax peaked in June, Tmin in July, and Tavg was highest in June and August, indicating a

Table 3. Climate Summary for Gothalapani (2024), including monthly temperature extremes, standard deviations, and rainfall variability indicators.

Month	Tmax	Tmin	Tavg	SDT	CVT	Rainfall	SDR	CVR
January	16.43	2.86	9.64	9.59	99.5%	0.00	0.00	0%
February	18.66	6.19	12.42	8.80	70.8%	25.73	66.61	259%
March	19.68	8.87	14.27	7.63	53.4%	61.82	560.70	907%
April	26.57	14.67	20.61	8.40	40.7%	0.65	7.18	1104%
May	33.40	18.80	26.09	10.31	39.5%	76.88	70.96	92%
June	35.92	19.60	27.76	11.54	41.5%	83.68	72.80	87%
July	30.09	19.97	25.03	7.15	28.5%	520.26	208.10	40%
August	32.27	19.57	25.92	8.98	34.6%	354.75	163.18	46%
September	29.68	18.97	24.33	7.57	31.1%	221.36	135.03	61%
October	27.47	15.27	21.37	8.61	40.2%	2.52	1.43	57%
November	22.39	10.86	16.62	8.17	49.1%	4.00	2.80	70%
December	16.38	5.24	10.81	7.85	72.6%	16.72	0.00	0%

prolonged summer. Rainfall showed strong monsoonal seasonality, with negligible precipitation in winter, a sharp increase from May, a peak in July, and a gradual decline thereafter.

Table 3 presents monthly climatic statistics for 2024. The coefficient of variation for temperature (CVT) was highest in January, reflecting strong daily variability, while CVT values were much lower during the monsoon months. Rainfall variability (CVR) was highest in March and April when precipitation was inconsistent, while CVR dropped below (40%-61%), during July–September, showing stable and persistent monsoon rainfall.

Temperature variability, as indicated by the standard deviation (SDT), is highest in June (11.54) and May (10.31), suggesting larger fluctuations during the summer months. However, the coefficient of variation (CVT) is highest in January (99.5%), indicating significant daily temperature swings during the winter. In contrast, the summer months (June–August) exhibit lower CVT values (28.5%–41.5%), implying relatively stable temperatures. Rainfall variability, as indicated by the coefficient of variation (CVR), is highest in March (907%) and April (1104%), where overall rainfall is still low and inconsistent. During the monsoon months (July to September), CVR drops sharply (40%–61%), showing more consistent and reliable precipitation during this season. This pattern confirms the monsoon's dominance in shaping the annual rainfall cycle. Overall, the climate pattern at Gothalapani in 2024 reflects a typical subtropical monsoon system, with hot, wet summers and cool, dry winters. The transition months of May and September mark the onset and retreat of the monsoon, respectively, while temperature and rainfall remain relatively stable during peak summer and highly variable during the winter and pre-monsoon months.

Correlation analysis

The relationship between temperature and rainfall was examined using three correlation measures: Pearson's, Kendall's, and Spearman's methods. Pearson's correlation coefficient was found to be r=0.61

with a p-value of 8.27×10^{-5}, indicating a statistically significant linear association. Kendall's rank correlation coefficient was $\tau = 0.48$ with a p-value of 3.07×10^{-5}, while Spearman's rank correlation yielded r_s=0.69. These results collectively suggest a statistically significant, moderate-to-strong positive association between temperature and rainfall, both in linear and monotonic terms. These correlation values were calculated using pooled monthly data from 2022–2024, ensuring that the results reflect the overall dependence structure across the full study period rather than a single year.

