

Article

Cloud-Model-Based Evaluation of Reference Evapotranspiration Variability for Reference Crops Within the Xizang Plateau's Agricultural Regions

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Abstract

Against the backdrop of ongoing climate change, the Qinghai–Tibet Plateau, a region highly sensitive to climatic variation, exhibits intricate spatiotemporal patterns in reference crop evapotranspiration (ET_O), with significant implications for regional water-resource planning. This study selected four agro-climatic zones across the plateau region (TSA, TSH, TAZ, and WCH). Long-term daily observations from 28 meteorological stations were used to estimate ET_O via the FAO 56 Penman–Monteith equation. This extensive dataset enabled robust trend analysis using the Mann–Kendall test, alongside a cloud-model framework, and analyses of sensitivity and contributions to evaluate ET_O 's spatiotemporal evolution, its distributional uncertainty, and the underlying drivers. Results reveal pronounced regional heterogeneity in the interannual variability of ET_O . Annual ET_O declined in TSH and TSA (trend rates of -1.12 and $-6.58 \text{ mm} \cdot 10a^{-1}$, respectively) and increased in TAZ and WCH (15.76 and $10.74 \text{ mm} \cdot 10a^{-1}$, respectively). At monthly and seasonal timescales, ET_O exhibited a unimodal pattern, with the greatest stability in winter and spring and lower stability in summer and autumn. The cloud-model parameter He indicates that ET_O stability is greatest in TSH and weakest in WCH, with He values of 7.15 and 12.29 mm , respectively. Contribution-rate analyses identify $T_{\max}$ and T_{mean} as the principal determinants of rising ET_O across all study zones, reflecting the largest individual contributions. Temperature-related factors together account for the majority of ET_O variability across the regions, with their absolute contributions ranging from 5.61% to 8.63% , well above those of aerodynamic factors ($0.62\text{--}1.78\%$). Stability assessments indicate that ET_O is generally more unstable than its meteorological drivers, with substantial regional disparities, implying that ET_O evolution cannot be explained by a single controlling factor. Overall, the study characterizes the uncertainty in ET_O variations under complex terrain, highlights the value of the cloud model for refined hydrological assessments, and provides a scientific basis for adaptive agricultural water-resource management in the region.



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Keywords: Xizang plateau; reference crop evapotranspiration (ET_O); cloud model; sensitivity analysis; contribution rate; uncertainty

1. Introduction

Against the backdrop of climate change, reference crop evapotranspiration (ET_O) serves as a key indicator of atmospheric evaporative demand and crop-water requirements. It underpins regional water resources planning, guides precision irrigation management, supports drought monitoring, and informs assessments of ecosystem responses under evolving climatic conditions [1–3]. Under ongoing climate change, fluctuations in meteorological variables—such as air temperature, solar radiation, wind speed, and humidity—drive the spatiotemporal variability of ET_O , posing substantial challenges to the balance between regional water supply and demand and to agricultural production security. Consequently, accurate estimation of ET_O and elucidation of its variation patterns and driving mechanisms are essential for developing sustainable water-resource management strategies and for improving irrigation management. Xizang lies at the ecological core and represents a sensitive frontier of the Qinghai–Tibet Plateau. The region features distinctive topography, high-altitude conditions, and fragile ecosystems [4,5], which render it particularly vulnerable to climate change. Therefore, an in-depth investigation of ET_O dynamics and their underlying drivers in Xizang has significant scientific and practical significance for quantifying agricultural water demand, informing sustainable water-resource utilization strategies, and optimizing irrigation management [6,7].

Recently, scholars from both domestic and international contexts have conducted extensive research on the variability of ET_O and its driving mechanisms. Methodologically, a range of techniques has been used to detect long-term trends in ET_O , including the Mann–Kendall trend test [8,9], linear trend analysis [10], and cumulative departure methods [11]. Additionally, methods such as partial correlation analysis [12], sensitivity analyses [13], and contribution-rate analyses [8,14] have been used to examine the contributions of meteorological factors to ET_O variation and the underlying mechanisms. These approaches, widely applied across regions, have effectively revealed the spatiotemporal evolution of ET_O and its response to climate change [8,15]. Global syntheses indicate that ET_O displays complex spatiotemporal variability across recent decades [16–18], with declines in some regions and increases in others. This variability closely tracks changes in meteorological factors, including net radiation, wind speed, air temperature, and relative humidity. In the Qinghai–Tibet Plateau, several studies have noted that [19–22], under rising temperatures and increased solar radiation, ET_O has generally risen; however, localized areas have declined or shown no significant change due to wind speed, relative humidity, and other factors. For instance, Tang et al. [8], based on data from 31 meteorological stations on the Tibetan Plateau, found that, with the exception of some Shigatse regions, most of Tibet exhibited an increasing ET_O trend directly related to changes in temperature and humidity. Furthermore, under climate warming, agricultural irrigation water demand in Tibet is projected to rise. Liu et al. [19], focusing on three major irrigation districts in Tibet, observed substantial differences in the spatiotemporal distribution patterns of ET_O . They identified average wind speed and relative humidity as key influencing factors and documented the existence of the “evaporation paradox” within the irrigation districts [23]. Additionally, machine-learning models, including support vector machines, artificial neural networks, random forests, and multilayer perceptrons, have demonstrated substantial potential in estimating ET_O and unveiling nonlinear relationships between meteorological factors and ET_O [24,25]. However, these models are frequently described as “black boxes” offering only limited insight into how their internal processes operate [26]. Moreover, their reliance on large training data sets creates obstacles to applying them in the Xizang region [27,28].

