

Spatio-Temporal Characterization of Reference Evapotranspiration in Supaul District, Bihar, India, Using the Fao-56 Penman–Monteith Method

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Abstract

Reference evapotranspiration (ET_0) represents atmospheric evaporative demand from a standardized reference surface and is widely used in irrigation scheduling, crop-water assessment, and hydroclimatic analysis. This study estimated monthly and annual ET_0 for 11 locations in Supaul District, Bihar, India, using the FAO-56 Penman–Monteith method and monthly meteorological inputs for 1990–2025. The dataset comprised 4,752 location-month records. Mean daily ET_0 averaged across locations and years ranged from 2.33 mm day⁻¹ in December to 7.76 mm day⁻¹ in April. The average of the location-level annual means was 1,724.2 mm year⁻¹; Basantpur recorded the lowest mean (1,664.5 mm year⁻¹), while Marauna recorded the highest (1,811.4 mm year⁻¹). The annual location-averaged series showed a negative ordinary least-squares slope of -13.72 mm year⁻¹. This trend is interpreted as an exploratory pattern because the annual series also exhibits strong lag-1 autocorrelation and requires autocorrelation-aware trend testing. The findings provide a quantitative baseline for regional irrigation planning, crop-water assessment, and hydroclimatic analysis.

Keywords: reference evapotranspiration; FAO-56 Penman–Monteith; Supaul; Bihar; irrigation planning; meteorological data; seasonal variability

1. Introduction

Evapotranspiration is a central component of the land–atmosphere water exchange and connects the surface energy balance with catchment hydrology, agricultural production, and irrigation demand. Reference evapotranspiration (ET_0) represents the evaporative demand of the atmosphere from a standardized, well-watered reference surface and provides a consistent climatic indicator that can be compared across locations and time periods. In operational water management, ET_0 is commonly combined with crop coefficients to estimate crop evapotranspiration (ET_c), supporting irrigation scheduling, seasonal water budgeting, and assessment of agricultural water requirements (Jensen et al., 1990; Allen et al., 1998; Allen et al., 2005). Reliable ET_0 estimates are therefore important in regions where rainfall is strongly seasonal and irrigation decisions must balance crop demand with available water

resources. Broader assessments of evapotranspiration also emphasize its role in ecosystem functioning, carbon–climate feedbacks, agricultural management, and water-resource planning (Fisher et al., 2017). Several approaches have been developed to estimate evapotranspiration, ranging from empirical temperature-based equations to physically based combination methods. Penman (1948) established a combination approach that integrates the energy available for evaporation with the aerodynamic transport of water vapour, while Monteith (1965) extended the framework by accounting for surface resistance. The FAO-56 Penman–Monteith method standardizes this approach for a hypothetical reference grass surface and is widely used as a reference method when the required meteorological variables are available (Allen et al., 1998). Alternative methods, including Hargreaves–Samani and Priestley–Taylor, can be useful where data availability is limited, but their performance may vary with climatic conditions and input-variable availability (Hargreaves and Samani, 1985; Priestley and Taylor, 1972; Xu and Singh, 2002; Tabari, 2010; Trajkovic, 2007). Radiation-based equations and software tools have also been developed to support estimation under different data constraints (Irmak et al., 2003; Gocic and Trajkovic, 2010). These comparisons highlight why method choice, input quality, and local evaluation matter when ET_0 is used for water-resource decisions.

In India, evapotranspiration demand varies with temperature, radiation, humidity, wind, elevation, and seasonal circulation. Studies have examined reference evapotranspiration and irrigation requirements in Bihar, regional ET_0 trends, and long-term changes in potential evapotranspiration across the country (Kumar, 2017; Verma et al., 2008; Rani et al., 2021). Changes in near-surface wind speed can also influence estimates of atmospheric evaporative demand, illustrating that trends in ET_0 cannot be attributed to temperature alone (McVicar et al., 2012). More recent work using bias-corrected climate-model simulations indicates that future ET_0 changes across Indian climatic regimes may differ by station and season, rather than following a uniform national pattern (Nayak et al., 2026). Such findings reinforce the need for geographically specific estimates and careful interpretation of spatial and temporal variability.

