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RESEARCH ARTICLE

Analysis of rainfall variability and spell dynamics in Coimbatore using copula function modelling

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Abstract

This study investigates the coupled dynamics of rainfall and evapotranspiration in Coimbatore, a major urban and agricultural hub in southern India, over 31 years (1994–2024). Aside from areas near the Noyyal River basin and episodic overflow from the Western Ghats, the region is predominantly dry, receiving approximately 665.5 mm of annual rainfall over about 45 rainy days and exhibiting a yearly average temperature of 25.4 °C. Advanced statistical techniques, including Gaussian, t, Frank, Roch-Alegre and BB5 copula-based models, are employed to analyse key hydroclimatic indicators: the conditional probability index (CPI), moisture availability index (MAI) and potential evapotranspiration (PET). These models facilitate forecasting of wet and dry spells and provide insights relevant to drought preparedness, sustainable water management and agricultural planning in monsoon-dependent regions. Rainfall patterns and drought risk are quantified using MATLAB, enabling discrimination between low- and high-rainfall trends that are critical for rainfed agriculture. Wet and dry spell dynamics are further evaluated using the Mann-Kendall and Spearman's Rho non-parametric tests at the 5 % significance level, supporting the identification of atmospheric demand patterns and characteristic monsoon periods. The results reveal substantial variability in hydrological regimes, characterized by abrupt transitions between extreme wet and dry spells and highlight years of pronounced moisture deficiency alongside periods of excessive moisture. This comprehensive framework, which employs the Gaussian copula function, enhances understanding of climate variability and offers actionable strategies for managing hydroclimatic risks in vulnerable regions.

Keywords: copula models; conditional probability index; moisture availability index; potential evapotranspiration; wet and dry spells

Introduction

Coimbatore is classified as one of the most industrialised and economically advanced districts in the state, relative to other regions. It is the third most populous city in the state and is commonly known as the "Textile city of South India" or the "Manchester of South India." Coimbatore is located at an elevation of about 427 m above mean sea level (1). Coimbatore experiences an average annual temperature of 25.4 °C and receives an average rainfall of 952 mm. The Coimbatore district experiences a tropical wet and dry climate, with a wet season from October to December and a Southwest monsoon from June to September, with most precipitation in October (2).

Agriculture plays the main role in the economy and development of the country. Agriculture in this region depends heavily on rainfall patterns, which vary significantly over time and across different areas (3). Seasonal rainfall plays a critical role in sustaining the region's ecosystem health and economic stability. Extended rainy periods enhance agricultural productivity and contribute significantly to national food security (4). Moreover, rainfall distribution directly influences water availability for agriculture, industry, households and hydroelectric power generation. In this study, we analyse the CPI, MAI, PET, wet spell and dry spell using different copula functions. Mann-Kendall and Spearman's Rho tests are conducted at the 5 % significance level to identify low and high rainfed trends in the Coimbatore zone. The model was made using MATLAB and illustrated a portfolio analysis based on meteorological data spanning the period from 1994–2024. The interdependence between rainfall and CPI, MAI and PET under different copula functions is modelled to identify low- and high-rainfall regimes.

A probability model for crop development and the growing season's water balance. To determine the optimal precipitation levels and estimate the water requirements for healthy crop growth, he considered 52 standard weeks covering the entire growing season and analysed them using probability theory (5). The mid-season floods are specifically associated with extreme wet periods (above the 99th percentile), which are linked to wet and dry spells, the CPI, MAI and PET (6). Crop productivity has been impacted by the increased frequency of dry periods, prolonged dry spells and premature and erroneous rainy season termination. Agricultural planning greatly benefits from the capacity to estimate the likelihood of a specific amount of rainfall.

The conditional probability of a wet week before a dry week is the probability that it will rain next week given that it rains this week and the conditional probability of a wet week followed by a dry week is the probability that it will rain next week given that it is dry this week (7). To date, only a few studies have analysed the influence of extreme dry and wet spells on agricultural yields, conditional probability index using the water satisfaction index (WSI) (8). However, as evident from the literature, there remains a lack of comprehensive analysis of CPI, MAI, PET and wet and dry spells trend assessments (9). To accurately characterise extreme dry and wet spells in agriculture using the CPI and the WSI, a robust predictive modelling framework is required.

To address this gap, the present study introduces "analysis of rainfall variability and spell dynamics in Coimbatore using copula function modelling". The study examines different copula functions, namely the Gaussian copula, t copula, Frank copula, Roch-Alegre copula and BB5 copula, compared with CPI, MAI, PET and wet and dry spells trend analysis. A copula as a function that joins bivariate distribution functions with uniform with [0, 1] (10). Copulas models make it possible to create a multidimensional distribution that is relatively diverse and does not necessarily belong to the same family of distributions. Copulas can also be used to analyse the frequency of droughts (11). Copula-based multivariate analysis of hydro-meteorological dryness using the streamflow dryness index (SDI) during 3 months was discussed in a previous study (12). However, due to the coarse spatial resolution of approximately 10 km, this study is less suitable for the application at the regional or local scale.

The two-dimensional copulas are used to analyse the joint distribution of drought duration and severity for drought frequency analysis (13). The hydrological and climatological literature has made use of over a dozen copula families (14). Recently, copula functions have been used for hydrological multivariate analysis of floods, drought, runoff and precipitation (15). The analysis of the choice of copula significantly influences the shape and accuracy of severity-duration-frequency (SDF) curves (16). However, most research focuses on a limited set of copulas, including BB5, Clayton, Gumbel, Frank, t- and Gaussian copulas. When random variables are not normally distributed, traditional correlation measures may not fully capture dependence, necessitating copula-based approaches. It is quite difficult to separate the impacts of random variables, particularly when assessing the level of positive and negative reliance. In addition, wavelets have been explored by other researchers (17–19).

By using nonparametric methods such as wavelet transformation, probit transformation and multi-resolution analysis and comparison, as well as the Kernel copula function to account for boundary effects, this study seeks to estimate copula density. The wavelet approach provides an automatic method to deal with boundary effects because it disregards whether the time series is stationary or nonstationary. Five distinct copula functions-the Gaussian, Frank, Tawn, Rotation Tawn and Joe copulas-were employed to produce data in the simulation. Both fixed and non-fixed threshold values were used to estimate the series; nevertheless, there were issues with automatically managing boundary effects. To improve accuracy, a continuous wave analysis of the series was conducted.

To resolve the identified challenges, this study introduces five copula families- Gaussian, t, Frank, Roch-Alegre and BB5 copulas are employed to analyse the interdependencies among key climatic indicators, including the CPI, PET and MAI. The MATLAB analysis focused on rainfall occurrence. It found low and high rainfall trends in the CPI, MAI and PET using Gaussian copula, t copula, Frank copula, Roch-Alegre copula and BB5 copula. This study examines the application of copula function in particular the Gaussian copula modelling will effectively capture the dependence structure and joint variability of rainfall spells in Coimbatore, facilitating a robust assessment of extreme drought and wet periods and variations in rainfall distribution and spell dynamics, revealed by copula-based statistical analysis, which will correspond with key agroclimatic risks affecting local agriculture in the Coimbatore region. The major objective is to examine rainfall variability, both low and high and utilise copula function principles to model its joint behaviour with hydrological variables, to evaluate its impact on water availability and agricultural planning.

Materials and Methods

Study area and data collection

The study was conducted in Coimbatore, which has an area of 4723 km^2, located in the western part of Tamil Nadu. A series of weekly precipitation data was collected from the automatic weather station (AWS) in Coimbatore for the period 1994-2024. The 30-year period is the standard for climate analysis. It provides a reliable baseline to study long-term weather trends and includes recent data for current relevance. Precipitation data from Coimbatore AWS were assessed for randomness, homogeneity and trend absence using autocorrelation analysis on the monthly time series.

Conditional probability index

Conditional probability index is useful for projecting the receipt of a particular quantity of rainfall to carry out specific agricultural operations, as well as for dryland agriculture activities. The primary role is to identify the rainfall patterns, extreme events and to assess the drought risk. However, the factors of crop water need and effective rainfall have not yet been considered when calculating their conditional likelihood for crop planning. The CPI values can be calculated by:

$$\text{CPI} = \text{Mean} - \text{X} / \text{SD} \qquad \text{(Eqn. 1)}$$

where, CPI is conditional probability index, X is the required rainfall and SD is the standard deviation (20). The conditional probability approach had the same estimated indices as the Lagrange approach within the accuracy limits. It required the same computational effort as the approximate method. Additionally, the conditional probability approach is more flexible because it does not need an optimisation-based adequacy evaluation model (21). Conditional probability rainfall analysis is a statistical approach used to understand the sequence of wet and dry spells every week. It measures the four key probabilities: the chance of a wet week being followed by another wet week, a wet week being followed by a dry week, a dry week being followed by another dry week and a dry week being followed by a wet week (22).