In summary, existing analytical approaches have proven effective in characterizing ET_O variation across multiple spatiotemporal scales and in identifying the primary meteorological drivers. Nevertheless, many investigations indicate that ET_O time series possess

intrinsic randomness and ambiguity [29,30], causing traditional statistical approaches to fall short in quantifying uncertainty properties like distributional uniformity and stability within ET_O dynamics. A quantitative assessment of ET_O uncertainty is essential for clarifying its spatiotemporal variability and the mechanisms driving it, and it provides a methodological basis for advancing ET_O theory and enhancing predictive accuracy. The cloud model, originally proposed by academician Deyi Li, provides a powerful framework for bridging qualitative concepts and quantitative representations and explicitly accommodates the coexistence of randomness and fuzziness in natural systems. Within this framework, the expectation (Ex), entropy (En), and hyper-entropy (He) characterize the central tendency, uniformity, and stability of a sequence [31]. Moreover, cloud diagrams facilitate intuitive visualization of distributional uniformity and structural stability [32]. Compared with traditional trend-based approaches, the cloud model provides a more refined quantitative description of attributes such as variation uniformity, fluctuation stability, and the evolution of distributional structure [33]. Accordingly, Bai et al. [34], Zhang et al. [35], Yang et al. [36], Sun et al. [37], and Liu et al. [19] have successfully applied the cloud model in climatological, hydrological, and agricultural studies, achieving significant advances. Notably, Liu et al. [19] were the first to introduce the cloud model to evaluate the temporal uniformity and stability of ET_O at the irrigation-district scale in Xizang. These findings provide a methodological basis for extending the cloud model to broader spatial scales in the present study.

Although considerable progress has been made in understanding the patterns of ET_O variation and its driving mechanisms on the Xizang Plateau, several limitations persist. Firstly, the majority of studies analyze either the plateau in its entirety or individual river basins [38], leaving insufficient attention to systematic, fine-scale comparisons across diverse agro-climatic zones. Consequently, the heterogeneity of ET_O dynamics and of its dominant controlling factors under complex climatic gradients and diverse cropping systems remains inadequately characterized, underscoring the need for targeted comparative analyses. Second, the majority of prior studies rely on deterministic modeling frameworks [20,21], whereas the uncertainty characteristics inherent in ET_O variability have received relatively little attention. This omission constrains a comprehensive understanding of the stochastic and structural features shaping ET_O evolution. Third, although fluctuations and stability of ET_O are likely influenced by the stability of its driving meteorological factors, empirical investigations into this relationship remain scarce. This information gap constrains a deeper understanding of regional water-resource dynamics and hampers the development of adaptive irrigation management strategies within Xizang's farming systems. Closing these gaps is essential to advance both the theoretical framework and the practical applications of ET_O research in high-altitude, climate-sensitive regions. Consequently, this study postulates the following core hypothesis:

We hypothesize that the temporal stability of ET_O in the Tibetan Plateau is generally lower than that of its primary meteorological driving factors; furthermore, the coupling relationship between ET_O and the stability of its driving meteorological factors is not a simple linear one; instead, it exhibits substantial regional heterogeneity, with its intricate nature being non-linearly modulated by the local climatic context and the synergistic effects of multiple influencing factors.

To address these identified limitations and rigorously test the proposed hypothesis, this study focuses on four representative agro-climatic zones in Xizang—the plateau temperate semi-arid zone, the semi-humid zone, the arid zone, and the cool temperate semi-humid zone—and systematically applies cloud-model theory to examine the multi-temporal variability of ET_O and its driving mechanisms. The principal contribution is a pioneering exploration: the first attempt to elucidate the coupling between the temporal stability of

ET_O and the stability of its dominant meteorological drivers. By applying this analytical framework, we refine our understanding of the processes that govern ET_O evolution and of the primary sources of uncertainty across the Xizang Plateau. These findings will thus provide a robust scientific basis for climate-change adaptation in Xizang agriculture, thereby supporting more efficient water-resource allocation and promoting sustainable agricultural development.

2. Materials and Methods

2.1. Overview of the Study Area

The study area covers the central Qinghai–Tibet Plateau within the Tibet Autonomous Region (see Figure 1). The terrain is complex and heterogeneous, with average elevations exceeding 4000 m. The region exhibits typical plateau climate characteristics, including strong solar irradiance and large diurnal temperature ranges, and marked spatial variability in hydrothermal conditions [39]. Annual precipitation is unevenly distributed and follows a distinct wet–dry seasonal pattern: May–September constitutes the wet season, while October through April of the following year constitutes the dry season. Owing to constraints imposed by terrain, topography, and water resources, cultivated land in Xizang is scarce, occurring mainly in belts or patches within valleys and basins [40].