ET_0 is also relevant to drought monitoring because it represents the atmospheric demand component used in indices such as the Standardized Precipitation Evapotranspiration Index (SPEI). SPEI and related approaches combine precipitation deficits with evaporative demand to characterize hydroclimatic stress at multiple time scales (Vicente-Serrano et al., 2010; Beguería et al., 2014). Although global drought assessments have emphasized the importance of considering both precipitation and evaporative demand, the interpretation of long-term changes remains sensitive to data quality, index construction, and the period analysed (Sheffield et al., 2012). Recent research by Raja et al. (2026) demonstrates the value of combining remote-sensing information with meteorological drought indices, while Kumar et al. (2026) examines machine-learning estimation of monthly potential evapotranspiration using Random Forest and Support Vector Machine approaches. Related machine-learning studies have compared tree-based and hybrid algorithms for ET_0 estimation, suggesting that data-driven approaches can be useful where a robust reference dataset is available (Feng et al., 2017; Tikhamarine et al., 2019). These methods complement, rather than replace, the need for a clearly defined physical reference calculation and transparent input-data handling.

Supaul District lies in the Kosi region of north-eastern Bihar, where agricultural water management is influenced by monsoon rainfall, seasonal changes in atmospheric demand, and the need to coordinate rain-fed and irrigated production. A district-wide average can conceal meaningful local differences, particularly where station environments and meteorological inputs vary. A consistent location-level ET_0

assessment can provide a baseline for comparing the seasonal cycle, identifying months of elevated atmospheric demand, and supporting subsequent crop-water analysis. At the same time, the quality of such an assessment depends on correct station metadata, consistent units, appropriate wind-height conversion, and the provenance and homogeneity of the meteorological series.

Against this background, the present study calculates monthly and annual reference evapotranspiration for 11 locations in Supaul District using the FAO-56 Penman–Monteith framework and the monthly meteorological dataset for 1990–2025. The objectives are to characterize the seasonal cycle, quantify differences among location-level annual estimates, compare monthly climatologies, and assess interannual variability through linear regression.

2. Materials and Methods

2.1 Study area and stations

The study covers 11 locations in Supaul District, Bihar, India: Basantpur, Bhaptiyahi, Chhatapur, Nirmali, Pipra, Raghopur, Triveniganj, Kishanpur, Marauna, Pratapganj, and Supaul. These locations represent the district's spatial distribution for the station-wise analysis. A latitude of 26.3° N and elevation of 50 m were used as the common reference parameters in the radiation calculations, while station-specific meteorological series were used to calculate ET_0 .

2.2 Meteorological data and temporal coverage

The monthly dataset contains 12 records per location per year for 1990–2025, yielding 4,752 location-month records (11 locations $\times$ 36 years $\times$ 12 months). The variables used were mean air temperature (T_{mean} , °C), maximum and minimum air temperature (T_{max} and T_{min} , °C), relative humidity (RH, %), wind speed (m s^{-1}), and solar radiation ($\text{MJ m}^{-2} \text{ day}^{-1}$). The analysis files supplied for this study consisted of monthly Excel workbooks for the 11 named locations. The accompanying files did not identify the original data provider or establish whether the values were direct station observations or gridded data extracted for each location. The data provider/product and station-versus-grid provenance should therefore be confirmed and reported before journal submission; they cannot be reliably inferred from the supplied workbooks alone.

2.3 FAO-56 Penman–Monteith method

Daily reference evapotranspiration was calculated using the FAO-56 Penman–Monteith equation (Allen et al., 1998):

$$ET_0 = [0.408 \Delta (R_n - G) + \gamma (900/(T + 273)) u_2 (e_s - e_a)] / [\Delta + \gamma (1 + 0.34u_2)]$$

where ET_0 is reference evapotranspiration (mm day^{-1}); R_n is net radiation at the reference surface ($\text{MJ m}^{-2} \text{ day}^{-1}$); G is soil heat flux ($\text{MJ m}^{-2} \text{ day}^{-1}$); T is mean daily air temperature (°C); u_2 is wind speed at 2 m (m s^{-1}); e_s and e_a are saturation and actual vapour pressure (kPa); Δ is the slope of the saturation vapour-pressure curve ($\text{kPa } ^\circ\text{C}^{-1}$); and γ is the psychrometric constant ($\text{kPa } ^\circ\text{C}^{-1}$).