Moisture availability index

Moisture availability index is uncertain due to the erratic and highly variable rainfall distribution across time and place. Moisture availability index is the ratio of assured rainfall to potential evapotranspiration during a specific period (23). Dryland crop productivity is highly uncertain, primarily influenced by seasonal rainfall patterns and moisture availability (24). It was introduced by Hargreaves, which quantifies the balance between reliable rainfall and potential evapotranspiration, offering a clear indicator of whether crops have enough water. The study demonstrates a significant link between crop output and levels of moisture sufficiency or shortage, indicating that agricultural productivity increases substantially when rainfall is equal to or greater than evapotranspiration needs (25). The classification of MAI into distinct categories, such as excessive moisture, adequate moisture, minimal deficit, moderate and very deficit, providing a framework for interpreting moisture conditions and their impact on crop productivity (Table 1).

Table 1. Moisture availability index

Moisture availability index	Category
0.00–0.33	Very deficient
0.34–0.67	Moderately deficient
0.68–1.00	Deficient
1.01–1.33	Adequate moisture
> 1.34	Excessive moisture

Potential evapotranspiration

Evapotranspiration (ET) refers to the process by which water changes from liquid to vapour at the land surface and moves into the atmosphere (26). ET can be estimated using different methodologies, including soil-water balance methods, lysimeter systems, Bowen ratio energy balance techniques, eddy covariance and scintillometer measurements, sap flow instrumentation and remote sensing technology (27). PET refers to the rate at which ET occurs when the surface is well supplied with water (28). The Food and Agriculture Organisation (FAO) has recommended the Penman-Monteith (FAO-56 PM) method for estimating PET (29). Future warming is predicted to increase ET in India, with a season-wise increase during the northeast winter monsoon and pre-monsoon periods (30). The Penman-Monteith method is highly reliable in estimating ET_0 in sub-humid regions (31). The ET_o method is more suitable for analysing extreme fire risks and climate change scenarios (32).

$$PET = \frac{0.408\ \Delta(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \qquad \text{(Eqn. 2)}$$

Where,

R_n = net radiation at the crop surface ($MJm^{-2}\ d^{-1}$)

G= soil heat flux density ($MJm^{-2}\ d^{-1}$)

T= mean daily air temperature at 2 m height (°C)

u_2= wind speed at 2 m height ($m\ s^{-1}$)

e_s= saturation vapour pressure (kPa)

e_a= actual vapour pressure (kPa)

e_s - e_a= saturation vapour pressure deficit (kPa)

Wet spell and dry spell

In the effective rainy period, if the simple ratio R/PE is not less than 1.5, we call the week as a wet spell. The week is referred to as a dry spell if the simple R/PE ratio is < 0.5 within a growing season (33). Wet and dry spell analysis involves determining their duration, frequency and time of occurrence throughout the year (34). Markov chain models (MC) are widely used to simulate daily transitions between wet and dry days (35).

Copula theory

Copula function formulation

A copula function is a uniformly distributed multidimensional joint distribution function within the domain of [0, 1] (36). Copulas are functions that link multivariate distribution functions to their one-dimensional margins, enabling the modelling of dependence structures separately from marginal behaviour (37).

If F (x, y) is a joint distribution function with continuous margins F_X (x) and F_Y (y), then there exists a unique copula C (38):

$$F(x, y) = C(F_X(x), (F_Y(y)) \qquad \text{(Eqn. 3)}$$

To ensure the continuity of the probability distribution function at the junction point, τ can be expressed as a function of μ and σ as follows:

$$\tau = -\mu \log\left(\frac{\mu}{\sigma}\right) \qquad \text{(Eqn. 4)}$$

If the hybrid exponential and generalized (HEG) distribution can be fully parameterized by P= [μ, k, σ], then five different types of copula functions: BB5 copula, Frank copula, Roch Alegre copula, t copula and Gaussian copula functions are investigated as follows:

The measurements are associated with two continuous random variables, X and Y, with Kendall's τ_n and Spearman's ρ_n (39).

Let $X(x_1, x_2, \cdots, x_p)$ and $Y(y_1, y_2, \cdots y_p)$ are sample series τ_n and ρ_n can be estimated as follows (40).

If $F(x_1, x_2, \cdots x_p)$ and $F(y_1, y_2, \cdots y_p)$ are functions of precipitation and PET, which are estimated non-parametrically, then actual copula C is defined as:

$$H(x, y) = C(F(x), F(y))$$

where, $(x_1, y_1), (x_2, y_2) \cdots (x_n, y_n)$ are random sample of unknown distribution H

Let R_i is probability of precipitation at i^{th} year, x_1 is day first day precipitation, x_2 is second day precipitation, x_3 is third day precipitation, up to 368 days, then

$$R_i = F(x_1) + F'(x_1)(x_1 - x_2) + F''(x_2)\frac{(x_2 - x_3)^2}{2!} + F'''(x_3)\frac{(x_3 - x_4)^3}{3!} + \cdots\cdots. \qquad \text{(Eqn. 5)}$$

Let S_i is probability of PET at i^{th} year, y_1 is the day one PET, y_2 is the day two PET, y_3 is third day PET, ……...up to 368 days., then

$$R_i = F(x_1) + F'(x_1)(x_1 - x_2) + F''(x_2)\frac{(x_2 - x_3)^2}{2!} + F'''(x_3)\frac{(x_3 - x_4)^3}{3!} + \cdots\cdot \qquad \text{(Eqn. 6)}$$

Let S_i is probability of potential evapotranspiration at i^{th} year, y_1 is the day one potential evapotranspiration, y_2 is the day two potential evapotranspiration, y_3 is third day potential evapotranspiration, ……...up to 368 days.,

then

$$S_i = F(y_1) + F'(y_1)(y_1 - y_2) + F''(y_2)\frac{(y_2 - y_3)^2}{2!} + F'''(y_3)\frac{(y_3 - y_4)^3}{3!} + \cdots \qquad \text{(Eqn. 7)}$$

Then,

$$\left(\frac{R_i}{n},\frac{S_i}{n}\right) = (F(x_i),F(y_i)),\ \text{i=1,2,}\cdots n \quad \text{(Eqn. 8)}$$

where, $\bar{R}$ and $\bar{S}$ are rank of precipitation and potential evapotranspiration of x and y respectively and

$$\bar{R} = \frac{1}{n}\sum_{j,k=1}^{n}\varphi_{jk}\,,\ \bar{S} = \frac{1}{n}\sum_{j,k=1}^{n}\psi_{jk}$$

If $F(x_1,x_2,\cdots x_p)$ is function of precipitation i^{th} year

at $x_i - x_{i+1} \le h,$ i=1,2,3,$\cdots$n,

then,

$$F'(x_1) = lim_{h\to 0}\frac{x_1-x_2}{h},\ F''(x_2) = \lim_{h\to 0}\frac{x_2-x_3}{h},$$

$$F'''(x_3) = lim_{h\to 0}\frac{x_3-x_4}{h},\cdots$$

If $F(y_1,y_2,\cdots y_p)$ is function of potential evapotranspiration i^{th} of year

at, $y_i - y_{i+1} \le h,$ i=1,2,3,$\cdots n$ then,

$$F'(y_1) = lim_{h\to 0}\frac{y_1-y_2}{h},\ F''(y_2) = \lim_{h\to 0}\frac{y_2-y_3}{h},$$

$$F'''(y_3) = lim_{h\to 0}\frac{y_3-y_4}{h},\cdots \quad \text{(Eqn. 9)}$$

The wet and dry spells are investigated by low and high rainfall trends through selected copula function families (40–42), which is shown in Table 2, supported by their following mathematical formulations and MATLAB-based implementation:

Results and Discussion

Summary of potential evapotranspiration

The FAO-56 Penman-Monteith method was employed to calculate the PET for the Coimbatore region over the period 1994–2024. Based on observations, the highest PET was recorded during week 18 of 2002 with a value of 74.04, indicating elevated atmospheric moisture demand (Fig. 1). This spike is likely attributable to higher temperatures or lower relative humidity, which intensify the rates of evapotranspiration. In contrast, the lowest PET was observed during week 30 of 2001 with a value of 3.65, corresponding to July. This decline may be associated with cooler temperatures, increased cloud cover or higher humidity levels, all of which suppress both evaporation and transpiration rates. It is important to emphasise that the application of the Penman-Monteith method for estimating PET has proven effective for determining the length of the growing season.