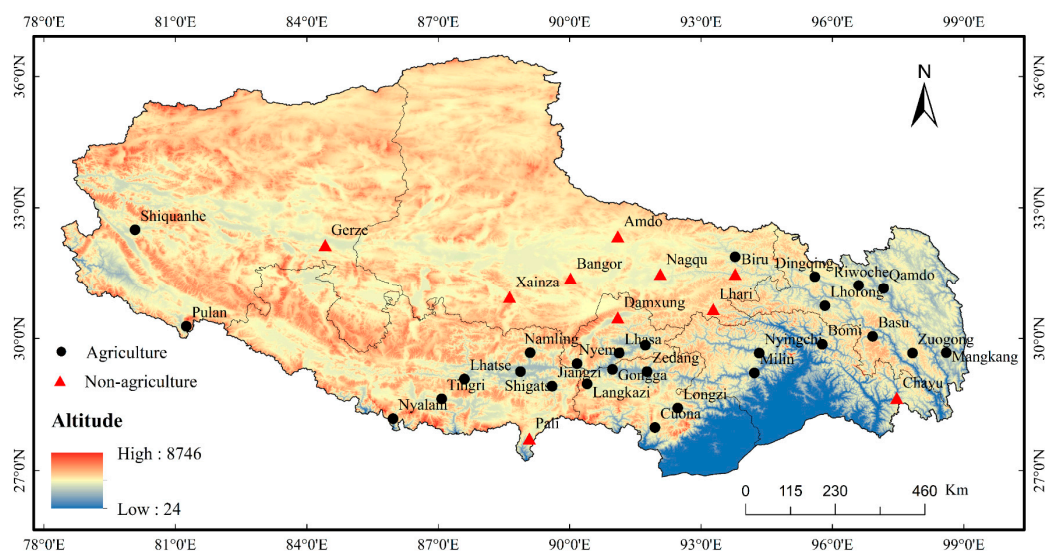


Figure 1. Topographic features and spatial distribution of meteorological stations in the Xizang Autonomous Region. Elevations derived from a digital elevation model (DEM) range from 24 m to 8746 m above mean sea level (m a.s.l.). Solid black circles (●) indicate meteorological stations located in agricultural zones, whereas red triangles (▲) denote stations in non-agricultural zones.

To systematically elucidate the spatiotemporal evolution of ET_O under varying climatic gradients, the study area was subdivided into four agro-climatic zones following the established agricultural climatic regionalization framework [41,42]: TSA (plateau temperate semi-arid), TSH (plateau temperate semi-humid), TAZ (plateau temperate arid), and WCH (plateau warm–cool temperate semi-humid). These zones exhibit marked variations in hydrothermal conditions and, together, encompass Xizang’s major agricultural production systems and key farming areas, thereby ensuring the representativeness and coherence of the analytical framework.

2.2. FAO 56 Penman–Monteith Model

The FAO 56 Penman–Monteith method is widely regarded as the standard approach for estimating ET_O because of its physical basis and accuracy [43]. In accordance with Allen et al. [44], the equation used in this study is shown below:

$$ET_O = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} U_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34U_2)} \quad (1)$$

In the equation, the following apply:

- ET_O : reference crop evapotranspiration ($\text{mm} \cdot \text{d}^{-1}$);
- Δ : slope of the saturation vapor-pressure curve with respect to temperature ($\text{kPa} \cdot ^\circ\text{C}^{-1}$);
- R_n : net solar radiation ($\text{MJ} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$);
- G : soil heat flux density ($\text{MJ} \cdot \text{m}^{-2} \cdot \text{d}^{-1}$);
- γ : psychrometric constant ($\text{kPa} \cdot ^\circ\text{C}^{-1}$);
- T : daily mean air temperature at a height of 2 m ($^\circ\text{C}$);
- e_s : saturation vapor pressure at temperature T (kPa);
- e_a : actual vapor pressure at temperature T (kPa);
- U_2 : daily mean wind speed at a height of 2 m ($\text{m} \cdot \text{s}^{-1}$).

2.3. Cloud Model

This section presents the core principles of the cloud model, explains the computation of its numerical descriptors (Ex , En , He), and describes the implementation adopted in this study [45]. In addition, this section delineates the physical interpretation of the cloud model with respect to quantifying uncertainty in evapotranspiration.

2.3.1. Fundamental Principles of the Cloud Model

The cloud model, proposed by academician Li Deyi, is a framework for transforming uncertainty between qualitative concepts and quantitative representations, drawing on traditional fuzzy-set theory and probability statistics [31]. The central idea is to represent a qualitative concept by quantitative values—referred to as “cloud drops”—encoded via a designated algorithm. Let D denote the universe of discourse for quantitative values, and C a qualitative concept defined on D . If a value $x \in D$ is a random realization of C , and its certainty degree $u(x) \in [0, 1]$ with respect to C exhibits a stable tendency, then the distribution of x over D is called a cloud, and each x is a cloud drop [45].

Unlike conventional probabilistic approaches that treat randomness alone, the cloud model characterizes uncertainty as the integration of randomness and fuzziness. This integrated representation renders it particularly suitable for analyzing hydro-meteorological variables such as ET_O , which are jointly regulated by multiple meteorological drivers and governed by complex interactions, and cannot be adequately described by any single deterministic or statistical metric [46].

2.3.2. Digital Characteristics of the Cloud Model and Their Computation

Within the cloud-model framework, a qualitative concept is defined by three numerical descriptors: the expectation (Ex), the entropy (En), and the hyper-entropy (He). For illustration, this study employs a one-dimensional normal cloud model, and the definitions and calculation procedures are provided below [47]. In practice, estimating these three parameters from a given set of deterministic observational data is achieved through the Backward Cloud Generator (BCG) algorithm based on statistical moments. The specific estimation formulas are as follows.

- (1) Ex denotes the point in the universe of discourse that best represents the qualitative concept; equivalently, it equals the mean of the cloud-droplet distribution. Numerically, Ex is computed as the sample mean:

$$Ex = \frac{1}{n} \sum_{i=1}^n x_i \quad (2)$$

where x_i denotes the i -th sample value ($i = 1, 2, 3, \dots, n$), and n represents the sample size.

- (2) En quantifies the uncertainty associated with a qualitative concept. It captures both the range of allowable values within the universe of discourse and the dispersion of cloud droplets in the cloud map. In the one-dimensional normal cloud model, En can be computed as follows:

$$En = \sqrt{\frac{\pi}{2}} \frac{1}{n} \sum_{i=1}^n |x_i - \bar{X}| \quad (3)$$

where $\bar{X}$ denotes the sample mean, and $\bar{X} = Ex$.