For each monthly record, extraterrestrial radiation was calculated using the common latitude and a representative day-of-year for the month; clear-sky radiation was estimated from extraterrestrial radiation and elevation; net shortwave radiation was derived using an albedo of 0.23; and net longwave radiation was estimated from T_{max} , T_{min} , actual vapour pressure, and the ratio of incoming to clear-sky solar radiation. Monthly soil heat flux was set to zero. Actual vapour pressure was estimated from mean relative humidity and mean saturation vapour pressure derived from T_{max} and T_{min} . A latitude of 26.3° N and elevation of 50 m were used in the radiation calculations for all locations. Wind speed was treated as a 2-

m value, and solar radiation was expressed in $\text{MJ m}^{-2} \text{ day}^{-1}$. These assumptions were applied consistently to standardize the calculations. The wind measurement height and the representativeness of the common latitude and elevation should be checked against the original metadata; if wind was measured at a different height, it must be converted to 2 m using the FAO-56 procedure.

2.4 Monthly and annual aggregation

The calculated ET_0 value for each station-month is a mean daily rate for that month. Monthly ET_0 depth (mm month^{-1}) was calculated by multiplying the daily rate by the number of calendar days in the month, accounting for leap years. Annual ET_0 was calculated as the sum of the 12 monthly depths. Station summaries were computed from the 36 annual totals. The monthly climatology was calculated as the average across all available station-month values for each calendar month.

2.5 Exploratory trend analysis

An ordinary least-squares (OLS) linear regression was fitted to annual ET_0 against year for each location and for the annual mean across locations. The slope is reported in mm year^{-1} , and R^2 describes the proportion of annual variability represented by the linear fit. For the location-averaged annual series, the OLS slope, R^2 , and nominal p-value were calculated for 1990–2025. Kendall's rank correlation and Sen's slope were also calculated as exploratory, distribution-robust summaries. Because the annual series may be serially correlated, the ordinary Mann–Kendall test and unadjusted OLS p-value should not be treated as definitive significance tests. Lag-1 autocorrelation was therefore examined, and the trend results are interpreted descriptively pending a formal autocorrelation-adjusted test and data-homogeneity assessment.

3. Results

3.1 Seasonal cycle of reference evapotranspiration

The mean daily ET_0 across the 11 locations showed a clear seasonal pattern, as illustrated in Figure 1. Values increased from 2.85 mm day^{-1} in January to 7.76 mm day^{-1} in April, then declined during the monsoon and post-monsoon months to a minimum of 2.33 mm day^{-1} in December. The high pre-monsoon demand corresponds to warmer conditions and greater available energy, whereas lower monsoon-season estimates correspond to reduced net radiation and humid, cloudy conditions.

