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Quantitative analysis of causal relationship between meteorological factors and evapotranspiration in the upstream basin of Dong Nai river

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Abstract: *Evapotranspiration (ET) in the basin results from the complex interaction between meteorological factors and surface conditions. This study quantitatively analyzes the aforementioned causal relationships spatially and temporally using the Convergent Cross Mapping (CCM) method. Meteorological data series from 1984 to 2023 at four meteorological stations in the Upstream basin of Dong Nai River were statistically processed and analyzed using the CCM method. The rEDM package in R software was utilized for calculations. The results indicate that in this basin, solar radiation n (ρ = 0,32) has the strongest causal relationship with ET and is positively correlated (*$\rho_s = 0{,}26$*). Next, relative humidity RH has a negative correlation and is the second strongest causal relationship (*$\rho = 0{,}23, \rho_s = -0{,}38$*). Wind speed u (ρ = 0,04) has a causal relationship but no correlation with ET (*$\rho_s = -0{,}03$*). Precipitation R (ρ = 0,09) has no causal relationship with ET. Causal analysis among meteorological variables shows an indirect causal relationship between n and T with ET through RH. Specifically, n is positively correlated and has a strong causal relationship with T (*$\rho = 0{,}30, \rho_s = 0{,}31$*), T is negatively correlated and has a strong causal relationship with RH (*$\rho = 0{,}21, \rho_s = -0{,}34$*), and RH is negatively correlated with ET (*$\rho = 0{,}23, \rho_s = -0{,}38$*). The weak relationship between u and RH (*$\rho = 0{,}03, \rho_s = 0{,}03$*) indicates that RH has no association with u. Therefore, when calculating ET using forecasting models, attention should be paid to the data of n, T, and RH for this basin.*

Keywords: *Meteorology; evapotranspiration; Convergent Cross Mapping (CCM); causal relationship; upper reaches of the Dong Nai River*

1. Introduction

According to Federer et al., potential evapotranspiration refers to the maximum possible evapotranspiration at the land surface, defined as either the interception layer or the root zone when water from the interception layer is depleted but soil water remains available (Federer et al., 1996, Nghị, 2016a). ET influences water loss through soil evaporation and plant transpiration, determining the water left in the catchment for modeling surface runoff and developing water table maintenance scenarios. Analyzing ET's sensitivity to biases (arising from data errors or actual climate changes) in one or more climate variables is essential for understanding the relationship between climate conditions and ET variability, as well as the relationship between data availability and the accuracy of ET estimates (Gong et al., 2006). Accurately understanding and forecasting ET in the context of climate change is crucial for water balance calculations, especially in agricultural regions and tropical monsoon climates, such as the upper Dong Nai River basin.

Over the years, research on ET and meteorological factors has enhanced our understanding of how variables like temperature, solar radiation, relative humidity, and wind speed influence land surface evaporation and plant transpiration. Howard Latimer Penman made significant contributions by studying natural evaporation from various surfaces, including open water, bare soil, and grass. He emphasized that evaporation's dependence on meteorological factors varies geographically and temporally (Penman, 1948). Later, Allen et al., in developing the Penman-Monteith equation, demonstrated that air temperature strongly affects evapotranspiration: higher temperatures enable air to hold more water vapor, thereby increasing both plant transpiration and soil evaporation (Allen et al., 1998).

Magali Garcia et al. studied the relationship between temperature and ET in arid climates, finding that rising temperatures significantly increase ET, especially in the dry season (Garcia et al., 2004). Tagele Mossie Aschale and colleagues demonstrated the potential impact of climate change on ET, noting that factors like solar radiation, temperature, and wind speed substantially affect ET_0, while relative humidity tends to decrease ET_0 in a Mediterranean climate (Tagele Mossie Aschale et al., 2023). Yu Luo, Peng Gao, and Xingmin Mu, using the Penman-Monteith method, identified solar radiation and temperature as the primary drivers of increased ET_0, while relative humidity reduced it (Luo et al., 2021). Tabari examined

ET sensitivity across four distinct climates—arid, warm semi-arid, cold semi-arid, and humid—showing that ET in arid climates is most sensitive to temperature and wind speed, while sunshine hours have a lesser impact. In contrast, wind speed was the most influential factor in warm semi-arid, cold semi-arid, and humid climates, with temperature and sunshine hours having a smaller effect (Hossein Tabaria and Talaee, 2014). In Vietnam, Phan Thi Ha et al. found that evapotranspiration is most sensitive to sunshine hours, followed by relative humidity and minimum temperature in Gia Lai province, a tropical highland monsoon region in the northern Central Highlands (Ha et al., 2024).

This literature review indicates that most studies on ET and meteorological variables primarily use statistical analysis, multivariate regression, and correlation analysis. Results suggest that ET sensitivity varies with different climates. However, these studies have not explored the bidirectional relationships between variables. Natural systems are dynamic, multidimensionally interactive, and often nonlinear, especially in climate systems where ET results from complex interactions among meteorological factors. This means that while factors like temperature and humidity affect ET, ET may also influence these factors in return. Quantifying the impact level and direction (positive/negative) of these effects on ET will improve our understanding of water demand impacts and support more accurate water balance calculations.

In addition to meteorological factors, vegetation cover significantly influences ET. Changes in vegetation structure can lead to shifts in climatic conditions, affecting ET. Studies by Bosch et al. and Zhang et al. have shown that forest vegetation has a more substantial impact on ET than other ecosystems, with denser vegetation, particularly forests, leading to higher ET compared to arid regions (L. Zhang et al., 2001, J.M. Bosch and Hewlett, 1982). Wang and Jin demonstrated that changes in vegetation cover significantly affect ET. During the vegetation recovery period from 1983 to 2014, vegetation cover increased from 30% to 60%, causing a corresponding increase in ET. Periods of high cover maintained a positive relationship between ET and vegetation, as trees enhanced transpiration and evaporation (Wang et al., 2018). Zhang et al. also confirmed that watersheds with forest cover tend to have higher ET than areas with fewer trees due to the strong transpiration from tree foliage (L. Zhang et al., 2001).