- (3) He describes the volatility of entropy, i.e., the uncertainty associated with entropy. It reflects the condensation level of the cloud map's droplet distribution and the overall thickness of the cloud, and serves as a key indicator of model stability. A larger He indicates greater dispersion of cloud droplets and hence greater instability of the cloud distribution. For the one-dimensional normal cloud model, He is calculated as follows:

$$He = \sqrt{S^2 - En^2} \quad (4)$$

$$S^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{X})^2 \quad (5)$$

where S^2 denotes the sample variance.

The three parameters Ex , En , and He constitute the cloud model's digital characteristic vector, jointly describing the central tendency, dispersion, and uncertainty structure of a sample sequence, respectively. In the forward normal cloud model, cloud droplets that effectively represent a qualitative concept are predominantly distributed within the interval $[Ex - 3En, Ex + 3En]$, and droplets outside this interval are typically neglected. This principle, known as the "3En rule" of the forward normal cloud model [48], preserves the concept's main structural characteristics while excluding extreme, low-probability fluctuations.

2.3.3. Implementation Procedure of the Cloud Model in This Study

In this study, the cloud model is applied to a multitemporal-scale analysis of ET_O and its driving meteorological factors across four agro-climatic regions—TSA, TSH, TAZ, and WCH. The implementation procedure is outlined below [49]:

- (1) The daily ET_O sequences calculated with Equation (1) and their corresponding meteorological factor sequences are aggregated across four agro-climatic zones (TSA, TSH, TAZ, and WCH) to produce time series at annual, seasonal (spring: March–May; summer: June–August; autumn: September–November; winter: December–February), and monthly scales.
- (2) Uncertainty estimation stage (backward process): For each grouped time series (e.g., the annual ET_O series in the TSA), the overall uncertainties are quantitatively estimated. Specifically, the uncertainty parameters En and He are extracted from the sequence's distribution using Equations (2)–(5).
- (3) Visualization stage (forward process): Taking En as the mean and He^2 as the variance, En'_i is drawn from a normal distribution: $En'_i = \text{NORM}(En, He^2)$.

- (4) Using Ex as the expectation and En'_i as the standard deviation, X_i is drawn from a normal distribution: $X_i = NORM(Ex, En'_i)$.
- (5) The certainty (membership degree) u_i of each cloud droplet is calculated as follows:

$$u_i = e^{-(X_i - Ex)/En'_i} \quad (6)$$

- (6) Each pair (X_i, u_i) defines a cloud droplet within the quantitative domain.
- (7) Steps (3)–(6) are repeated to generate n cloud droplets; for example, a cloud of 1000 droplets as in Figure 2, illustrating ET_O 's distribution range, central tendency, and dispersion.
- (8) The cloud-model parameters (Ex , En , and He) are compared across diverse agro-climatic zones and time scales. These parameters are then associated with meteorological factor trends, sensitivities, and contribution rates to reveal the spatiotemporal heterogeneity and driving mechanisms of uncertainty in ET_O changes.

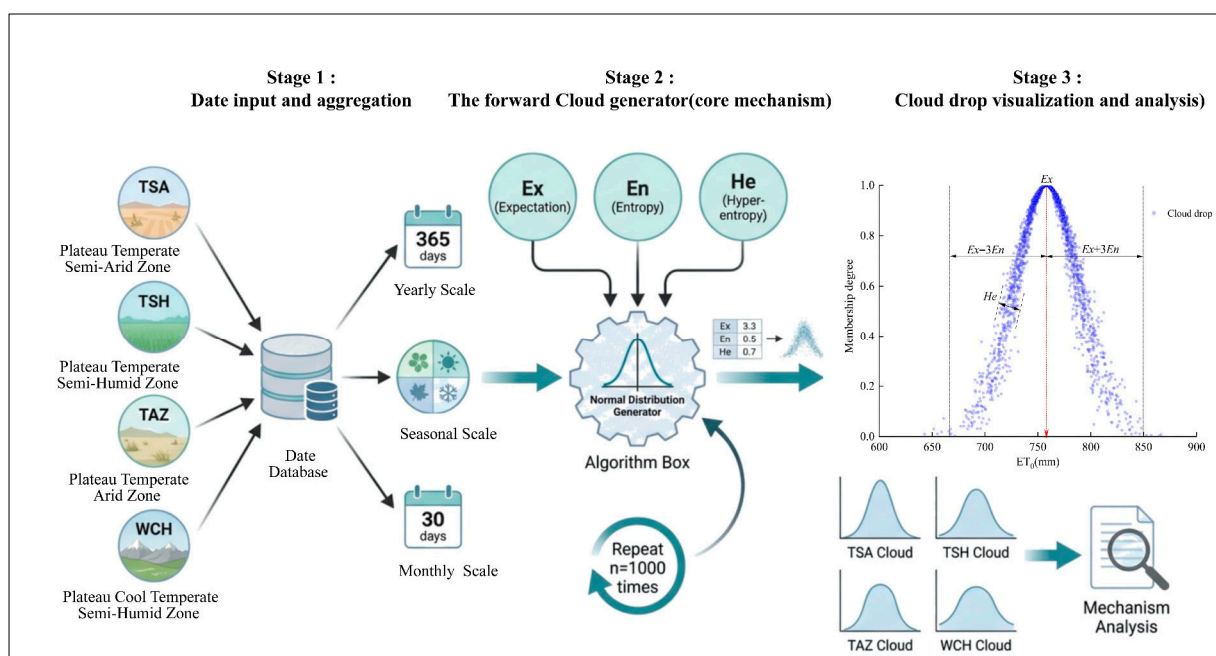


Figure 2. Illustration of the flowchart for the multi-time-scale ET_O uncertainty analysis based on the Forward Cloud Generator. In this figure, each membership degree μ corresponds to a specific ET_O value x , and each μ is associated with a probability of membership. A set of 1000 distinct membership-degree samples is depicted as blue dots. Ex denotes the expected value (i.e., the mean) of the ET_O distribution within the universe of discourse. The interval $[Ex - 3En, Ex + 3En]$ represents the ET_O values that can be represented by the qualitative concept within the universe of discourse. En reflects the dispersion of ET_O around its mean, and its magnitude influences He , which reflects the density of cloud droplets and the overall thickness of the cloud.