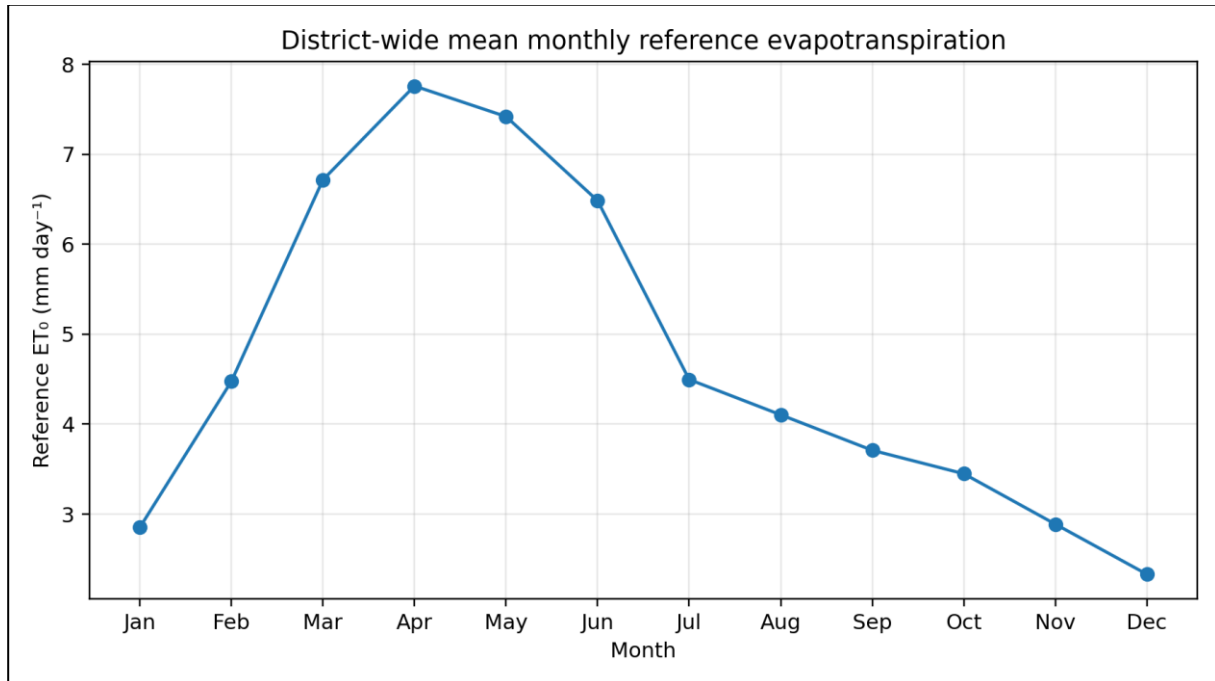


Figure 1. Mean daily reference ET₀ by calendar month, averaged across the 11 locations and the full supplied period (1990–2025).

3.2 Spatial differences among stations

Figure 2 compares the station-wise annual estimates. Mean annual ET₀ averaged 1724.2 mm year⁻¹ across the 11 location summaries. Marauna had the highest station-average estimate (1811.4 mm year⁻¹), while Basantpur had the lowest (1664.5 mm year⁻¹). The difference between these station means was 146.9 mm year⁻¹, or approximately 8.8% of the lower value. This contrast demonstrates spatial variation in estimated atmospheric evaporative demand across Supaul District.