The upper Dong Nai River basin, essential for providing forest environmental services to downstream and surrounding areas, has a tropical monsoon climate with distinct rainy and dry seasons. Seasonal variations in temperature, rainfall, sunshine hours, and humidity significantly influence ET. Furthermore, from 1994 to 2014, 23% of the forest area in the basin was converted for agricultural and hydropower development. During this period, agricultural land increased from 18.2% to 31.3%, and water surface area expanded from 0.9% to 2.2% (Hung et al., 2019), affecting total ET across the basin.

As discussed above, further research is necessary to understand the non-linear and multidimensional causal relationships between climate variables and ET, as well as the interactions among the climate variables themselves. The Convergent Cross Mapping (CCM) analysis method can address this by detecting virtual correlations, isolating weak correlations, and identifying bidirectional causal relationships within complex natural systems. However, CCM does not indicate the direction (positive/negative) of causal effects, so Spearman correlation analysis can be used alongside CCM to determine this. Additionally, using reference evapotranspiration (ETo) enables standardized ET estimates across varying conditions. The Food and Agriculture Organization (FAO) has recommended the Penman-Monteith method as the standard for estimating ETo (FAO, 2006, Allen et al., 1998).

This study focuses on two main objectives: (1) Applying the Convergent Cross Mapping (CCM) method combined with Spearman correlation analysis to quantitatively assess the bidirectional causal relationship between meteorological factors and seasonal ET in the upper Dong Nai River basin, using 39 years of observational data (1984–2023). (2) Analyzing the sensitivity of each meteorological factor to ET. The Penman-Monteith equation is employed to calculate ETo, with temperature, humidity, wind speed, and sunshine hours adjusted within a range of ±20% (−5%, −10%, −20%, +5%, +10%, +20%) relative to the actual calculated values. The study results will help determine the required accuracy when measuring climatic variables for ET estimation and aim to simplify ET calculations in water balance models and hydrological simulations in the upper Dong Nai River basin.

2. Geological background

2.1. Description of the Study Area

The upstream Dong Nai River in Lam Dong province covers an area of 6,767 km², including the main branches of Da Nhim, Da Dang, and Dak R'Tih (originating from Dak Nong province). The northern part of the study area has elevations ranging from 1,300 m to over 2,000 m, while the central area consists of low hills and mountains with altitudes varying between 700 and 1,300 m. The southern area is a transitional zone between the plateau and the plains, with elevations ranging from 50 to 700 m. The location and elevation model of the study area is shown in Figure 1. This basin plays an essential role in providing environmental services to downstream and surrounding areas, including water supply for hydropower development, daily life, agriculture, industry, pollutant dilution, and regional climate regulation.

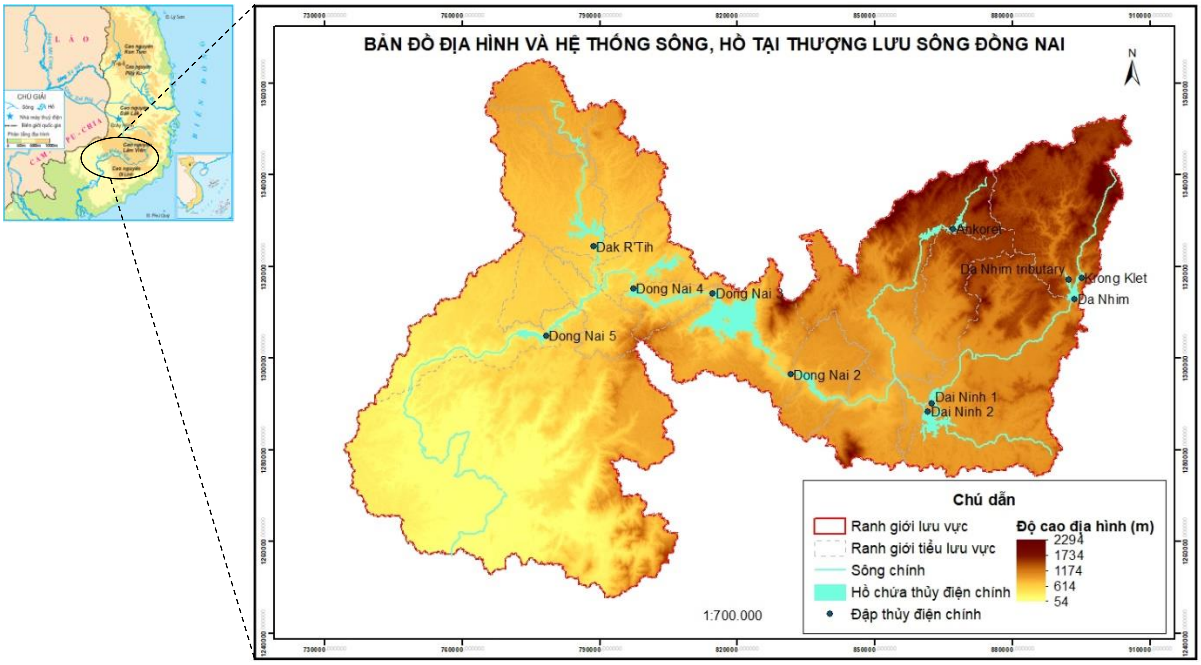

Fig. 1. The upstream Dong Nai River

The study area has a tropical monsoon climate, with an average temperature of 18–25ºC. There are significant temperature variations across regions, with temperatures decreasing as altitude increases. The temperature difference between the hottest and coldest months ranges from 3–6ºC. The basin experiences two distinct seasons: the rainy season, from May to November, and the dry season, from December to April of the following year. During the rainy season, the basin receives substantial rainfall, with average annual totals ranging from 1,750 mm to 3,150 mm. August typically has the highest rainfall, averaging about 356 mm, and this season often features high cloud cover, sometimes reaching up to 95%. The dry season is characterized by dry, sunny weather, especially from December to March when cloud cover is low and rainfall averages less than 50 mm. Daytime temperatures during this season can range from 28ºC to 32ºC, while nighttime temperatures drop to around 18ºC – 20ºC. Water loss due to infiltration and evaporation accounts for 43–44% of total annual rainfall (LamDong, 2023).