The findings suggest that the cultivation of food crops during the analysed years was largely appropriate when guided by PET-based assessments. The Penman-Monteith FAO-56 method integrates climate variables to estimate PET, helping optimize crop water management in Coimbatore. PET peaks reflect dry, hot conditions, while lower values indicate cooler, humid periods. This approach aids in timing crop cultivation and adapting to seasonal changes.

Summary of conditional probability index

CPI for Coimbatore station over the period 1994–2024 is presented in Fig. 2. CPI values and the associated probabilities of consecutive dry and wet weeks are calculated for all 52 standard meteorological weeks (Table 3). Analysis reveals that the years 2006, 2010 and 2016 featured several weeks with markedly low CPI values, particularly during the early part of the season. These low readings suggest an increased likelihood of dry weeks, indicating early-season drought conditions rather than random weekly anomalies. The recurrence of such weeks within these years implies broader seasonal drought impacts that could substantially influence crop development and soil moisture availability. Notably, weeks 33 (1999, 2006) and 50 (2009, 2010) occur across multiple years, indicating recurring late-season dryness. Likewise, week 1 of 2008 and week 2 of 2010 underscore early-season drought risks that may disrupt winter crop cultivation and hinder soil moisture replenishment. These patterns may be linked to climatic drivers such as ENSO phases, monsoon irregularities or shifts in local atmospheric circulation factors, especially pertinent to Coimbatore's semi-arid climate.

In contrast, week 42 of 2008 recorded an exceptionally high CPI value, likely attributable to a heavy Northeast monsoon downpour, suggesting a strong probability of above-normal rainfall during that period. Low CPI values recurring in early and late meteorological weeks indicate ongoing seasonal drought risks in Coimbatore, which adversely affect crop growth and soil moisture levels. These trends are closely linked to regional climate factors, highlighting the importance of adaptive agricultural practices. Conversely, high CPI values during certain weeks reflect strong monsoon rainfall, providing relief from drought conditions.

Table 2. Copula families and their closed-form mathematical description

Name	Mathematical Description	Reference
Gaussian	$C(u,v) = \int_{-\infty}^{\Phi^{-1}(u)}\int_{-\infty}^{\Phi^{-1}(v)} \frac{1}{2\pi\sqrt{1-\theta^2}}\exp\left(\frac{2\theta xy - x^2 - y^2}{2(1-\theta^2)}\right) dxdy^{b}$	(41)
t	$C(u,v) = \int_{-\infty}^{t_v^{-1}(\theta_1)}\int_{-\infty}^{t_v^{-1}(\theta_1)} \frac{\Gamma\left(\frac{\theta_1+\theta_2}{2}\right)}{\Gamma\left(\frac{\theta_2}{2}\right)\pi\theta_2\sqrt{1-\theta_1^2}}\left(1+\frac{x^2-2\theta_1 xy - y^2}{\theta_2}\right)^{\theta_2+2/2} dxdy$	(41)
Frank	$C^{Frank}(u,v) = \psi_\theta(\psi_\theta^{-1}(u)+\psi_\theta^{-1}(v)) = -\frac{1}{\theta}In\left(1+\frac{(e^{-\theta u}-1)(e^{-\theta v}-1)}{(e^{-\theta}-1)}\right)$	(41)
Roch-Alegre	$C^{Roch}(u,v) = exp\left\{1-[(((1-In(X))^{\theta_1}-1)^{\theta_2}+((1-In(Y))^{\theta_1}-1)^{\theta_2})^{\frac{1}{\theta_2}}+1]^{\frac{1}{\theta_2}}\right\}$	(42)
BB5	$C(u,v)^{BB5} = exp\left\{-\left[(-\log u)^{\theta}+(-\log u)^{\theta}-\left((-\log u)^{\delta\theta}+(-\log v)^{\delta\theta}\right)^{1/\delta}\right]^{1/\theta}\right\}$	(40)

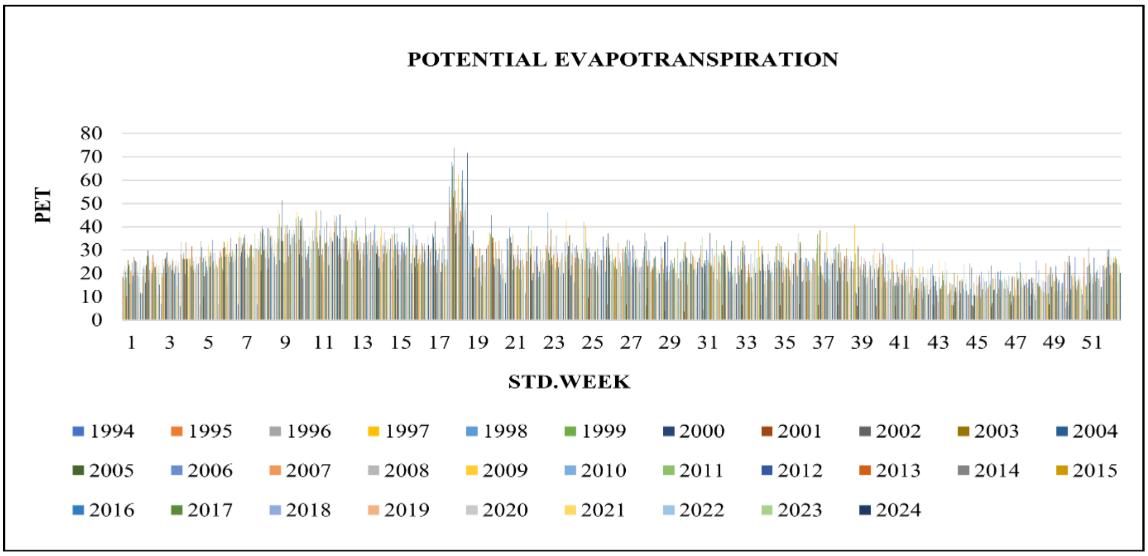

Fig. 1. The analysis of potential evapotranspiration for Coimbatore (1994–2024).

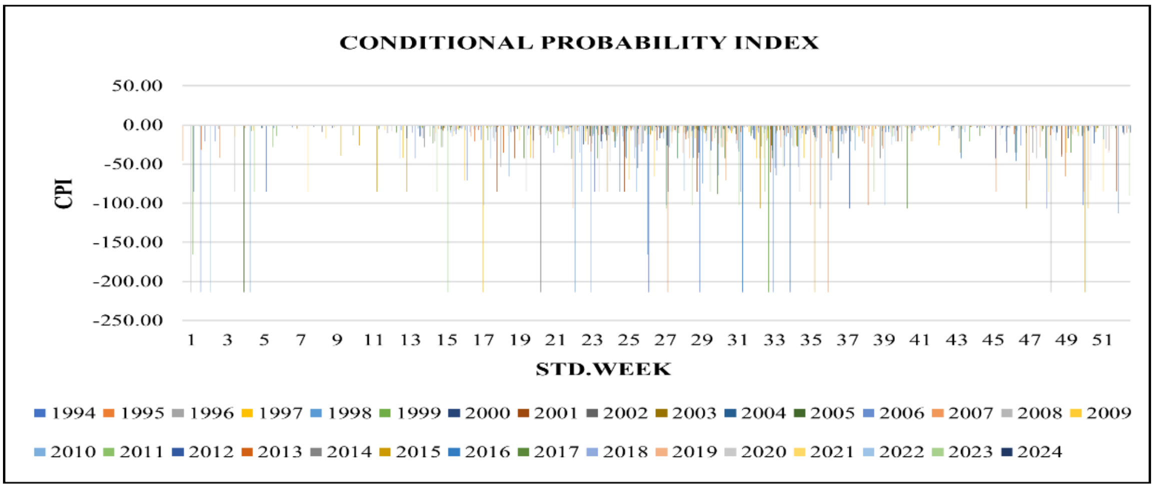

Fig. 2. The analysis of conditional probability index for Coimbatore (1994–2024).