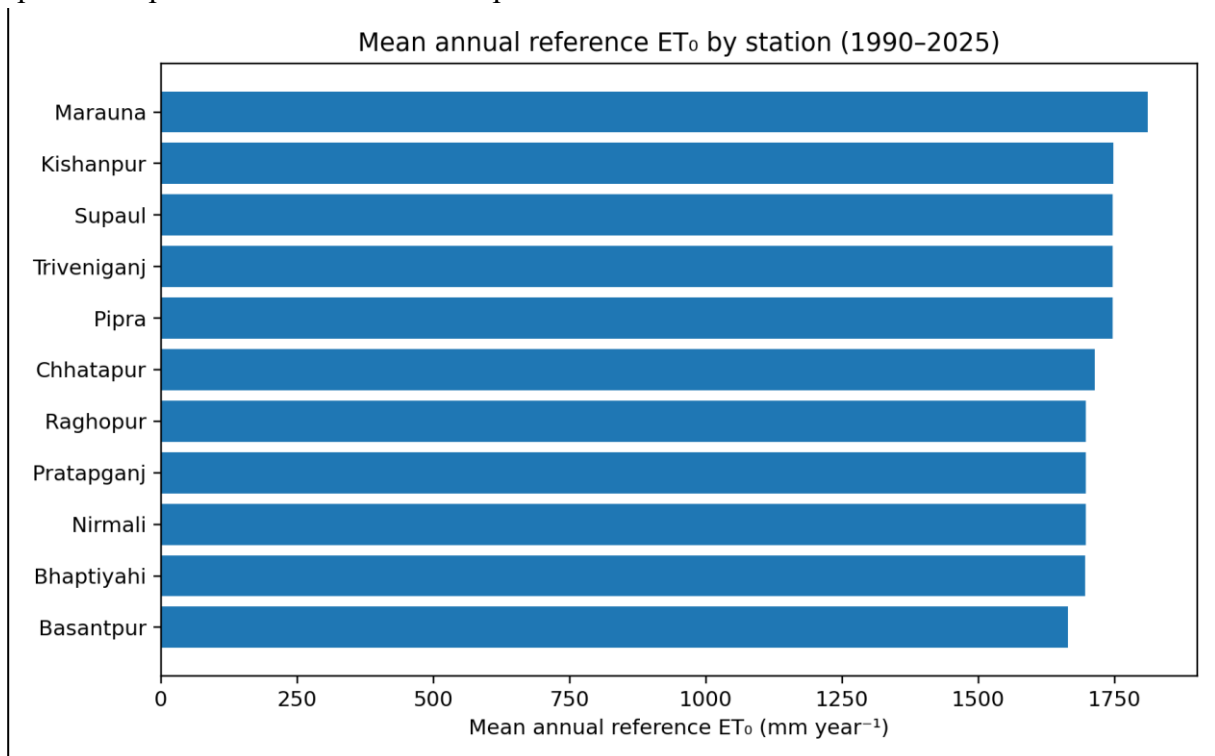


Figure 2. Mean annual reference ET_0 at each station over 1990–2025.

3.3 Station-wise annual ET_0 statistics

Table 1 summarizes the annual reference evapotranspiration (ET_0) estimates for the 11 locations over the 1990–2025 study period. The mean annual ET_0 represents the average of the 36 annual totals for each location, whereas the minimum and maximum values indicate the lowest and highest annual totals in the calculated series. Together, these statistics describe the typical level of estimated atmospheric evaporative demand and the range of interannual variability at each location.

Marauna recorded the highest mean annual ET_0 (1811.4 mm yr⁻¹), followed by Kishanpur (1748.1 mm yr⁻¹), Supaul (1747.0 mm yr⁻¹), Triveniganj (1746.9 mm yr⁻¹), and Pipra (1746.8 mm yr⁻¹). Basantpur showed the lowest mean annual ET_0 (1664.5 mm yr⁻¹), while Chhatapur averaged 1713.5 mm yr⁻¹. The difference between the highest and lowest location means was 146.9 mm yr⁻¹, equivalent to approximately 8.8% of the Basantpur mean. Bhaptiyahi, Nirmali, Pratapganj, and Raghobpur had closely grouped means between 1695.8 and 1697.5 mm yr⁻¹, indicating relatively small differences among their calculated annual averages.

The range between minimum and maximum annual ET_0 also varied among locations. Marauna ranged from 1472.3 to 2192.4 mm yr⁻¹, while Basantpur ranged from 1304.3 to 2034.8 mm yr⁻¹. The highest annual maximum was recorded at Marauna (2192.4 mm yr⁻¹), and the lowest annual maximum was recorded at Basantpur (2034.8 mm yr⁻¹). These ranges show that the annual series capture both differences in average ET_0 among locations and substantial year-to-year variation. Minimum and maximum values are most informative when considered alongside the mean, rather than used alone to characterize a location.

Overall, the table provides a comparative summary of the calculated location-wise ET_0 series and complements the seasonal pattern shown in Figure 1 and the spatial comparison in Figure 2. Higher annual ET_0 indicates greater estimated atmospheric demand from the standardized reference surface under the meteorological inputs used in the calculation; it does not directly represent actual crop water use. Crop-specific evapotranspiration can be estimated by combining ET_0 with suitable crop coefficients and accounting for crop growth stage and field water conditions.

Station/block	Mean annual ET_0 (mm yr ⁻¹)	Minimum annual ET_0 (mm yr ⁻¹)	Maximum annual ET_0 (mm yr ⁻¹)
Basantpur	1664.5	1304.3	2034.8
Bhaptiyahi	1695.8	1346.9	2068.4
Nirmali	1696.9	1346.4	2067.7
Pratapganj	1697.5	1346.9	2068.4
Raghobpur	1697.5	1346.9	2068.4
Chhatapur	1713.5	1328.2	2122.7
Pipra	1746.8	1371.4	2156.6
Triveniganj	1746.9	1371.5	2156.8
Supaul	1747.0	1371.6	2156.9
Kishanpur	1748.1	1371.2	2156.3

Marauna	1811.4	1472.3	2192.4
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Table 1. Summary statistics for annual reference ET_0 at each station for 1990–2025.