Annual rainfall is unevenly distributed in both space and time, ranging from 1,600 to 2,700 mm. The southwest windward slope receives significant rainfall, totaling between 3,200 and 3,500 mm annually. To the east and northeast, rainfall gradually decreases to only 600–1,700 mm. During the dry season, rainfall accounts for just 10–15% of the annual total, often leading to drought, which is highly unfavorable for production. The average number of sunshine hours per year is 1,890–2,500, supporting the development of resort tourism, temperate crops, and livestock. Average air humidity ranges from 78% to 84%, with dry season humidity between 75% and 80% and rainy season relative humidity from 84% to 88%. Wind potential is concentrated in the north, with speeds of 7.5–8 m/s, while the southern region experiences average wind speeds of 6.5–7 m/s. Although storms are rare, the area is frequently affected by low-pressure systems from the East Sea, resulting in prolonged winds and rain.

The characteristic terraced terrain, along with favorable natural conditions such as soil and climate, creates an ideal environment for the development of ecosystems (ES), animal and plant species, and crops and livestock of subtropical and temperate origins within the equatorial tropics. Forest ecosystems occupy the largest area (about 60% of the natural area) and include major vegetation types such as evergreen broadleaf, mixed broadleaf and coniferous, coniferous, deciduous broadleaf, bamboo mixed with scattered trees, bamboo/shrubland, and grassland. In this basin, deforestation began in 1996, with the highest rate occurring in 1999 (Nguyen Cung Que Truong et al., 2018). From 1994 to 2014, 23% of the forest area in the basin was converted for agricultural development and hydropower projects, with agricultural land increasing from 18.2% to 31.3% and water surface area expanding from 0.9% to 2.2% (Hung et al., 2019).

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These changes have led to increased water loss due to evaporation from the ground and transpiration from plants.

2.2. Data

Meteorological data were provided by the Central Highlands Regional Hydro-Meteorological Station. Six parameters were selected for quantitative analysis of causal relationships and for calculating ETo using the Penman-Monteith equation. These parameters, collected from four meteorological stations over the period 1981–2023, include air temperature (T, °C), relative humidity (RH, %), wind speed (u, m/s), sunshine hours (n, h), rainfall (R, mm), and evapotranspiration (ETo, mm/day). Before conducting calculations and analyses, monthly data were processed statistically to ensure accuracy. Table 1 describes the geographic and climatic characteristics of the stations.

The R software, along with the Openair and rEDM packages, was utilized as computational tools to support this analysis.

Tab. 1. Geographic and climatic characteristics of the stations.

Station	Longtitude (N)	Latitude (E)	Altitude (m)	T (ºC)	RH (%)	n (h)	u (m/s)	R (mm)	ET (mm/day)
DaLat	11.57	108.27	1513	18.1	85.5	6.2	2.4	155,1	69,1
BaoLoc	11.32	107.49	850	22.1	85.5	5.6	1.5	244.0	55.1
DakNong	12.00	107.41	424	22.9	83.3	6.6	2.1	208.5	72.1
PhuocLong	11.50	106.59	45	25.9	79.2	7.1	1.7	55.7	95.4

T:Air temperature; RH: Relative Humidity; u:Winds peed (10 m); n: Sunshine hours.

3. Methodology

3.1. Statistical analysis and data normalization

R is a programming language, primarily used for statistical analysis and data visualization. Developed from the S language in the early 1990s, R has become a standard tool in various fields, including biology, finance, social sciences, and climate science, due to its capacity to process and visualize complex data.

The input data requirements for analyses in R software are: (1) Data with no missing values, no measurement errors, and no outliers that could distort the analysis; (2) Data that ensures continuity, reliability, and accurately represents the climate factors or systems under analysis.

With a 39-year monthly average data series (1984 – 2023) containing six meteorological factors—air temperature (T, °C), relative humidity (RH, %), wind speed (u, m/s), sunshine hours (n, h), rainfall (R, mm), and evapotranspiration (ETo, mm/day). The data processing packages include: Dplyr – Summary statistics for each meteorological variable, including calculations of the mean, median, standard deviation, min, max, and percentiles; Tidyr – Sorting and reorganizing data; Naniar – Visualizing missing data; Outliers and Scales – Detecting and handling outliers; Ggplot2 – Visualizing descriptive data using histograms, boxplots, or density charts.

3.2. Quantifying the impact of meteorological factors on ET by applying the CCM method

The theoretical basis of the Convergent Cross Mapping (CCM) method lies in nonlinear dynamical systems and manifold theory, especially as applied to systems where causation can be indirect or non-obvious. Developed by George Sugihara and colleagues, CCM is designed to detect causal relationships in complex systems where traditional correlation or linear causality methods may fail, particularly in the presence of weakly coupled variables or non-separable systems (Sugihara et al., 2012, Takens, 1981).

This approach allows CCM to reveal causal interactions by observing how well each variable's history can predict the other's dynamics in a reconstructed space, even when experimental interventions are impractical. Specifically, the key equations in Convergent Cross Mapping (CCM), illustrating the method for identifying causal relationships between two time series, X and Y, based on state space reconstruction. First, X and Y are the two variables to be considered as follows.

$$\{X\} = \{X(1), X(2), \ldots., X(L)\} \quad (1)$$

$$\{Y\} = \{Y(1), Y(2), \ldots., Y(L)\} \quad (2)$$

Where, L is the length of period (sample size). Correspondingly, for a variable Y observed over time, we construct a lagged vector using an embedding dimension E and time lag τ:

$$x(t)=(X(t), Xt-\tau), X(t-2\tau), \ldots, X(t-(E-1)\tau)) \quad (3)$$

$$y(t)=(Y(t), Y(t-\tau), Y(t-2\tau), \ldots, Y(t-(E-1)\tau)) \quad (4)$$

Where, t ranges from 1+ (E-1)τ to L; E is the number of dimensions of the space under consideration and is chosen to ensure that the reconstructed space captures the dynamics of the system; τ is the time lag, often determined experimentally.