2.3.4. Physical Interpretation of Cloud-Model Parameters

To develop an uncertainty analysis framework tailored for agro-hydrological processes, this study provides explicit physical interpretations for the cloud-model parameters (Ex , En , He), using ET_O as an illustrative case.

- (1) Ex denotes the baseline regional evapotranspiration demand under long-term climatic conditions; it reflects the mean ET_O imposed on the regional agricultural system and serves as an indicator of the background hydro-thermal regime [50].

- (2) En quantifies the dispersion of the ET_O distribution. A larger En indicates greater fluctuations around the mean, reflecting higher sensitivity of evapotranspiration to climatic disturbances and increased variability in agricultural water demand [51].
- (3) He characterizes the uncertainty structure of the ET_O distribution and captures the combined effects of randomness and fuzziness [52,53]. A higher He implies more irregular evolution of ET_O and reduced predictability, signaling greater uncertainty for agricultural water-resource planning. By contrast, a lower He indicates more stable system behavior and stronger structural coherence [50].

Within agro-hydrological research, the cloud-model parameters Ex , En , and He acquire clear physical significance, transforming the cloud-model from a purely mathematical descriptor into a structured analytical framework for ET_O uncertainty assessment.

By integrating the cloud-model framework with conventional trend analysis, this study provides a dual-level characterization of ET_O across the Tibetan Plateau's four agro-climatic zones, ranging from long-term variation trends to process-level stability and structural uncertainty. This integrated approach supports evaluating the vulnerability and adaptive capacity of regional agricultural water resources under climate change.

2.4. Mann–Kendall Trend Test

The Mann–Kendall (M-K) trend test is a widely utilized nonparametric statistical method for identifying monotonic trends in time series data. Its extensive adoption is due to its robustness to distributional assumptions and insensitivity to outliers. For a time series $x = \{x_1, x_2, \dots, x_n\}$ of length n , the computational procedure for this test, as outlined in [54], is as follows.

The Mann–Kendall statistic S is computed as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_i - x_j) \quad (7)$$

where the function $\text{sgn}(x_i - x_j)$ is defined as follows:

$$\text{sgn}(x_i - x_j) = \begin{cases} 1 & x_i - x_j > 0 \\ 0 & x_i - x_j = 0 \\ -1 & x_i - x_j < 0 \end{cases} \quad (8)$$

Here, x_i and x_j are data values at time points i and j , respectively.

For $n > 10$, the variance of S is given by the following:

$$\text{Var}(S) = \frac{n(n-1)(2n+5)}{18} \quad (9)$$

The standardized test statistic Z is then calculated as follows:

$$Z = \begin{cases} \frac{(S-1)}{\sqrt{\text{Var}(S)}} & S > 0 \\ 0 & S = 0 \\ \frac{(S+1)}{\sqrt{\text{Var}(S)}} & S < 0 \end{cases} \quad (10)$$

The computed Z statistic is compared against the standard normal distribution's critical values. A positive Z value signifies an increasing trend, whereas a negative one denotes a decreasing trend. At a significance level of $\alpha = 0.05$, an increasing trend is considered significant if $Z > 1.645$ and a decreasing trend if $Z < -1.645$. If $|Z| \leq 1.645$, no trend is statistically significant at $\alpha = 0.05$ [55].

However, a fundamental assumption of the standard M-K test is that the time series data are independent. In practice, hydrometeorological time series often exhibit significant serial correlation (autocorrelation), which can inflate the variance of the M-K statistic and lead to an overestimation of trend significance (increased Type I error rate). To address this issue, the presence of autocorrelation in each time series (ET_O and other meteorological factors) was first assessed.

The Ljung–Box Q test was employed to statistically detect overall autocorrelation at various lags. Additionally, correlograms, including the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, were visually inspected to identify the pattern and strength of autocorrelation. If significant autocorrelation was detected (e.g., p -value from Ljung–Box test less than 0.05 at initial lags), the Trend-Free Pre-Whitening (TFPW) method, as proposed by Yue et al. [56], was applied prior to performing the M-K test.

The TFPW procedure involves the following steps:

- (1) Estimate the trend: First, the linear trend (or Sen's slope trend) of the original time series (x_t) is estimated. Let this trend component be T_t .
- (2) Detrend the series: The detrended series (Y_t) is obtained by subtracting the estimated trend from the original series: $Y_t = x_t - T_t$.
- (3) Estimate lag-1 autocorrelation: The lag-1 autocorrelation coefficient (r_1) of the detrended series (Y_t) is calculated. This coefficient quantifies the strength of the short-term memory in the series after removing the monotonic trend.
- (4) Pre-whiten the original series: A new series, the TFPW-transformed series (x'_t), is constructed by removing the serial correlation component from the original series using the estimated r_1 : $x'_t = x_t - r_1 x_{t-1}$ for $t = 2, \dots, n$. This step effectively "pre-whitens" the original series by removing its AR(1) component while preserving the underlying trend.
- (5) Apply M-K test to the TFPW-transformed series: Finally, the standard M-K test (Equations (7)–(10)) is applied to the TFPW-transformed series (x'_t) to assess the trend's significance. This approach ensures that the M-K test's assumption of independence is met, leading to more robust and reliable trend detection results.

For time series where no significant autocorrelation was detected, the standard M-K test (Equations (7)–(10)) was directly applied.