3.4 Monthly climatology by station

The seasonal cycle was broadly similar across stations, although the magnitude of daily ET_0 differed. Figure 3 presents the station-by-month heatmap and enables direct comparison of seasonal atmospheric demand across locations. Higher values occur mainly during the pre-monsoon months, while lower values characterize the monsoon and winter period. These patterns help identify the seasonal windows of greatest atmospheric demand for crop-water planning. To estimate crop water use, reference ET_0 can be combined with crop coefficients and information on effective rainfall, soil-water storage, irrigation efficiency, and crop growth stage.

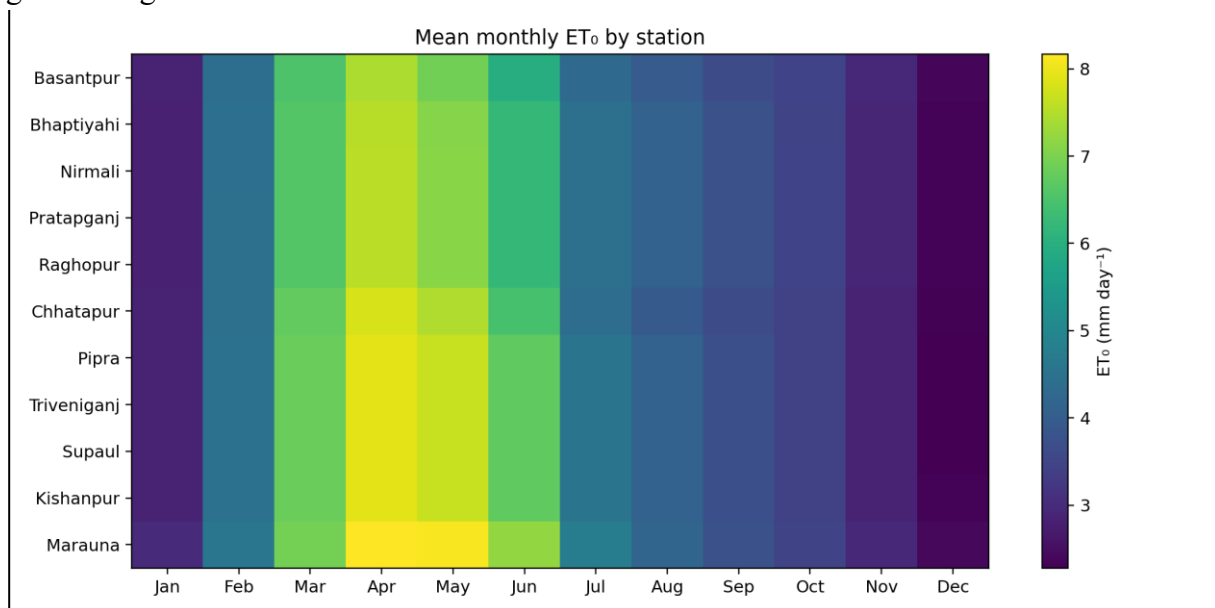


Figure 3. Mean daily reference ET_0 by station and calendar month.

3.5 Interannual variability and trend analysis

Figure 4 presents the annual reference evapotranspiration (ET_0) series for the 11 locations from 1990 to 2025. The annual location-averaged series shows an overall downward pattern, with substantial year-to-year fluctuations and short periods of recovery. The OLS regression yielded a slope of $-13.72 \text{ mm year}^{-1}$, $R^2 = 0.660$, and a nominal p-value of 1.76×10^{-9} . Exploratory Kendall analysis gave $\tau = -0.651$ (nominal $p = 2.34 \times 10^{-8}$), and Sen's slope was approximately $-13.64 \text{ mm year}^{-1}$. The lag-1 autocorrelation of the annual location-averaged series was approximately 0.781, indicating strong temporal dependence. Consequently, the nominal p-values may overstate the evidence for a monotonic trend unless serial correlation is accounted for. These statistics describe the supplied calculated series; they do not by themselves establish a causal climatic trend.