For Crossing Mapping and Prediction, CCM uses the reconstructed space of Y to predict values of X. It is based on the idea that if Y contains information about X (due to a causal link), then it should be possible to approximate X using the state space of Y. Given a point Y(t) in Y's reconstructed state space, the nearest neighbors to Y(t) are used to estimate X:

$$\hat{X}(t) = \sum_{i=1}^{k} w_i X(t_i) \quad (5)$$

Where, $\hat{X}$(t) is the estimated value of X at time t; w_i are weights for the nearest neighbors, typically defined as:

$$w_i = \frac{\exp\left(-{d_i}/{d_1}\right)}{\sum_{j=1}^{k} \exp\left(-{d_j}/{d_1}\right)} \quad (6)$$

with d_i being the distance from Y(t) to its i-th nearest neighbor, and d_1 as the smallest distance to ensure normalized weights.

The correlation coefficient ρ between the observed values of X and the predicted values $\hat{X}$assesses the accuracy of cross mapping:

$$\rho = \text{correlation}(X, \hat{X}) \quad (7)$$

If ρ increases with larger library sizes, it suggests that Y has causal information about X. By increasing the library size L, we observe if ρ converges, confirming the causal relationship between X and Y:

$$\lim_{L \to \infty} \rho(L) = \rho_{max} \quad (8)$$

where ρ_{max} indicates the stable causal influence of Y on X as more historical data is incorporated.

Values of rho (ρ):

ρ = 1: This indicates a strong causal relationship, meaning the target variable can be accurately predicted from the state space of the source variable.

ρ > 0 and < 1: This shows a causal relationship, but not an entirely strong one. The larger the value, the clearer the relationship.

ρ ≈ 0: When rho is close to 0, this suggests that there is no clear causal relationship between the two variables.

In this study, the rEDM package version 4.2.0 in R software was used to implement the CCM method. The rEDM package, developed by the Sugihara Laboratory at the Scripps Institution of Oceanography, University of California San Diego, contains mathematical techniques, including the CCM method, which utilizes experimental data through manifold reconstruction to simulate a time-varying system. The input data provided to the rEDM package for CCM calculations consists of paired time series data of ET and each meteorological factor. Five meteorological factors are considered, resulting in five pairs of time series: ET and T, ET and RH, ET and u, ET and n, ET and R. To observe the impacts of meteorological factors on ET over time, the pairs of time series are divided by month. Accordingly, CCM calculations are performed monthly at each station for each pair of time series.

Additionally, to detect interactions between meteorological factors and examine the indirect effects of these factors on ET through their direct impact on other meteorological factors, time series pairs among the five meteorological factors are considered. These include T and RH, T and u, T and n, T and R, RH and u, RH and n, RH and R, u and n, u and R, and n and R.

The parameter settings for CCM analysis are as follows: (1) Embedding Dimension (E): This represents the number of dimensions necessary to capture the characteristics of the time series in the state space. The optimal value of E can be determined through trial and error, typically ranging from 3 to 7. In this study, E is set to 3 to achieve a strong correlation coefficient between variables. (2) Library Size (Libsize): This is the number of samples used to determine the relationship between variables. In this study, the library size is 38. (3) K-nearest neighbors (knn): knn specifies the number of nearest neighboring points required to interpolate and reconstruct the state space for the target variable. These neighbors are used to predict the target variable's values based on the source variable's state space. Here, knn is set to E + 1. (4) Sample: This defines the number of random repetitions for each libSize value. This parameter specifies the number of samples randomly selected from the data library to calculate the rho correlation coefficient between variables. A starting value of sample = 100 is commonly used, allowing sufficient sampling for reliable results without overly taxing computational performance.

After performing the CCM calculations, the results produced convergent cross maps and ρ values to evaluate the impact of meteorological factors on ET.

3.4. Determining the Direction of the Impact of Meteorological Factors on ET Using Spearman Correlation Analysis

Spearman's rank correlation coefficient, commonly denoted as Spearman's ρ (ρ_s), is a nonparametric measure that assesses the strength and direction of association between two ranked variables. Unlike Pearson's correlation (ρ), which evaluates only linear relationships, Spearman's correlation (ρ_s) captures monotonic relationships, making it suitable for data that may not follow a normal distribution or linear pattern.

The Spearman correlation coefficient is calculated based on the ranks of the data values, using the formula:

$$\rho_s = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \qquad (9)$$

Where, d_i is the difference between the ranks of each data pair, and nnn is the number of observations (data pairs).

Interpreting Spearman's ρ: ρ_s = +1: Perfect positive monotonic relationship; ρ_s = -1: Perfect negative monotonic relationship; ρ_s = 0: No monotonic relationship.

In analyzing the influence of meteorological factors on evapotranspiration (ET), the Convergent Cross Mapping (CCM) method helps identify whether factors like temperature, humidity, precipitation, and wind speed have a causal effect on ET. However, CCM mainly focuses on establishing causality and does not provide information on the direction or strength of these relationships. To fill this gap, Spearman correlation analysis is conducted after CCM to determine both the direction and intensity of these relationships.

Once CCM confirms a causal relationship, Spearman correlation analysis provides additional insights: (1) Direction of the Relationship: Spearman analysis indicates whether the relationship is positive or negative. A positive Spearman coefficient (ρ_s) suggests that as the meteorological factor increases, ET also increases; conversely, a negative ρ_s implies that ET decreases as the factor increases; (2) Strength of the Relationship: The absolute value of ρ_s indicates the strength of the relationship, making it easier to compare the influence of various meteorological factors on ET. A ρ_s value close to 1 (or -1) signifies a strong relationship, while a ρ_s value near 0 indicates a weak or non-existent relationship.