2.5. Sensitivity Analysis and Contribution-Rate Assessment

2.5.1. Sensitivity Analysis

Sensitivity analysis quantifies how a dependent variable responds to changes in its driving factors. In this study, the sensitivity of ET_O to each meteorological factor is defined as the ratio of the relative variation in ET_O to the relative variation in the factor, expressed through the sensitivity coefficient Se_{vi} :

$$Se_{vi} = \lim_{\Delta v_i} \left(\frac{\frac{\Delta ET_O}{ET_O}}{\frac{\Delta v_i}{v_i}} \right) = \frac{\partial ET_O}{\partial v_i} \cdot \frac{v_i}{ET_O} \quad (11)$$

where v_i denotes the i -th meteorological factor (e.g., temperature and wind speed), ΔET_O and Δv_i are the corresponding infinitesimal changes, and Se_{vi} is the dimensionless sensitivity coefficient. The sign of Se_{vi} indicates the direction of the effect: Se_{vi} means ET_O increases with the factor, while Se_{vi} means ET_O decreases as the factor increases. This definition follows the standard elasticity concept in economics and is widely applied in hydro-climatological studies [57,58]. The partial derivative $\frac{\partial ET_O}{\partial v_i}$ is derived analytically

from the FAO 56 Penman–Monteith equation (Equation (1)) by treating all other factors as constants.

2.5.2. Contribution Rate of Meteorological Factor to the Change in ET_O

Sensitivity analysis reveals how ET_O responds to climate change, but it does not quantify the extent to which changes in meteorological factors influence ET_O [57]. To determine the contribution rate of meteorological-factor changes to ET_O variations, the sensitivity coefficient is combined with meteorological-factor changes [58]. The contribution rate CR_{vi} is defined as follows:

$$CR_{vi} = R_{vi} \cdot Se_{vi} \quad (12)$$

where R_{vi} is the annual relative change rate of vi , defined as follows:

$$R_{vi} = \frac{n \cdot Trend_{vi}}{\bar{vi}} \quad (13)$$

Here, CR_{vi} denotes the contribution rate of the meteorological factor vi . If $CR_{vi} > 0$, changes in vi lead to an increase in ET_O ; conversely, $CR_{vi} < 0$ indicates that ET_O decreases as vi changes. R_{vi} denotes the annual relative change rate of vi . $Trend_{vi}$ denotes the slope of the simple linear regression of vi on time, typically expressed as the rate of change per decade. The sample length is n , and $\bar{vi}$ is the mean value of vi .

Furthermore, to evaluate the regional impact, the composite contribution rate for a specific agro-climatic region ($CR_{vi,region}$) is aggregated based on the meteorological stations within that zone. The mathematical expression is explicitly given as follows:

$$CR_{vi,region} = \frac{1}{m} \sum_j^m CR_{vi,j} \quad (14)$$

where $CR_{vi,region}$ denotes the contribution rate of the meteorological factor vi at the j -th station within the specific region, and m represents the total number of meteorological stations in that region. The sign of the resulting total determines the overall regional driving direction.

2.6. Data Sources and Processing

2.6.1. Data Sources

The daily-scale meteorological data, including maximum air temperature, minimum air temperature, mean air temperature, relative humidity, sunshine duration, and wind speed, used in this study were obtained from the China Terrestrial Climate Data Daily Value Dataset (V3.0), developed by the China National Meteorological Science Data Center (<https://data.cma.cn>, accessed on 15 January 2026). This dataset, designated SURF_CLI_CHN_MUL_DAY_CES (Version 3.0), underwent rigorous quality-control protocols, comprising checks for climatic threshold values, station extremes, internal consistency, temporal consistency, spatial consistency, and manual verification and correction. The data exhibit an accuracy approaching 100% and completeness exceeding 99%. For this analysis, observational data from 28 meteorological stations located within four agro-climatic zones on the Tibetan Plateau (Figure 1) were used. The geographical locations and basic meteorological characteristics of these stations are presented in Table 1.

Table 1. Means of 28 meteorological variables for meteorological stations across the agricultural regions of Xizang.

Agricultural Regionalization	Station	Longitude	Latitude	Altitude	T _{mean}	RH	U	SH	Length of Data
		(°)	(°)	m	°C	%	m·s ^{−1}	h	Year
Plateau temperate semi-humid zone (TSH)	Nyingchi	94.33	29.67	2991.80	8.93	63.23	1.68	5.49	1956–2017
	Milin	94.22	29.22	2950.00	8.92	68.95	1.41	4.52	1991–2015
	Bomi	95.77	29.87	2736.00	8.64	70.46	1.64	4.11	1955–2017
Plateau temperate semi-zone (TSA)	Namling	89.10	29.68	4000.00	6.21	42.88	1.37	7.98	1991–2015
	Shigatse	88.88	29.25	3836.00	6.69	42.42	1.66	8.79	1955–2017
	Jiangzi	89.60	28.92	4040.00	5.13	44.58	2.38	8.75	1956–2017
	Nyemo	90.17	29.43	3809.40	7.20	40.00	1.47	8.25	1973–2017
	Lhasa	91.13	29.67	3648.90	8.15	42.39	1.90	8.26	1955–2017
	Gongga	90.98	29.30	3555.30	8.95	46.56	1.60	8.50	1991–2015
	Zedang	91.77	29.25	3551.70	8.82	42.48	2.59	7.98	1956–2017
	Qamdo	97.17	31.15	3306.00	7.77	50.27	1.16	6.51	1954–2017
	Lhorong	95.83	30.75	3640.00	6.13	52.14	2.35	6.98	1992–2017
	Zuogong	97.83	29.67	3780.00	4.81	53.97	1.43	6.09	1978–2017
Plateau warm–cool semi-humid zone (WCH)	Nyalam	85.97	28.18	3810.00	3.82	65.02	4.15	6.99	1966–2017
	Dingqing	95.60	31.42	3873.10	3.58	56.54	1.54	6.76	1954–2017
	Suo County	93.78	31.88	4022.80	2.01	54.08	1.88	6.67	1956–2017
	Riwoche	96.60	31.22	3810.00	3.53	57.94	1.34	6.13	1991–2015
	Mangkang	98.60	29.68	3870.00	4.23	58.83	1.86	7.18	1991–2015
	Mozhugongka	91.73	29.85	3804.30	6.60	46.49	2.41	8.71	1991–2015
	Biru	93.78	31.48	3940.00	3.90	53.62	1.28	6.27	1991–2015
Plateau temperate arid zone (TAZ)	Cuona	91.95	27.98	4280.30	0.04	74.11	3.81	7.11	1967–2017
	Pulan	81.25	30.28	4900.00	3.67	46.56	3.30	8.74	1973–2017
	Shiquanhe	80.08	32.50	4278.60	0.87	32.34	2.88	9.58	1961–2017
	Tingri	87.08	28.63	4300.00	2.78	41.08	2.51	9.21	1959–2017
	Lhatse	87.60	29.08	4000.00	7.12	33.54	2.40	8.62	1977–2017
	Longzi	92.47	28.42	3860.00	5.46	53.09	2.57	8.27	1959–2017
	Basu	96.92	30.05	3260.00	10.98	39.49	1.92	7.54	1991–2015
Plateau temperate arid zone (TAZ)	Langkazi	90.40	28.97	4432.40	3.47	44.74	2.34	7.78	1991–2017