The time series also contains marked interannual variability, including pronounced peaks in the early 1990s and a sharp reduction around 2020. Such features can influence a linear regression and make the estimated slope sensitive to the period analysed. Therefore, the trend should be interpreted together with the temporal pattern in Figure 4 rather than as a uniform year-by-year decrease. Formal monotonic-trend

testing, serial-correlation assessment, and homogeneity checks were not included in this linear-fit summary; the reported slope, R^2 , and p-value should consequently be read as descriptive regression statistics for the available series.

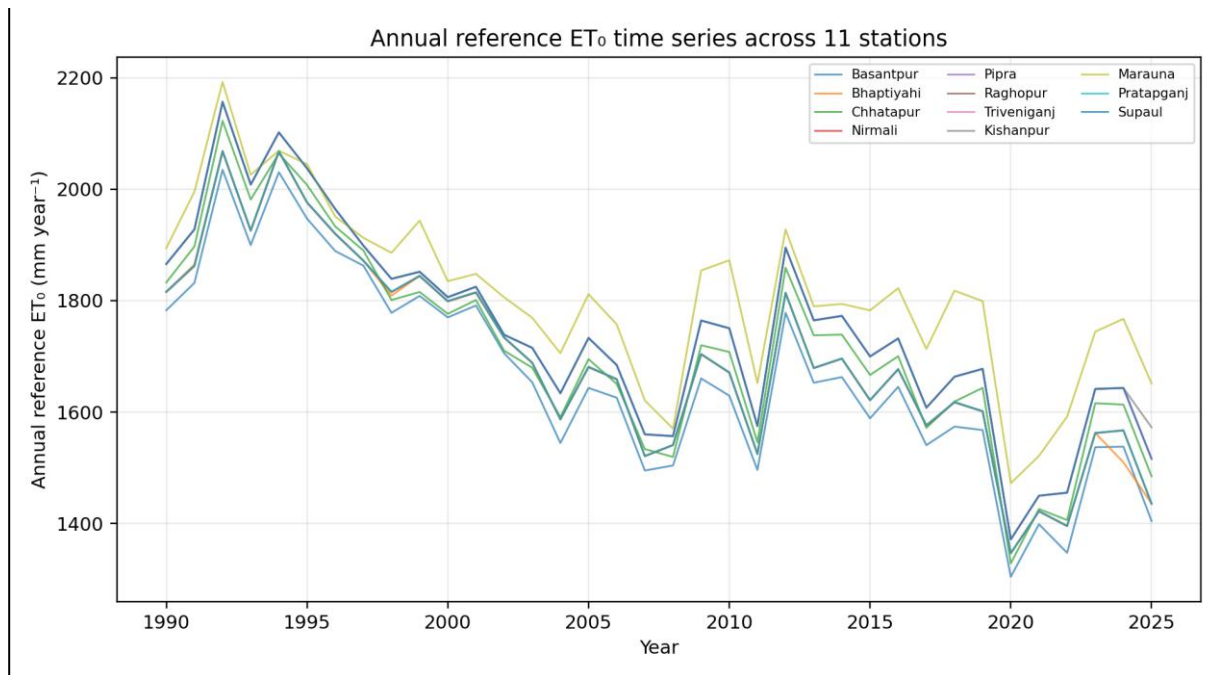


Figure 4. Annual reference ET_0 series for the 11 locations during 1990–2025, illustrating interannual variability and the overall downward tendency.

4. Discussion

The results demonstrate spatial differences in reference evapotranspiration (ET_0) across Supaul District. Station-level annual means ranged from $1664.5 \text{ mm year}^{-1}$ at Basantpur to $1811.4 \text{ mm year}^{-1}$ at Marauna, showing that atmospheric evaporative demand varies across the study area. These differences emphasize the value of station-wise ET_0 estimates rather than relying solely on a single district-wide average.

The estimated annual ET_0 values and seasonal cycle describe atmospheric evaporative demand under the meteorological inputs and assumptions used in the calculation. The calculations incorporate temperature, radiation, humidity, and wind speed. Actual vapour pressure was estimated from mean relative humidity and mean saturation vapour pressure derived from $T_{\max}$ and $T_{\min}$. Monthly meteorological inputs were used to estimate mean daily ET_0 for each month; monthly depths were obtained by multiplying the daily rate by the number of days in the month, and annual totals were calculated by summing the monthly depths. This consistent procedure enables comparison among locations, although the common latitude and elevation and assumed 2-m wind speed should be verified against the source metadata.