This combined approach provides a comprehensive understanding of both the presence and nature of interactions between meteorological factors and ET.

3.5. Evaluation of ET sensitivity with Penman-Monteith Equation

Sensitivity analysis of evapotranspiration (ET) to climate variables is essential to understanding how changes in factors like temperature, wind speed, and sunshine hours influence water requirements for agriculture, water resource planning, and climate adaptation strategies. The analysis can reveal which climate variables most significantly impact ET across different climate types, which helps prioritize variables in weather models, supports water management decisions, and anticipates the effects of climate change on hydrological cycles in diverse regions. Building on the causal relationships and directional impacts between ET and climate variables identified through Convergent Cross Mapping (CCM) and Spearman correlation analysis, sensitivity analysis further clarifies how fluctuations in air temperature (T, °C), relative humidity (RH, %), wind speed (u, ms^{-1}), and sunshine hours (n, h) affect ET. This incremental approach enabled the study to quantify the precise impact of each climate variable on ET, complementing the CCM and Spearman analyses by showing the extent of ET's sensitivity to shifts in individual climate factors.

The Penman-Monteith equation, widely adopted by the Food and Agriculture Organization (FAO) in FAO-56, is a standardized formula for estimating reference evapotranspiration (ETo) based on meteorological factors. The Penman–Monteith method assumes the ETo as that from a hypothetical crop with an assumed crop height (0.12m) and a fixed canopy resistance (70sm−1) and albedo (0.23), closely resembling the evapotranspiration from an extensive surface of green grass cover of uniform height, actively growing, and not short of water,which is given by Allen et al.(Allen et al., 1998) as follows:

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The Penman-Monteith equation is expressed as (FAO, 2006, Hossein Tabaria and Talaee, 2014, Allen et al., 1998)

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \qquad (10)$$

Where ETo is the reference evapotranspiration ($mmday^{-1}$); R_n is the net radiation at the crop surface (MJm-²day-1); G is the Soil heat flux density ($MJm^{-2}day^{-1}$), typically close to zero when calculated over a day period; T is the mean daily air temperature (°C); u_2 is the wind speed at 2 meters above ground (ms^{-1}); e_s is the Saturation vapor pressure (kPa); e_a is the actual vapor pressure (kPa); $(e_s - e_a)$ is the vapor pressure deficit (kPa); Δ is the slope of the vapor pressure curve (kPa°C^{-1}); γ is the psychrometric constant (kPa°C^{-1}). It should be noted that the 24-h wind speed was recorded at a 10m height at the study stations, and the necessary corrections were applied to determine its values at a 2 m height.

ETo calculations, established using baseline climate data from each station and calculated with the Penman-Monteith equation, provided the foundation for this analysis. Each climate variable was adjusted individually, increasing and decreasing by increments of ±5%, ±10%, and ±20% from long-term average values. The findings will demonstrate that ETo's response varies with changes in each parameter, highlighting the practical significance of each climate variable's influence on evapotranspiration.

4. Results

4.1. Causal effects between ET and meteorological factors

The CCM analysis for the upper Dong Nai River basin identified and quantified causal relationships between five pairs of individual meteorological factors and ET (denoted as ET–R, ET–T, ET–RH, ET–n, ET–u) as well as ten pairs of interacting meteorological factors (T–R, T–RH, T–n, T–u, R–RH, R–n, R–u, RH–n, RH–u, n–u). The causal strength of individual meteorological factors on ET was measured using the ρ value. Additionally, to determine the direction of these causal relationships, the ρ_s value was calculated using Equation (9) in Section 3.4, and the results are illustrated in Figures 2, 3, and 4.

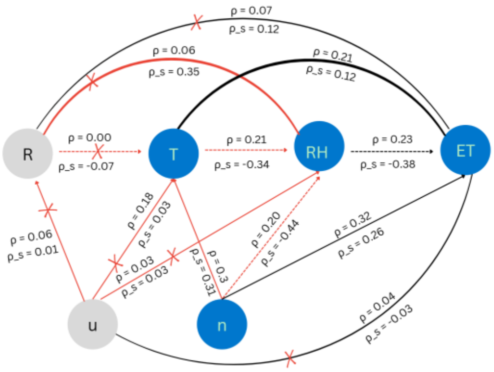

Fig. 2. Diagram of causality and direction of impact of meteorological factors on ET in the upper Dong Nai River basin. The black line describes the relationship between ET and factors, and the red line describes the relationship between factors.

—— Direct causality

------ Reverse causality

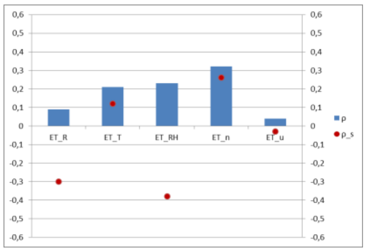

Fig. 3. Impact level and direction of causal relationship between individual meteorological factors and ET.

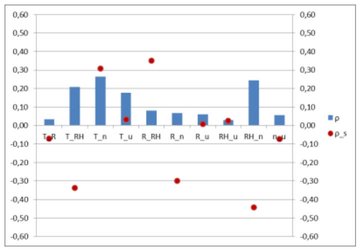

Fig. 4. The level of impact and direction of impact of the causal relationship between meteorological factors.