Table 3. Values of copula functions for potential evapotranspiration

Year	Gaussian	t	Frank	Roch-Alegre	BB5
1994	9.466255	3.544175	1.86326	3.782	2.481
1995	2.255371	1.691676	1.72404	0.58854	0.37778
1996	4.910336	3.675526	1.84449	2.6621	1.7426
1997	6.399902	4.2281	1.79465	2.6559	1.8008
1998	1.5714	1.669932	1.86504	6.0849	2.244
1999	8.084087	8.37363	1.86522	4.7112	2.9789
2000	2.805599	1.285838	1.71503	0.86886	0.66489
2001	7.460619	3.031052	1.86548	6.5451	3.951
2002	3.723778	1.665725	1.86417	2.6282	1.7463
2003	3.776819	3.175576	1.72279	0.81359	0.64050
2004	8.928424	3.675526	1.86204	3.4162	2.2686
2005	5.483647	1.672027	1.86215	2.623	1.7643
2006	1.0158	1.280815	1.86508	4.9902	3.158
2007	8.262189	2.680841	1.86465	4.1104	2.6504
2008	7.512845	3.539391	1.86296	3.3137	2.1932
2009	8.384279	3.536836	1.86521	4.7719	3.0161
2010	6.443375	3.539391	1.86383	3.295	1.1138
2011	7.450282	3.178704	1.86536	4.9072	3.0767
2012	2.406245	2.936196	1.61742	1.0321	0.41023
2013	3.530273	3.675526	1.79283	9.596845	0.72844
2014	8.004976	2.929061	1.86523	4.7091	2.9766
2015	5.350557	3.184814	1.83048	1.7635	1.2368
2016	1.600525	3.536836	1.70086	0.50073	0.40325
2017	4.520942	1.673073	1.75815	1.3847	1.0145
2018	5.29179	1.688605	1.81415	1.4159	1.0429
2019	1.3277	2.669646	1.86516	5.5288	3.4714
2020	1.344977	3.675526	1.65376	4.04697	3.3327
2021	3.690454	3.675526	1.84935	1.6842	1.1877
2022	4.401365	2.927856	1.84762	1.7296	1.225
2023	1.0625	2.675902	1.86446	4.5032	1.1059
2024	8.518823	3.675526	1.86442	4.0255	2.6064

Summary of the moisture availability index

Moisture regime is an important agroclimatic factor governing the planting time of a crop. The sowing window, which is a range of time for sowing of crops, is narrower for rainfed crops than for those grown with irrigation. In areas with limited or no irrigation facilities, identification of sowing windows is necessary for guiding the farmers to sow their crops at appropriate times for achieving higher yields. By employing the database on a Standard Meteorological Week (SMW) basis, the assured weekly rainfall amounts at 25, 50 and 75 % probability levels were computed employing incomplete gamma distribution techniques. At a 25 % probability level, i.e., in 25 out of 100 years, the earliest period of sowing of rainfed crops with MAI ≥ 0.33 varied from 16 to 23 SMW in the Coimbatore districts in Tamil Nadu (Fig. 3–7).

Fig. 3 shows that in the very deficient category, which mostly indicates extreme moisture deficiency, there was no effective moisture availability during those periods, especially in January and April. Fig. 4 shows that the moderately deficient category on the 30th week of 2022, while a critical moisture deficit occurred in the 23rd week of 1994. A sharp decline in the deficient category occurred in the 40th week of 2015 and the 38th week of 2001 (Fig. 5, 6). However, the highest MAI occurred in the 20th week of 1998 and the lowest in the 46th week of 2003. Fig. 7 shows that excessive moisture occurred in the 42nd week of 2001 and the 29th week of 2022. The highest and lowest values of MAI are shown in Table 4. The moisture regime determines the sowing period for rainfed crops in Coimbatore, where limited irrigation requires precise timing. Analysis of meteorological weeks reveals periods of moisture deficit and excess. Identifying these critical weeks helps align crop planting with favourable moisture conditions to improve yield.

Summary of wet and dry spells for conditional probability index

CPI can be computed to reflect the impact of wet and dry spells on the availability of the different water resources. Fig. 8 shows that wet spells mostly occur in October to November, that is, the post-monsoon season; however, the most significant wet spell was observed in the 42nd week of 2008. Fig. 9 shows the dry spell analysis of Coimbatore during 1994–2024 and observed that the highest dry spell occurred in the 33rd week of 1999 and 2006, also in the 50th week of 2009 and 2010, which is highlighting critical periods of water stress for agriculture.

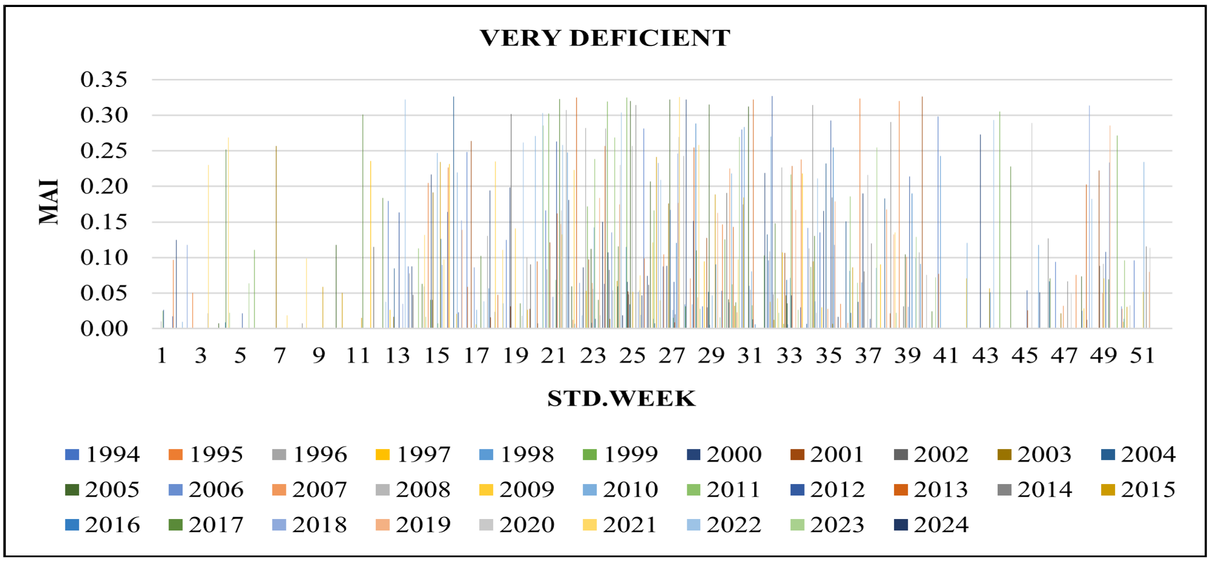

Fig. 3. The moisture availability index for the very deficient category.

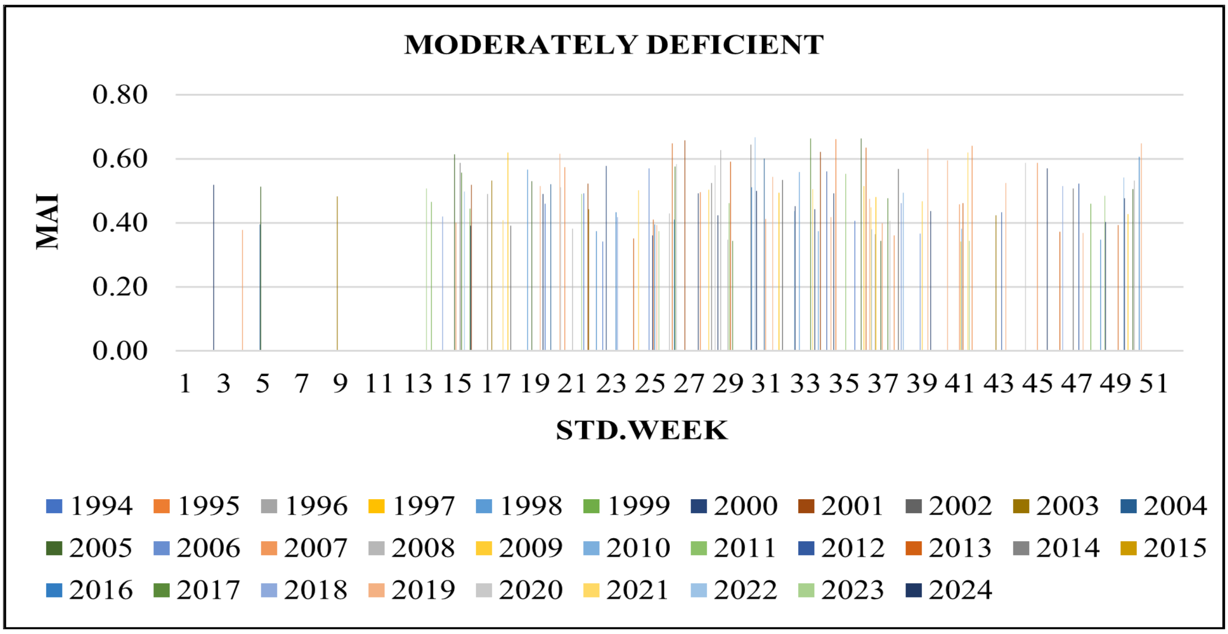

Fig. 4. The moisture availability index for the moderately deficient category.