Copula-based analysis

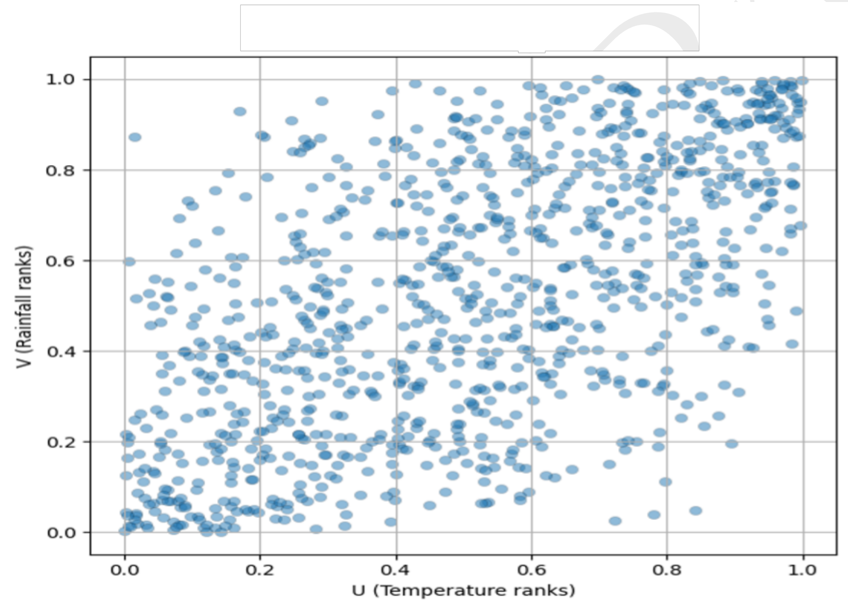

Figure 4. Scatter plot of pseudo-observations from the Gaussian copula fitted to temperature and rainfall data [Kendall's $\tau = 0.48, \rho = 0.62$].

Among the candidate families considered (Gaussian, Clayton, and Gumbel), model selection was performed using information criteria to ensure an objective comparison of fit quality. The Gaussian copula yielded the lowest values of both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), indicating superior overall performance relative to the Clayton and Gumbel alternatives. This statistical evidence supports selecting the Gaussian copula as the most appropriate dependence structure for the available dataset, despite its known limitation in capturing tail dependence. Fig. 4 illustrates the dependence structure between temperature and rainfall using a Gaussian copula model. Each point in the plot represents a pseudo-observation, i.e., the empirical cumulative distribution ranks of temperature (U) and rainfall (V), both scaled to the unit interval [0,1]. The observed relationship between these variables is quantified using Kendall's rank correlation coefficient (τ=0.48), indicating a moderate positive dependence. The corresponding Gaussian copula parameter is ρ=0.62, consistent with the theoretical relationship $\tau = \frac{2}{\pi} arcsin\,(\rho)$, further validating the copula model's goodness of fit. The scatter of points reveals a generally increasing trend, confirming that higher temperature ranks are associated with higher rainfall ranks. However, the spread around the diagonal implies variability in this association, typical of empirical climatic data. Notably, there is no pronounced clustering in the lower-left or upper-right corners, indicating the absence of significant lower or upper tail dependence. This is consistent with the Gaussian copula's known limitation in modeling tail dependence, which may restrict its applicability in extreme value analysis [29, 30]. The Gaussian copula results highlight that extreme rainfall events do not necessarily coincide with extreme temperature events. This finding has practical implications: risk assessments for floods, heatwaves, or droughts in this region should not assume simultaneous extremes in temperature and rainfall. For agricultural and water management planning, this means resilience strategies must separately address high rainfall and extreme temperature conditions, as they are not strongly coupled in the tails. Overall, the Gaussian copula provides a suitable model for capturing the central dependence structure between temperature and rainfall in this dataset. However, for studies focused on extreme co-movements, alternative copula families, such as t-copulas or Archimedean copulas, may perform better due to their ability to capture tail dependence.

IV. Conclusion

This study investigated the statistical relationship between temperature and rainfall in Gothalapani, Baitadi, using three years of meteorological records (2022–2024). The results highlighted a distinct monsoonal cycle, with peak rainfall recorded in July 2024 (520.26 mm) and the highest average temperature observed in June 2024 (27.76 °C). Rainfall variability, measured by the coefficient of variation (CVR), exceeded 900% during the pre-monsoon months, when baseline precipitation was low and unevenly distributed, but declined to below 50% during the monsoon season, reflecting greater stability in rainfall patterns.

Correlation analysis confirmed a moderate to strong positive dependence between rainfall and temperature (Pearson's r = 0.61, Spearman's $\rho = 0.62$, Kendall's $\tau = 0.62$), indicating that warmer conditions generally coincided with higher rainfall. Copula modelling further supported this association, with the Gaussian copula providing the best fit to the observed data. However, the analysis revealed no evidence of tail dependence, suggesting that extreme rainfall events are not systematically associated with extreme temperatures. This finding carries important implications for climate risk management, suggesting that adaptation strategies should treat extreme rainfall and temperature events as largely independent hazards.

A major limitation of this study is its limited temporal coverage of only 3 years, which constrains the ability to infer long-term climatic trends. The results should therefore be regarded as exploratory rather than definitive. Future research should extend the dataset over longer time horizons and incorporate additional climatic variables, such as humidity, evaporation, and soil moisture, while also exploring alternative copula families (e.g., Student's t) to assess potential tail dependencies in larger datasets.

Overall, the findings underscore the dominant influence of the South Asian monsoon on local climate variability and demonstrate the utility of combining traditional statistical techniques with copula-based models for regional climate assessments.

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