Figure 2 indicates that, in this basin, initial consideration of the pairs ET–R and ET–u reveals distinct findings. For the ET–R pair, rainfall (R) does not have a direct causal relationship with ET, as shown by ρ = 0.07 and ρ_s = 0.12. This can be explained as follows: during the rainy season, rainfall supplies water to the soil and vegetation, increasing soil and air humidity. With the influence of temperature, ET rises rapidly; however, once soil and crops reach saturation and air temperature stabilizes, ET decreases and eventually ceases (Penman, 1948, Allen et al., 1998). During the dry season, lower rainfall results in reduced soil and air humidity, coupled with a stable temperature, promoting evaporation from the soil and plant transpiration, thereby causing an increase in ET. Due to the characteristics of the rainy and dry seasons lasting six months each, with average rainfall of 233 mm/month during the rainy season and 46 mm/month during the dry season, and a temperature difference of 1–2°C between the two seasons, rainfall in the basin exhibits a causal relationship with ET (ρ = 0.21), but inversely (ρ_s = -0.38). This indicates that R impacts ET

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indirectly through T and RH. Notably, the CCM analysis of R–T and R–RH pairs indicates no direct causal relationship between R and T (ρ = 0.00, ρ_s = -0.07) or RH (ρ = 0.06, ρ_s = 0.35), suggesting that the direct relationship between R and ET can be disregarded. For the ET–u pair, wind speed (u) shows no causal relationship with ET, as the ρ and ρ_s values are minimal (ρ = 0.04, ρ_s = -0.03). Theoretically, wind speed (u) can positively influence ET through its effect on RH (increased u leads to higher water loss from soil and plants, reducing RH, which in turn increases ET and vice versa). However, the CCM analysis reveals that the factor pairs RH–u (ρ = 0.03, ρ_s = 0.03) and T–u (ρ = 0.18, ρ_s = 0.03) lack causal relationships (Figures 3 and 4).

Penman and Allen observed that sunshine hours (n) and relative humidity (RH) are typically inversely related. As sunshine hours increase, solar radiation raises air temperature, enabling the air to retain more water vapor, which generally lowers RH as the air becomes drier and more prone to evaporation. Conversely, reduced sunshine hours (such as on cloudy or rainy days) increase RH as the air becomes more saturated with moisture, decreasing ET (Allen et al., 1998, Penman, 1948). The CCM analysis results demonstrate that n and T have causal relationships with ET through RH (Figure 2). Spearman's analysis further indicates the degree of positive and negative correlations between these factors and ET. The results show that sunshine hours (n) and T have positive causal relationships, where increased n raises air temperature T (ρ = 0.3, ρ_s = 0.31). In contrast, T and RH have negative causal relationships, where higher T accelerates evaporation from soil and plants, reducing RH (ρ = 0.21, ρ_s = -0.34). RH and ET exhibit a negative causal relationship, with reduced RH leading to increased ET (ρ = 0.23, ρ_s = -0.38). The findings indicate that, among the pairs ET–n and ET–RH, sunshine hours (n) most strongly affect ET, displaying a positive correlation (ρ = 0.32, ρ_s = 0.26), followed by RH, which has a negative causal relationship with ET (ρ = 0.23, ρ_s = -0.38) (Figure 3). Additionally, n impacts ET through RH, with a negative causal relationship between n and RH (ρ = 0.20, ρ_s = -0.44) (Figure 2). In summary, for the upper Dong Nai River basin, the CCM analysis demonstrates that sunshine hours (n) have the strongest influence on ET through air temperature (T) and relative humidity (RH). Sunshine hours are positively related to T, T negatively affects RH, and RH negatively influences ET (Figure 5).

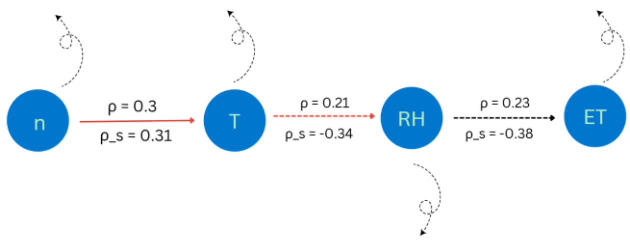

Fig. 5. Illustration of the causal relationship between n and ET in the upper Dong Nai River basin.

Seasonally, in the rainy season, the relationships between the factors and ET remain consistent, reflecting the overall basin characteristics (Figures 6, 7, 8, 9). In the dry season, in addition to the influence of temperature (T), sunshine hours (n), and relative humidity (RH), wind speed also plays a role. However, ρ and ρ_s values between pairs decrease significantly, especially for T–RH and n–RH pairs. This can be attributed to the following: during the dry season, factors such as temperature, wind, and sunlight have a strong effect on ET. However, under limited soil moisture conditions, where water in the soil is insufficient, the effects of these factors become restricted since ET cannot increase further without an adequate water supply for evaporation or transpiration (Nghị, 2015, Nghị, 2016b, Federer et al., 1996). Consequently, although sunshine hours increased by 13% and wind speed by 3% compared to the rainy season (according to statistical data from 1984 to 2023), the strength of causal relationships with ET decreased due to soil water deficits limiting plant transpiration, making the direction of impact less clear (as indicated by low ρ_s values such as the T–u pair ρ_s = -0.02 despite ρ = 0.23, and the T–RH pair ρ_s = -0.01 despite ρ = 0.15, and RH–u pair ρ_s = 0.06 despite ρ = 0.2). Although the strength of causal relationships weakens, ET continues to be primarily influenced by RH (with the highest ρ = 0.23), followed by u and T (ρ = 0.2), and n (ρ = 0.14). In the rainy season, n has the most significant influence on ET, with clear causal direction reflected by high ρ_s values (Figure 10). Conversely, in the dry season, RH becomes the dominant factor affecting ET, with less defined directional impacts (low ρ_s values), while RH itself is influenced by n and u (RH–n ρ = 0.14, RH–u ρ = 0.2) (Figures 11).

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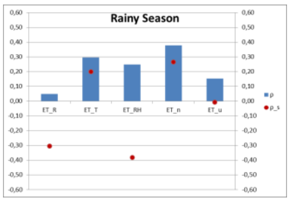

Fig. 6. Impact level and direction of the causal relationship between individual meteorological factors and ET in the rainy season.

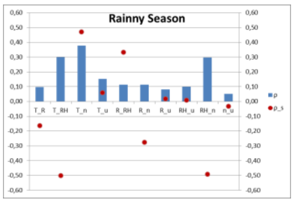

Fig. 7. The level of impact and direction of impact of the causal relationship between meteorological factors in the rainy season.