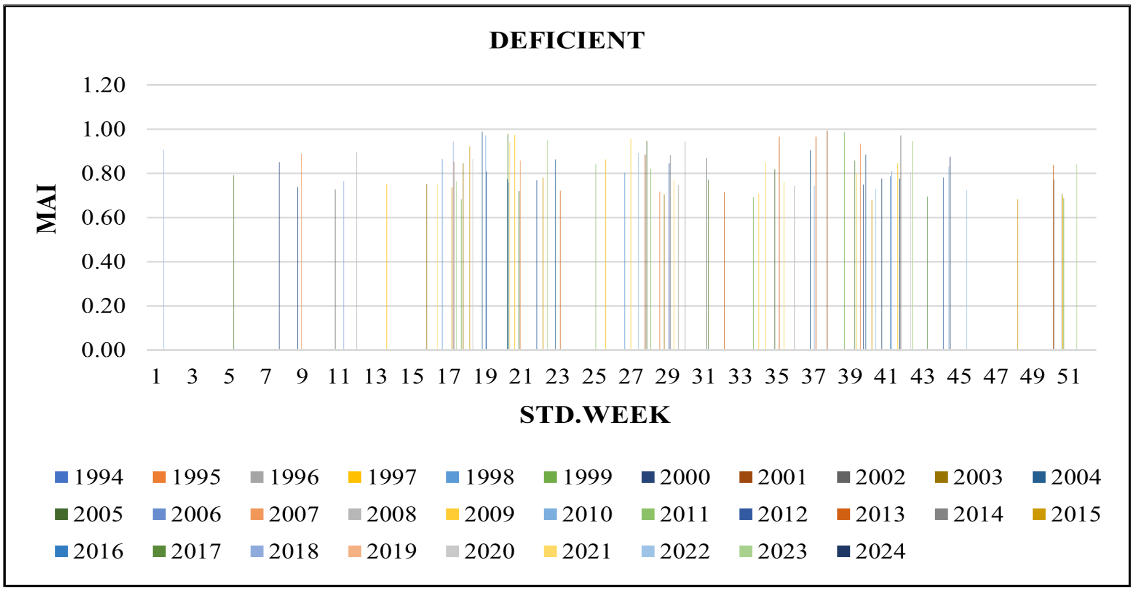

Fig. 5. The moisture availability index for the deficient category.

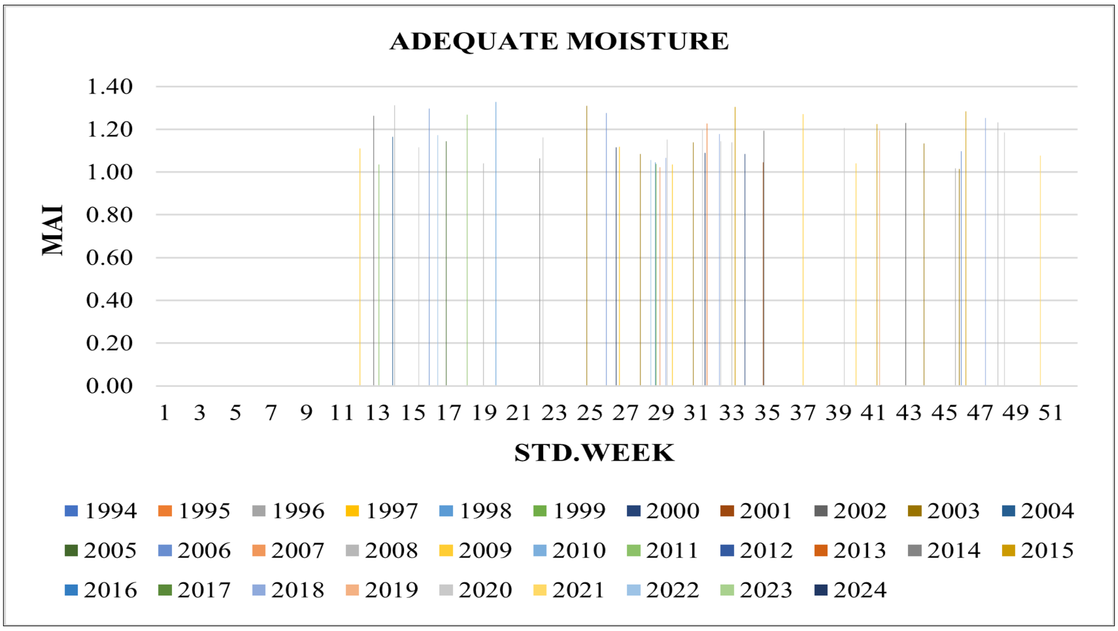

Fig. 6. The moisture availability index for the adequate moisture category.

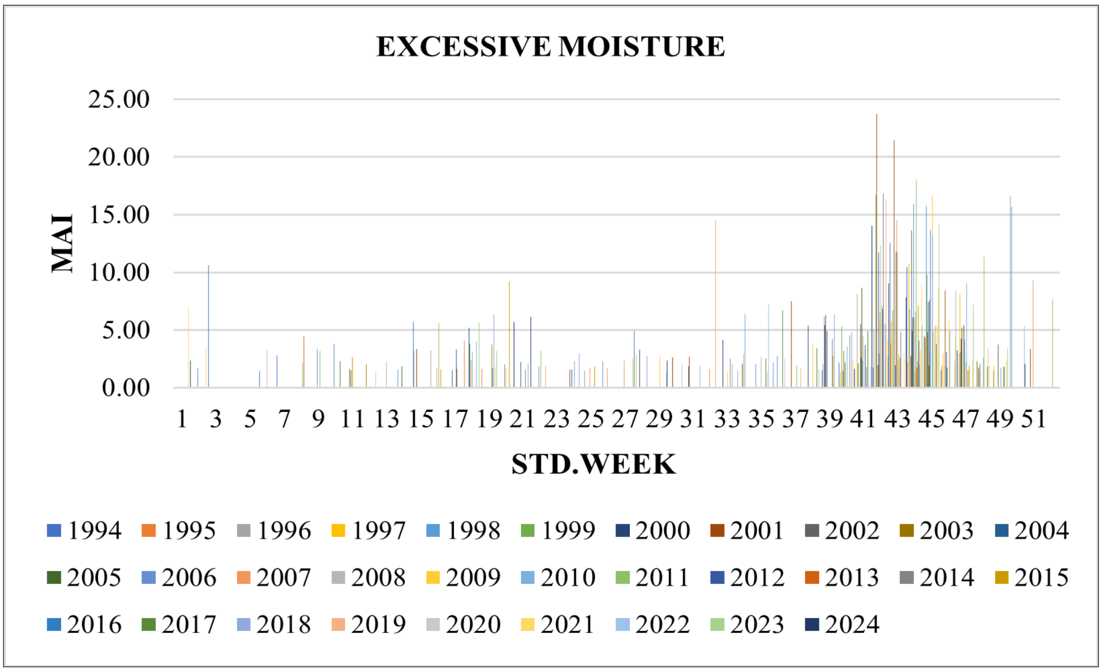

Fig. 7. The moisture availability index for the excessive moisture category.

Table 4. The highest and the lowest values of MAI

Category	Highest values	Lowest values
Very deficient	2012 (32nd week): 0.33	Mostly occurred in Jan to Apr: 0
Moderately deficient	2022 (30th week): 0.67	1994 (23rd week): 0.34
Deficient	2001 (38th week): 0.99	2015 (40th week): 0.68
Adequate moisture	1998 (20th week): 1.33	2003 (46th week): 1.01
Excessive moisture	2001 (42nd week): 23.71	2022 (29th week): 1.34

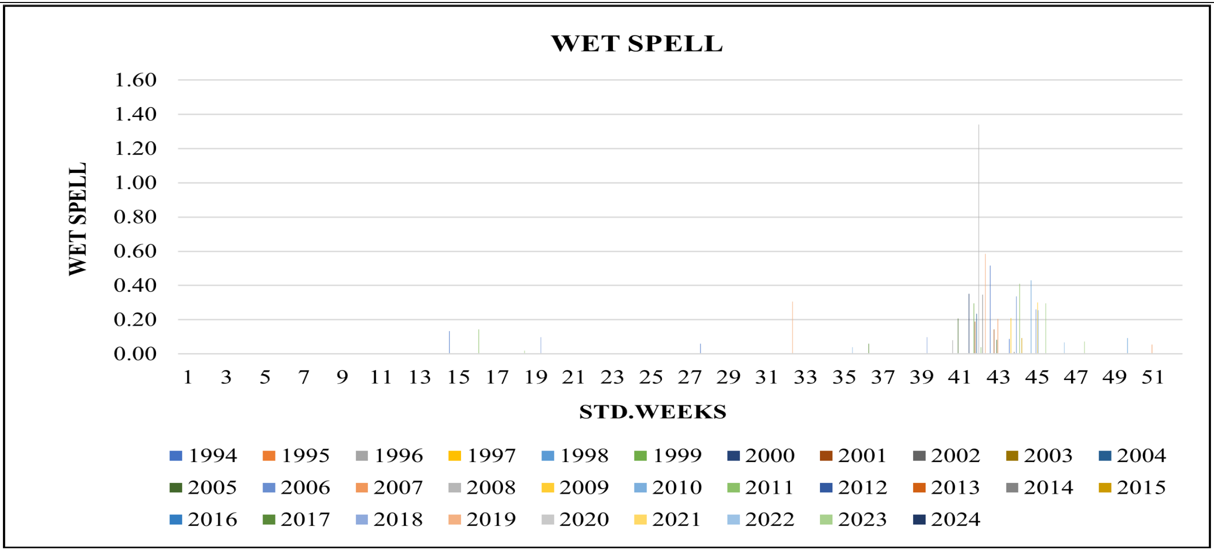

Fig. 8. The analysis of wet spells of conditional probability index for Coimbatore (1994–2024).