The annual series show an overall downward tendency, accompanied by substantial interannual variability. The location summaries for Bhaptiyahi, Pratapganj, and Raghapur have identical reported minima and maxima, indicating highly similar annual ET_0 behaviour among these locations. These similarities should be checked against the input workbooks to determine whether the locations share identical or near-identical meteorological inputs. The regression slope summarizes the direction of change in the supplied series, but the strong lag-1 autocorrelation means that inferential trend claims require an

autocorrelation-aware test and checks for data homogeneity and possible changes in the underlying data source.

For agricultural application, ET_0 provides the climatic reference term for estimating crop water requirements. Station-specific ET_0 can be combined with crop calendars, stage-specific crop coefficients (K_c), effective precipitation, soil properties, and irrigation application efficiency to estimate crop evapotranspiration and support irrigation scheduling. The spatial variation reported here can help tailor crop-water assessments to local conditions.

The broader literature supports interpreting these results within the established framework of reference evapotranspiration and agricultural water management. Standardized reference ET procedures and irrigation guidance provide the basis for converting atmospheric demand into crop-water requirements (Allen et al., 1998; Allen et al., 2005; Jensen et al., 1990). Empirical and radiation-based alternatives are useful in different data and climate settings (Hargreaves and Samani, 1985; Priestley and Taylor, 1972; Xu and Singh, 2002; Tabari, 2010; Trajkovic, 2007; Irmak et al., 2003; Gocic and Trajkovic, 2010). Regional studies in India and research on wind-speed change demonstrate the importance of local climate context (Kumar, 2017; Verma et al., 2008; Rani et al., 2021; McVicar et al., 2012; Nayak et al., 2026). For drought applications, ET_0 is a useful evaporative-demand input when interpreted alongside precipitation and other hydroclimatic variables (Vicente-Serrano et al., 2010; Beguería et al., 2014; Sheffield et al., 2012). Machine-learning studies, including Raja et al. (2026) and Kumar et al. (2026), provide further opportunities for ET_0 estimation and integration with broader water-resource analyses (Feng et al., 2017; Tikhamarine et al., 2019).

5. Conclusions

This study estimated reference evapotranspiration (ET_0) for 11 locations in Supaul District, Bihar, using the FAO-56 Penman–Monteith framework and monthly meteorological inputs for 1990–2025. The average of the location-level annual means was $1,724.2 \text{ mm year}^{-1}$. Basantpur had the lowest mean ($1,664.5 \text{ mm year}^{-1}$), while Marauna had the highest ($1,811.4 \text{ mm year}^{-1}$), a difference of $146.9 \text{ mm year}^{-1}$. Mean daily ET_0 was highest in April (7.76 mm day^{-1}) and lowest in December (2.33 mm day^{-1}). The annual location-averaged series had an OLS slope of $-13.72 \text{ mm year}^{-1}$, indicating a downward tendency in the calculated series. Because lag-1 autocorrelation was high, this slope should be regarded as descriptive until confirmed using an autocorrelation-aware trend test and data-homogeneity checks. Location-wise ET_0 summaries and monthly climatologies provide a basis for crop-water assessment when combined with crop coefficients, crop calendars, effective rainfall, soil-water storage, and irrigation efficiency. ET_0 represents atmospheric demand from a standardized reference surface rather than actual crop water use.

The station-wise results show that a single district-wide ET_0 value may not fully represent local atmospheric demand. Monthly climatologies and annual summaries provide a practical basis for crop-water assessments when combined with crop coefficients, crop calendars, effective rainfall, soil-water storage, and irrigation efficiency. ET_0 represents atmospheric demand from a standardized reference surface; crop-specific water use can be estimated using the relevant crop coefficient and field conditions. The results also provide a foundation for integration with remote sensing, drought indices, and machine-learning models in future water-resource studies.

Data availability

The derived ETo results and analysis workbook may be obtained from the corresponding author upon reasonable request. The original meteorological data provider and access conditions should be specified here once confirmed.

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