Monthly and annual meteorological data, along with ET_O, for each station were derived from daily data through aggregation or averaging. Seasonal definitions followed the standard in reference [59]: spring (March–May), summer (June–August), autumn (September–November), and winter (December–February of the following year).

2.6.2. Data Preprocessing and Quality Control

To ensure data reliability, accuracy, and temporal consistency, we implemented rigorous quality-control procedures and performed imputation of missing values for the daily observations across all stations.

(1) Outlier detection and removal

We identified observations outside climatologically plausible ranges using the three-sigma rule (3σ criterion) [60]. Detected outliers were cross-validated against data from neighboring stations for the same period [61]. If a value could not be validated, it was treated as missing.

(2) Missing-value imputation

For short-term missing sequences (e.g., single-day observations), linear interpolation is applied, utilizing the mean of observed values from the two adjacent days. Conversely, long-term missing sequences (e.g., continuous monthly data gaps) or previously identified and removed continuous outliers are replaced by the multi-year average for the corresponding month at that station [62]. This methodology aims to maximize the preservation of the data series' statistical characteristics.

2.6.3. Data Analysis and Visualization

All data processing and statistical analyses were performed in MATLAB R2022 using in-house scripts. The procedures included the extraction of the cloud-model's digital characteristics (Ex , En , and He), the implementation of the cloud-droplet-generation algorithm, the Mann–Kendall trend test, and the calculation of sensitivity coefficients and contribution rates. All figures were generated and formatted using OriginPro 2025.

3. Results

3.1. Annual Variation Characteristics of ET_O

Figure 3 presents the interannual evolution of ET_O across four agricultural climate zones of the Xizang Plateau—TSH, TSA, WCH, and TAZ. ET_O exhibited substantial interannual fluctuations in all regions, with long-term mean values ranging from 684.08 to 1052.18 mm and pronounced spatial variability. Linear trend analysis (Figure 3, Table 2) reveals significant increasing trends in ET_O for TAZ and WCH (Mann–Kendall $Z > 1.64$). Specifically, TAZ exhibits the largest increase, 15.76 mm per decade ($Z = 5.61$), followed by WCH (10.74 mm per decade, $Z = 4.65$). In contrast, TSA shows a significant decline of 6.58 mm per decade ($Z = -4.39$), whereas TSH shows a non-significant decline of 1.12 mm per decade ($Z = -0.34$); ET_O remains relatively stable overall. The five-year moving-average curves align closely with the linear trends, reinforcing the persistence of these patterns and suggesting that interannual fluctuations do not alter the long-term trajectories.

Although traditional trend analyses—including linear trend analysis, moving-average curves, and the Mann–Kendall trend test—describe the linear evolution of ET_O , they do not capture the uniformity and stability of its temporal distribution. To address this limitation, cloud-model theory is employed to characterize the uniformity and stability of ET_O 's distribution through its numerical characteristics (Ex , En , and He) and the corresponding cloud maps (Figure 4). The results in Table 2 indicate that TAZ and TSA exhibit the highest annual ET_O expectations (Ex) of 984.36 mm and 963.31 mm, respectively, while TSH and WCH show lower Ex values of 754.70 mm and 758.05 mm, reflecting baseline differences in evapotranspiration potential among regions. According to the cloud-model “3 En ” rule, the contributing cloud drops for TSH, TSA, WCH, and TAZ are distributed primarily within the intervals [680.36, 829.04], [848.08, 1078.54], [642.61, 873.49], and [873.90, 1094.82], respectively. The relative positions of Ex and these interval endpoints indicate that TSH has the narrowest interval span, implying minimal fuzziness and dispersion in its ET_O distribution; by contrast, TSA and WCH show the widest spans, suggesting greater fuzziness and dispersion. Regarding stability, WCH has the largest hyper-entropy ($He = 12.29$ mm), corresponding to the most dispersed cloud drops and the greatest cloud thickness in Figure 4, indicating the poorest uniformity and stability. By contrast, TSH has the smallest He (7.15 mm), reflecting the most concentrated and stable distribution with highly condensed cloud drops and a thinner cloud layer. The stability of ET_O in TAZ and TSA is intermediate between these extremes.