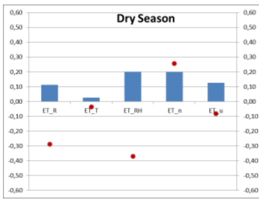

Fig. 8. Impact level and direction of the causal relationship between individual meteorological factors and ET in the dry season.

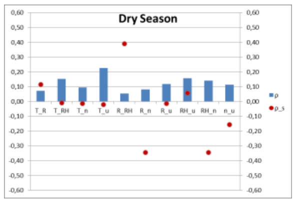

Fig. 9. Impact level and direction of causal relationship between meteorological factors in the dry season.

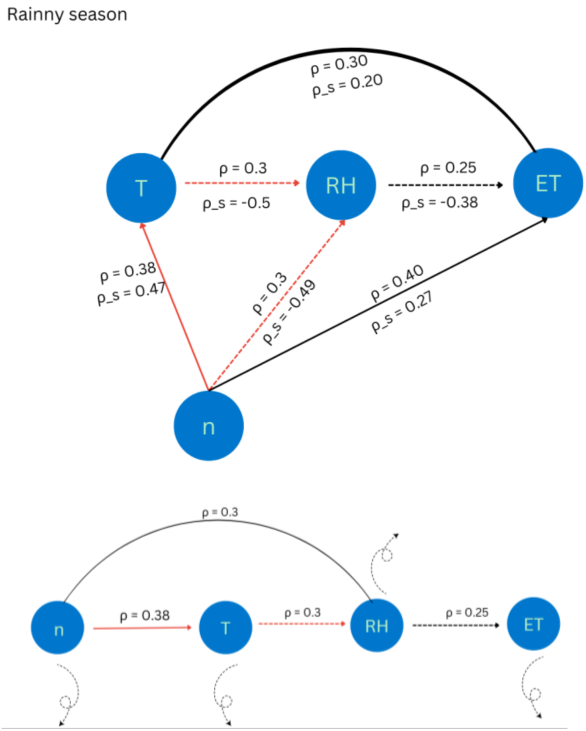

Fig. 10. Diagram of causality and direction of impact of meteorological factors on ET in the rainy season. The black line describes the relationship between ET and the factors, and the red line describes the relationship between the factors.

—— Direct causality

------ Reverse causality

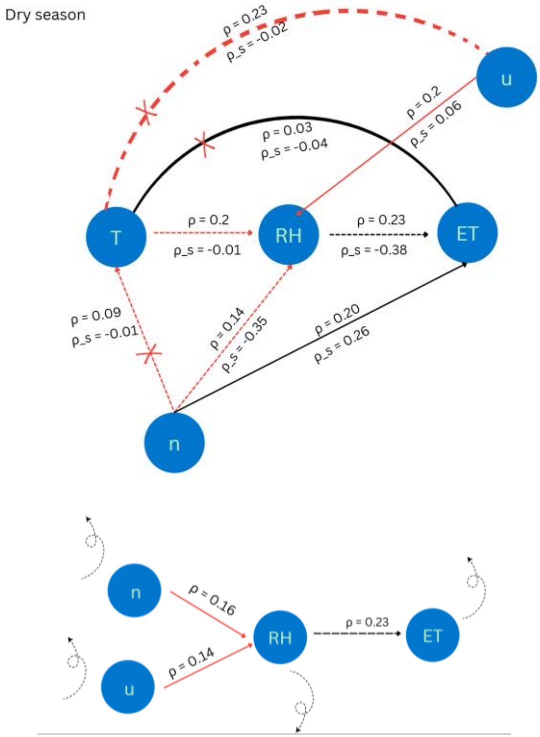

Fig. 11. Diagram of causality and direction of impact of meteorological factors on ET in the dry season. Black lines describe the relationship between ET and factors, red lines describe the relationship between factors with each other.

—— Direct causality

------ Reverse causality

4.2. Sensitivity of ET to meteorological factors

The changes in ETo, when climatic factors were adjusted within a range of ±20% in 5% increments, are shown in Table 2. The results showed that ET was most sensitive to RH. Each 5% increment of RH change resulted in an inverse change in ET of 3.6%. Theoretically, RH is an important factor in evapotranspiration, as it directly affects the ability of the air to hold water vapor. As RH increases, the air becomes more saturated, reducing evaporation from soil and plant surfaces, thereby reducing ET. This means that when the air is deficient in moisture, it promotes evaporation from the deficient soil and transpiration from plants (FAO, 2006, Allen et al., 1998). Any change in RH within 5% will result in a change in ET within 3.6%. This sensitivity reflects that under high humidity conditions, the ability to evaporate water from the soil surface and leaves is limited. Conversely, when RH decreases, the drier air

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will increase evaporation and transpiration, increasing ET. Next to RH is air temperature T. Temperature plays an important role in regulating ET because it affects the saturation of water vapor pressure. As temperature increases, the ability of air to hold water vapor also increases, leading to faster evaporation and transpiration. Similar to RH, when T changes by 5%, ET changes by 3.1%. And the third sensitive factor to ET is n. When n changes in 5% steps, ET changes by 1.8%. So far, no study has evaluated the sensitivity of ET to meteorological factors in the tropical monsoon region such as the upper Dong Nai River basin. Therefore, this result indicates that ET is most sensitive to RH, followed by T, which can be explained by the fact that air saturation has a more rapid and direct impact on evaporation than air temperature. Meanwhile, although temperature has a significant influence, it is not as strong as the change in relative humidity.

Tab. 2. Sensitivity of Eto to climatic change in the upper Dong Nai River basin

Factors	ΔETo (%) – Total basin								
	-20,0%	-15,0%	-10,0%	-5,0%	0,0%	5,0%	10,0%	15,0%	20,0%
T (ºC)	-11,9%	-9,0%	-6,0%	-3,0%	0,0%	3,1%	6,2%	9,4%	12,7%
RH (%)	14,1%	10,6%	7,1%	3,6%	0,0%	-3,6%	-7,2%	-10,8%	-14,4%
n (h/day)	-7,1%	-5,3%	-3,6%	-1,8%	0,0%	1,8%	3,6%	5,3%	7,1%
u (m/s)	-0,4%	-0,3%	-0,2%	-0,1%	0,0%	0,1%	0,2%	0,3%	0,4%

T:Air temperature; u: Wind speed; n: Sunshine hours.