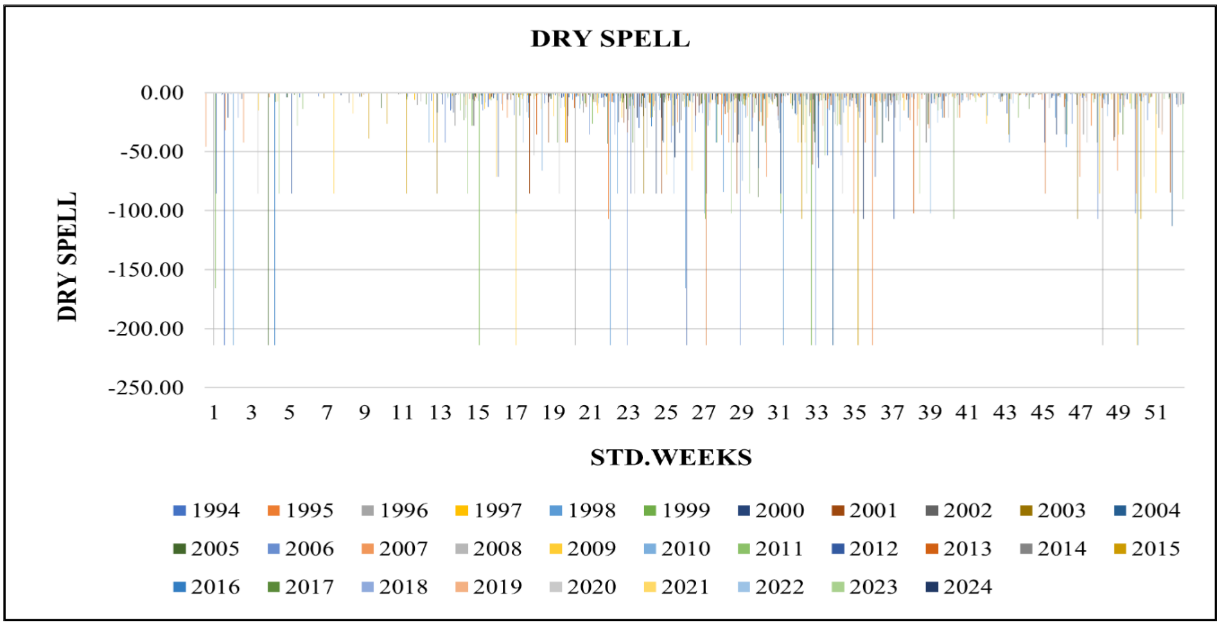

Fig. 9. The analysis of dry spells of conditional probability index for Coimbatore (1994–2024).

Summary of wet and dry spells for moisture availability index

Wet spells mostly occur in October to November (Fig. 10), that is, the post-monsoon season; however, the highest wet observed in the 42nd week of 2001. Fig. 11 shows the dry spell analysis of Coimbatore during 1994–2024, showing that the dry spell occurred in the last week of December to the first week of April, which is the summer season, indicating critical dry periods for agriculture.

Summary of copula functions for potential evapotranspiration

In this study, PET with copula functions was calculated. The weekly rainfall and PET values were fitted in copula functions to optimize the distribution function, which had a better mathematical and statistical theoretical basis. This suggests that the selected distribution function can fit wet and dry spells and the water availability index and can be utilized for drought monitoring. This study employed copula functions (Gaussian copula, t copula, Frank copula, Roch-Alegre copula and BB5 copula functions) for the implementation of PET analysis.

The outcomes of PET analysis using five distinct copula functions: the Gaussian copula, the t copula, the Frank copula, the Roch-Alegre copula and the BB5 copula are shown in Fig. 12. Among these, the Gaussian copula produced the highest value of 9.466255 in the 43rd week of 1994 and the Roch-Alegre exhibits the highest value of 9.596845 in the 40th week of 2013. The values of copula functions with PET are categorised in Table 3. Copula functions effectively model the combined behaviour of weekly rainfall and PET, providing a solid statistical framework for drought monitoring. Gaussian and Roch-Alegre copulas capture the highest PET values, indicating their strength in representing extreme hydrological events.

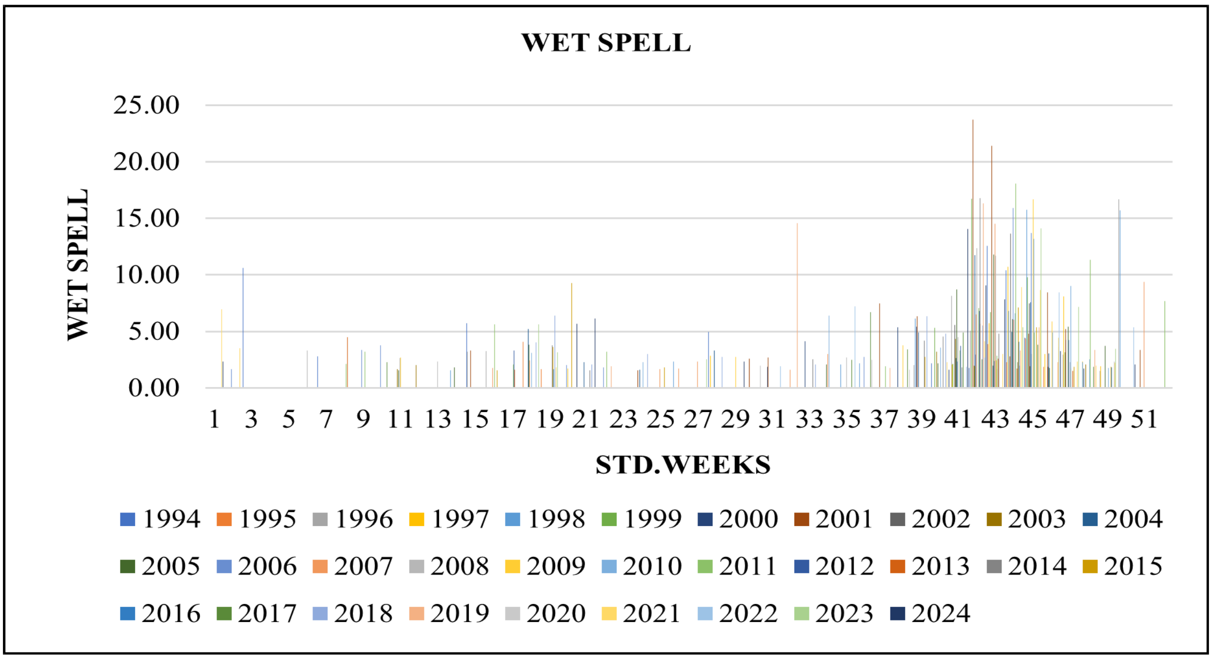

Fig. 10. The analysis of wet spells of MAI for Coimbatore (1994-2024).