At each meteorological station, Figure 12 shows that RH and T are two factors affecting the sensitivity of ET, in which DaLat and DakNong stations show the clearest sensitivity, followed by BaoLoc and PhuocLong stations. These meteorological stations are located at different altitudes and have different meteorological characteristics (Table 1), however, the simulation results are quite similar in terms of the influence of RH, T, and n on ET.

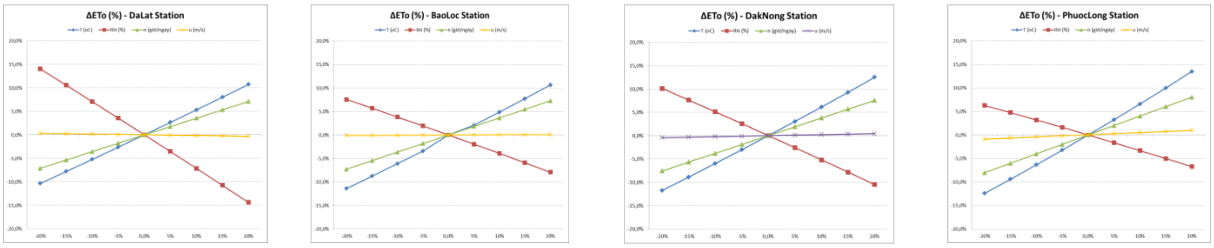

Fig. 12. Representation of the change in ETo when the climatic factors are adjusted within ±20% with a step of 5% at each meteorological station.

5. Discussion

This study applied the CCM analysis method combined with Spearman correlation and sensitivity analysis to identify the meteorological factor that most strongly influences ET, as well as the direction of its impact. The results revealed that sunshine hours (n) have an indirect causal relationship with ET through their effects on air temperature (T) and relative humidity (RH), highlighting that solar radiation plays a decisive role in promoting the evapotranspiration process. Specifically, when n increases by 5%, ET increases by 1.8%; when T rises by 5%, ET increases by 3.1%; and when RH increases by 5%, ET decreases by 3.6%. These findings underscore the importance of monitoring solar radiation and sunshine hours for effective irrigation management and water demand forecasting in agriculture.

Relative humidity (RH) is the most sensitive factor directly affecting ET, with a negative relationship ($\rho = 0.28$, $\rho\_s = -0.38$). When RH increases by 5%, ET decreases by 3.6%, emphasizing the need for careful monitoring. During periods of low humidity, ET increases, indicating reduced soil moisture and higher crop water demand, which is crucial for water resource management during the dry season in the basin. Temperature (T) has a positive relationship with ET ($\rho = 0.21$, $\rho\_s = 0.12$) and ranks as the second most influential factor after RH (when T increases by 5%, ET increases by 3.1%). However, CCM analysis shows that the T–ET relationship is mediated by RH (T–RH has $\rho = 0.21$, $\rho\_s = -0.34$). Seasonal analysis reveals that during the rainy season, T has a strong influence on ET ($\rho = 0.3$, $\rho\_s = 0.20$), whereas in the dry season, T's impact is weaker ($\rho = 0.03$, $\rho\_s = -0.04$). This is an important consideration for future evaluations, particularly in the context of climate change, as temperature fluctuations in the basin and globally are expected to increase and vary by season.

The CCM method, while having notable strengths in analyzing causal relationships in nonlinear and complex systems, has certain limitations. The main observations regarding its application in this study are as follows:

- ✓ **Time Series and Data Quality Requirements**: CCM performs best with long time series and high-resolution data. The Pearson correlation coefficient ρ tends to increase with larger library sizes (L). Insufficient observations or noisy data may hinder the detection of causal relationships. This study utilized monthly data over a 39-year period (1984–2023), equating to 468 data points. If daily data were used, the analysis would likely yield higher accuracy.
- ✓ **Sensitivity to Noise and Data Accuracy**: Noisy or skewed data can challenge CCM's ability to detect true causal relationships. For instance, inaccurate temperature or sunshine hour measurements may interfere with the analysis. Thus, meticulous data processing is essential, including noise removal and multiple iterations with different E and knn values to achieve the highest ρ value.
- ✓ **Limitations in Detecting Weak or Complex Relationships**: CCM may struggle with weak or highly complex causal relationships. This was evident during dry season analyses, where RH was simultaneously influenced by n, u, and T. Sensitivity analysis of ET to climatic factors was required to validate and accurately assess ET's responsiveness to variable climate conditions, especially in temperate climates within the tropical monsoon zone of the upper Dong Nai River basin.
- ✓ **Limitations in Generalizability**: The results of causal analyses between climate factors and ET may be region-specific and not generalizable to areas with different climatic conditions.

6. Conclusion

This study contributes to understanding ET sensitivity to meteorological factors, emphasizing the need for precise data on sunshine hours, temperature, and RH in tropical monsoon areas like the Dong Nai River basin. Accurate data collection enhances the reliability of ET estimations for drought forecasting and water balance models, particularly for calculating irrigation water demand during dry seasons.

While significant research exists on the relationship between ET and meteorological factors, gaps remain regarding specific climate zones like tropical monsoons and climate change impacts. Future studies should address these gaps to provide a more comprehensive understanding of ET, thereby supporting better water resource management and climate adaptation strategies.

Although CCM is effective for detecting causal relationships in complex, nonlinear systems, it has limitations such as the need for extended time series, sensitivity to noisy data, and challenges in handling highly complex relationships. When applied to the analysis of ET and meteorological factors, CCM should be used cautiously, particularly with noisy and asynchronous data. Combining CCM with other analytical methods can help overcome these limitations and offer a more holistic understanding of the relationships between meteorological factors and ET.

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