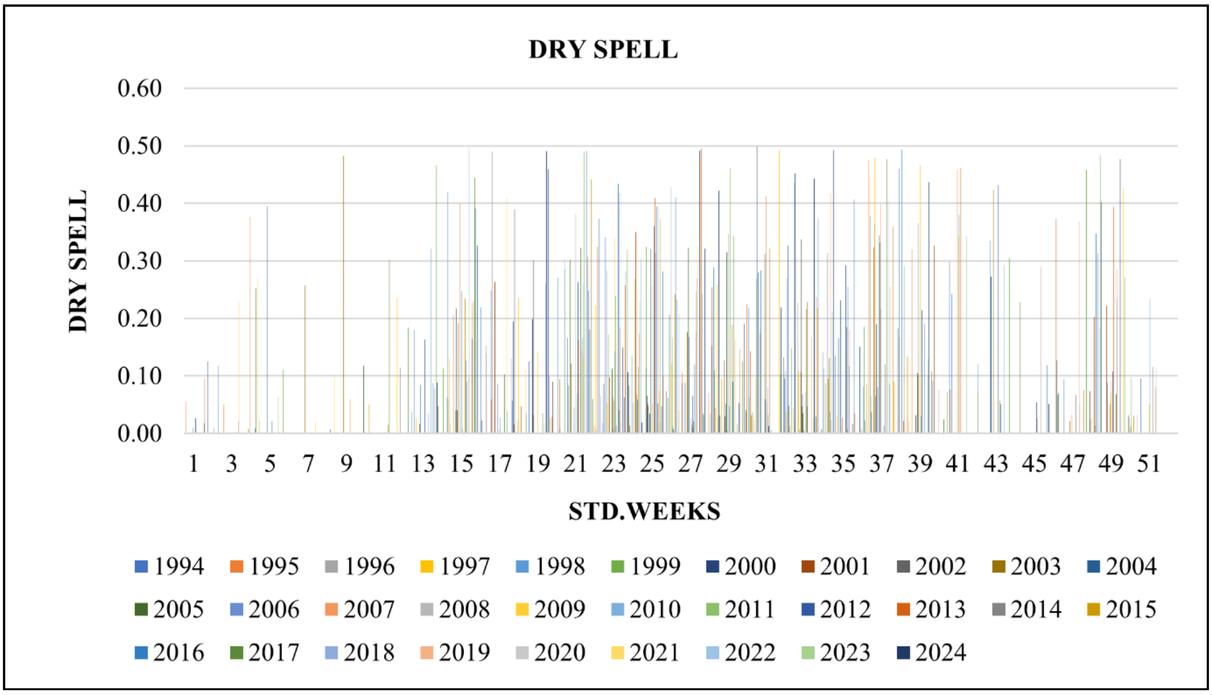

Fig. 11. The analysis of dry spells of moisture availability index for Coimbatore (1994-2024).

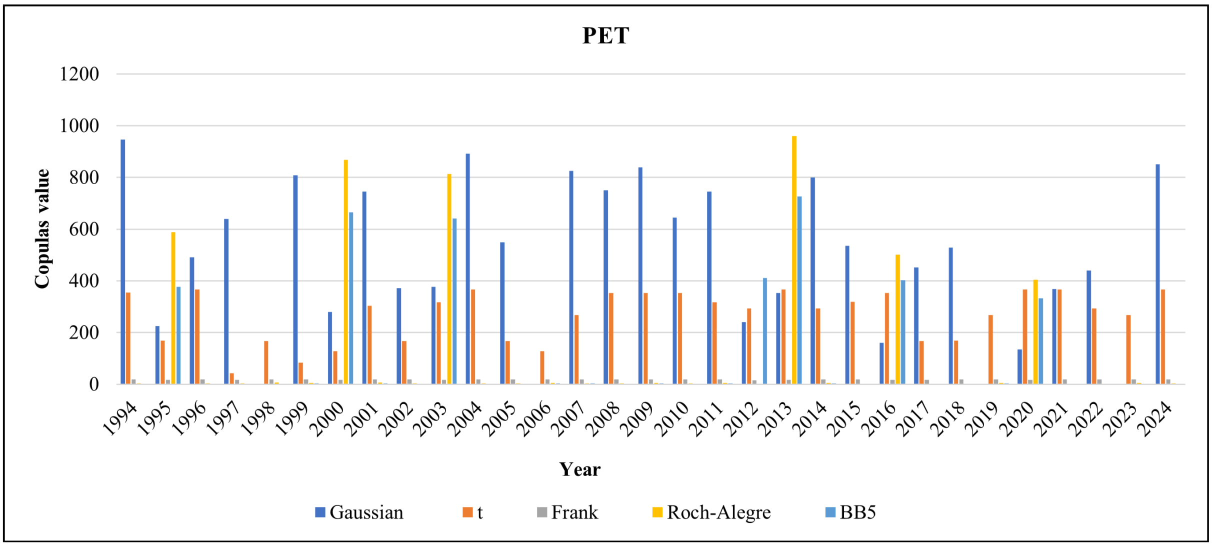

Fig. 12. The analysis of copula functions for potential evapotranspiration in Coimbatore (1994-2024).

Summary of copula functions for conditional probability index

In this study, the CPI with copula functions was calculated. The weekly rainfall and CPI values were fitted in copula functions to optimize the distribution function, which had a better mathematical and statistical theoretical basis. This study employed copula functions (Gaussian copula, t copula, Frank copula, Roch-Alegre copula and BB5 copula functions) for the implementation of CPI analysis. MATLAB-based computational techniques were used to apply these methods and copula functions. The outcomes of CPI analysis using five distinct copula functions: the Gaussian copula, the t copula, the Frank copula, the Roch-Alegre copula and the BB5 copula are shown in Fig. 13. Among these, the Gaussian copula produced the highest value of 9.247945 in the 41st week of 2024 and the Roch-Alegre exhibits the highest value of 3.605454 in the 42nd week of 2008. The values of copula functions with CPI are categorized in Table 5. The CPI with copulas for drought assessment, with Gaussian and Roch-Alegre copulas, shows strong performance in capturing extremes. MATLAB supported efficient computation and the multi-copula approach improved water availability modelling. It offers a solid framework for hydrometeorological risk analysis.

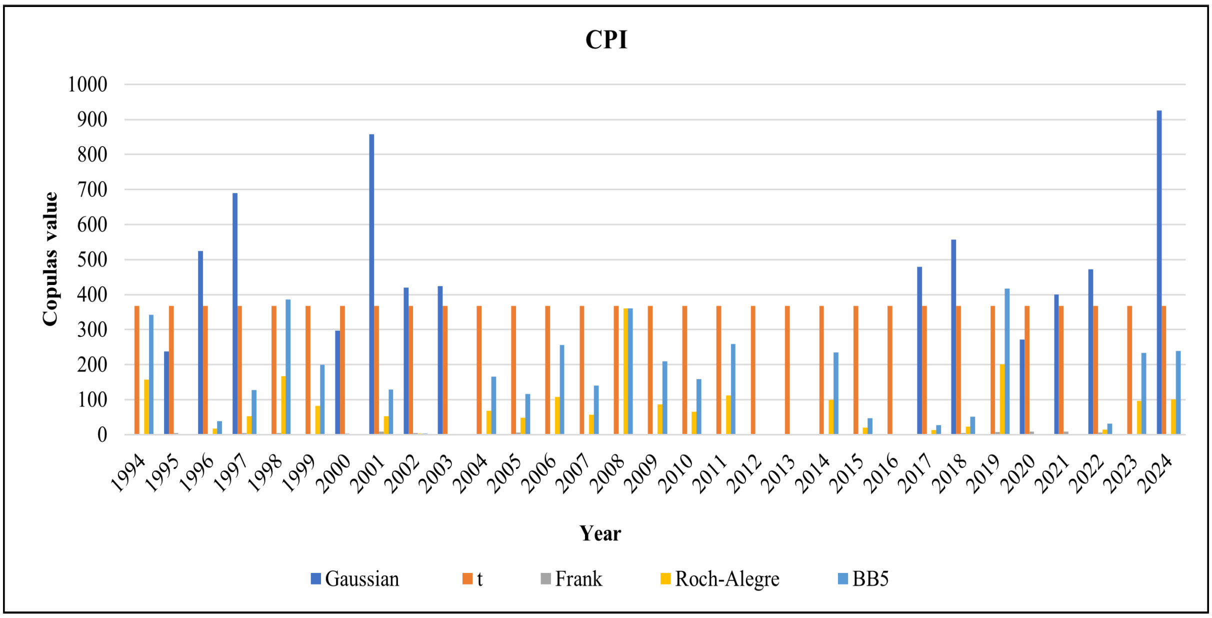

Fig. 13. The analysis of copula functions for conditional probability index in Coimbatore (1994-2024).

Table 5. Values of copula functions for conditional probability index

Year	Gaussian	t	Frank	Roch-Alegre	BB5
1994	1.6957	3.675526	2.1004	1.569063	3.416136
1995	2.374775	3.675526	4.466	0.6667	0.0104
1996	5.24035	3.675526	2.0535	1.79187	3.919
1997	6.889292	3.675526	4.114	0.52613	1.273574
1998	1.6832	3.675526	4.146	1.669567	3.8594
1999	1.6962	3.675526	2.1007	0.82334	1.99023
2000	2.975109	3.675526	3.4584	0.6667	0.0104
2001	8.579203	3.675526	8.3178	0.531059	1.294296
2002	4.191613	3.675526	4.0187	2.5948	2.9928
2003	4.236304	3.675526	1.0421	0.6667	0.0103
2004	1.6962	3.675526	2.1007	0.676886	1.6569
2005	1.6962	3.675526	5.6451	0.48541	1.167639
2006	1.6962	3.675526	2.1007	1.072596	2.565199
2007	1.6962	3.675526	1.0421	0.572432	1.398982
2008	1.6962	3.675526	2.1007	3.605454	3.600884
2009	1.6962	3.675526	2.1007	0.866187	2.090086
2010	1.6962	3.675526	1.0054	0.65688	1.586405
2011	1.6962	3.675526	1.6284	1.121162	2.586554
2012	1.6962	3.675526	2.1007	0.6667	0.0104
2013	1.6962	3.675526	2.1007	0.6667	0.0103
2014	1.6962	3.675526	2.1007	0.987876	2.341613
2015	1.6962	3.675526	2.1007	2.08254	4.65897
2016	1.6962	3.675526	2.1007	0.6667	0.0103
2017	4.784567	3.675526	1.0421	1.30294	2.69082
2018	5.56147	3.675526	5.1816	2.28841	5.18823
2019	1.4234	3.675526	6.9195	2.00605	4.175204
2020	2.711697	3.675526	8.3178	0.6667	0.0053
2021	4.00537	3.675526	8.3178	0.6667	0.0089
2022	4.72539	3.675526	6.477	1.50011	3.18485
2023	1.1452	3.675526	1.0054	0.963502	2.337994
2024	9.247945	3.675526	1.0421	1.010075	2.396686

Summary of copula functions for moisture availability index

In this study, the MAI with copula functions was calculated. The weekly rainfall and MAI values were fitted in copula functions to optimize the distribution function, which had a better mathematical and statistical theoretical basis. This study employed copula functions (Gaussian copula, t copula, Frank copula, Roch-Alegre copula and BB5 copula functions) for the implementation of MAI analysis. Table 6 displays the outcomes of MAI analysis using three distinct methods: the Gaussian copula, the t copula and the Frank copula. The outcomes of MAI analysis using five distinct copula functions: the Gaussian copula, the t copula, the Frank copula, the Roch-Alegre copula and the BB5 copula are shown in Fig. 14. Among these, the Gaussian copula produced the highest value of 9.465994 in the 43rd week of 1994 and the Roch-Alegre exhibits the highest value of 9.603615 in the 42nd week of 2013. The values of copula functions with MAI are categorized in Table 6. By implication, copulas with MAI offer a flexible way to capture the dependence between rainfall and moisture conditions. By applying multiple copula types, it demonstrated how different models can effectively represent moisture variability. This approach enhances the understanding of water availability patterns, supporting more accurate drought assessment and agricultural planning.

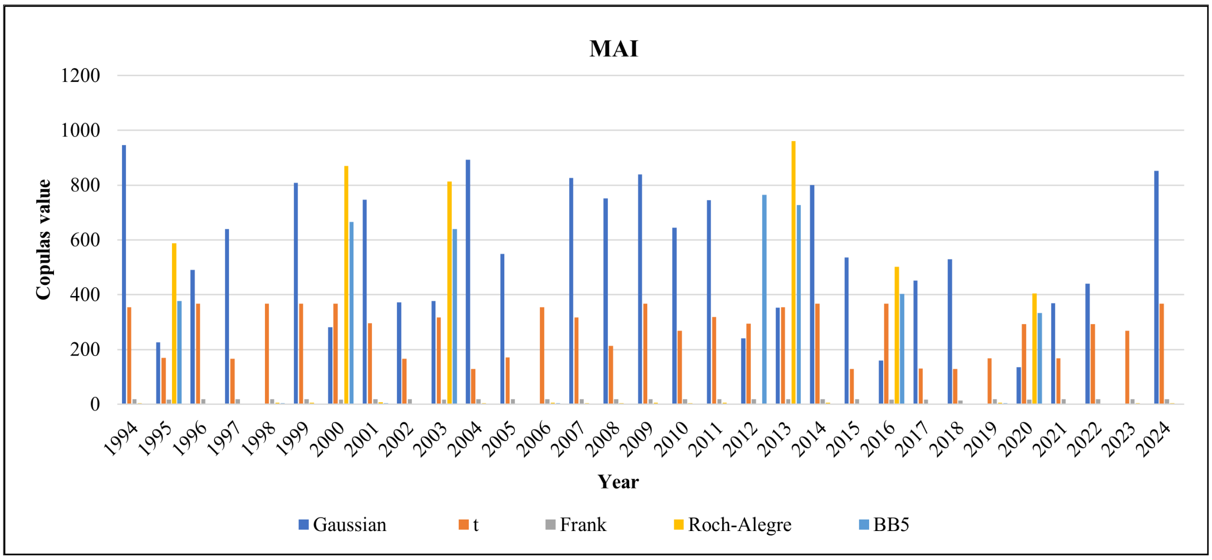

Fig. 14. The analysis of copula functions for moisture availability index in Coimbatore (1994-2024).

Table 6. Values of copula functions for moisture availability index

Year	Gaussian	t	Frank	Roch-Alegre	BB5
1994	9.465994	3.545303	1.86326	3.7835	2.4825
1995	2.255504	1.686552	1.72418	5.878155	3.774563
1996	4.910412	3.675526	1.86521	2.6619	1.7425
1997	6.400073	1.665725	1.85982	2.6549	1.8002
1998	1.5714	3.675526	1.86504	6.0838	3.8123
1999	8.083952	3.675526	1.8227	4.7121	2.9793
2000	2.805512	3.675526	1.71511	8.693571	6.652132
2001	7.460696	2.963085	1.77378	6.5445	3.9507
2002	3.72369	1.665725	1.86417	2.6288	1.7466
2003	3.776854	3.173464	1.72271	8.134058	6.403869
2004	8.928475	1.285002	1.8379	3.4159	2.2684
2005	5.483486	1.70684	1.84971	2.6221	1.7638
2006	1.0158	3.539391	1.86508	4.9886	3.1572
2007	8.262095	3.162581	1.86466	4.1109	2.6507
2008	7.512662	2.134614	1.86297	3.3148	2.1938
2009	8.384417	3.675526	1.86521	4.771	3.0156
2010	6.443499	2.678379	1.86383	3.2942	2.1682
2011	7.450282	3.18381	1.86536	4.9072	3.0767
2012	2.406297	2.940863	1.8244	1.0318	7.63884
2013	3.530138	3.539391	1.79298	9.603615	7.272789
2014	8.004751	3.675526	1.86523	4.7105	2.9774
2015	5.350435	1.293324	1.83053	1.5932	1.1534
2016	1.600437	3.675526	1.7012	5.01222	4.0358
2017	4.520831	1.301572	1.75799	1.3853	1.0148
2018	5.29179	1.293324	1.37467	1.4159	1.0429
2019	1.3277	1.676203	1.86516	5.5278	3.4708
2020	1.344896	2.929061	1.65421	4.05147	3.33582
2021	3.69055	1.676203	1.8515	1.6837	1.1873
2022	4.401471	2.929061	1.84759	1.729	1.2247
2023	1.0625	2.678379	1.86446	4.5042	2.8974
2024	8.518775	3.675526	1.86442	4.0258	2.6066

Conclusion

The analysis showed that the maximum atmospheric water demand (PET) occurred in the 18th week of 2002, while the minimum was recorded in the 30th week of 2001, reflecting the combined influence of temperature and humidity fluctuations. The Gaussian copula modelling approach demonstrated the highest performance for PET values. Conditional probability index data indicated severe dry spells in the years 2006, 2010 and 2016 and highlighted rainy spells, especially during the 42nd week of 2008, which corresponds with post-monsoon periods in Coimbatore. Dry and wet spell analyses further showed the 33rd and 50th weeks of several years as critical periods of dryness, with the Gaussian copula also providing optimal modelling results for CPI. Moisture availability index analysis identified substantial moisture deficiency from January to April, with peak wetness and dryness distributed across different weeks and years; again, the Gaussian copula emerged as the most effective modelling approach for predicting moisture availability. Taken together, the Gaussian copula functions consistently demonstrated superior reliability for modelling and forecasting climate variability across PET, CPI and MAI indices during the study period.

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Authors' contributions

PP carried out the research work, designed the methodology, and prepared the initial draft of the manuscript. RR guided the study area, data collection, coding tool learning and assisted in software analysis. VG facilitated meteorological expertise by analyzing rainfall variability and aiding in the study of spell dynamics. RS facilitated to choose weather parameter that is critically affecting crop growth aspects and yield during different seasons. RK helped to include meteorological parameters that are critical in the agronomical aspect into the models for analysis. CSS guided to form codes based on models and to choose software tools for running data. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interests to declare.

Ethical issues: None

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