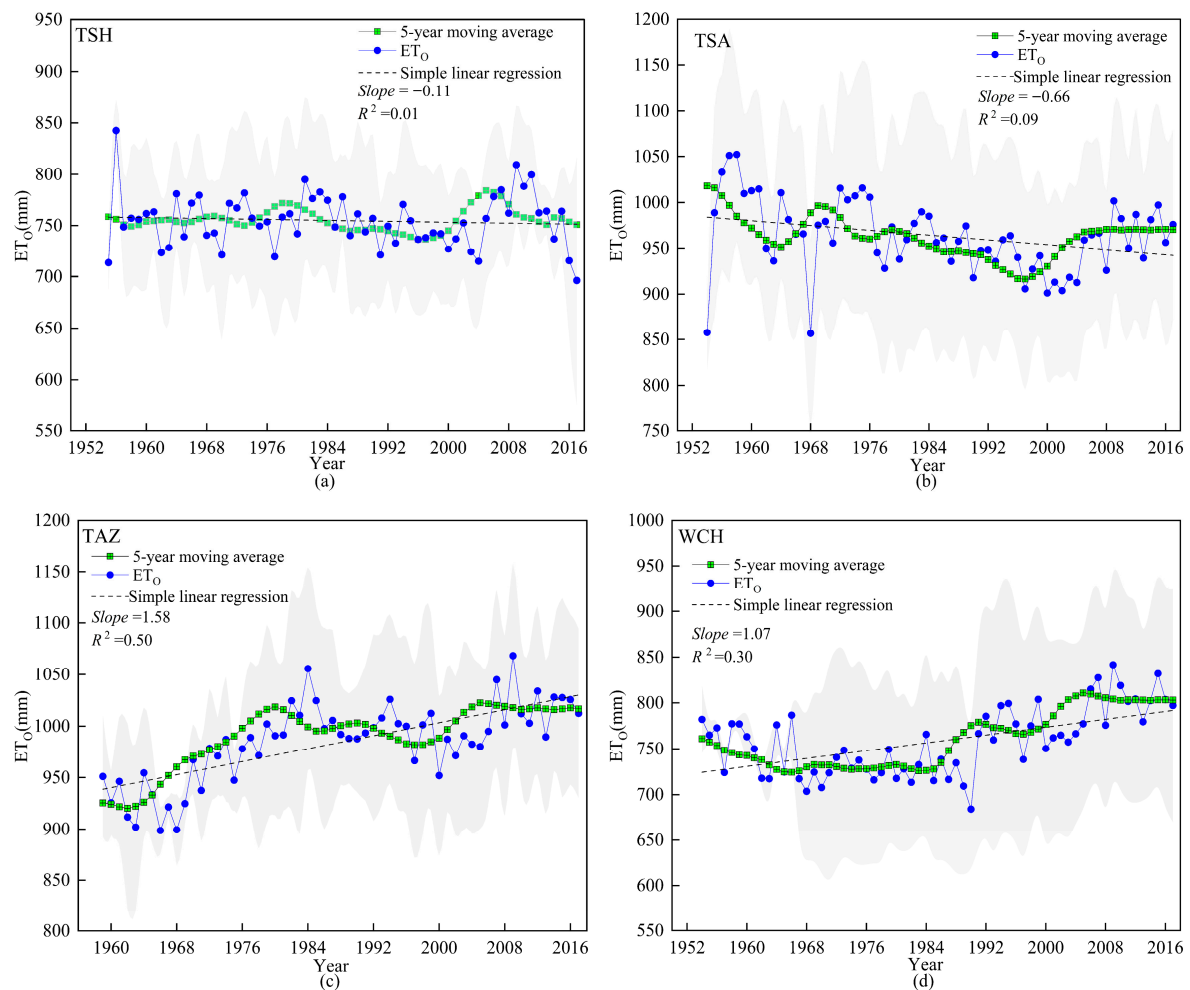


Figure 3. Annual variation in ET_O across four plateau agro-climatic zones in Xizang. The annual ET_O time series are shown for (a) the plateau temperate semi-humid zone (TSH), (b) the plateau temperate semi-arid zone (TSA), (c) the plateau temperate arid zone (TAZ), and (d) the plateau warm-cool semi-humid zone (WCH). Blue dots represent observed annual ET_O , green squares denote the 5-year moving average, and dashed lines indicate linear regression trends. The corresponding slope and coefficient of determination (R^2) are provided in each panel. The gray shaded band represents the mean $\pm$ SD, reflecting the inter-annual variability among sites within the region.

Table 2. Change and cloud-model characteristics of annual ET_O across four agricultural regions in Xizang.

Agricultural Regionalization	Linear Trend Characteristics		M-K Statistic		Cloud-Model Digital Characters		
	Slope	R^2	Z	Significance	Ex (mm)	En (mm)	He (mm)
TSH	−0.112	0.01	−0.34	–	754.70	24.78	7.15
TSA	−0.658	0.09	−4.39	*	963.31	38.41	10.68
WCH	1.074	0.30	4.65	*	758.05	38.48	12.29
TAZ	1.576	0.50	5.61	*	984.36	36.82	10.30

Note: The linear-trend characteristics include the slope of the climatic tendency (i.e., the trend rate) and the coefficient of determination (R^2), which quantify the direction, magnitude, and explanatory power of long-term changes in annual ET_O . The Mann–Kendall (M–K) test statistic Z and its associated p -value indicate the presence and statistical significance of monotonic trends. The cloud-model-derived characteristics comprise the expectation (Ex), entropy (En), and hyper-entropy (He), representing the central tendency, dispersion, and stability of the uncertainty in the annual ET_O time series. An asterisk denotes statistical significance at the 0.05 level.

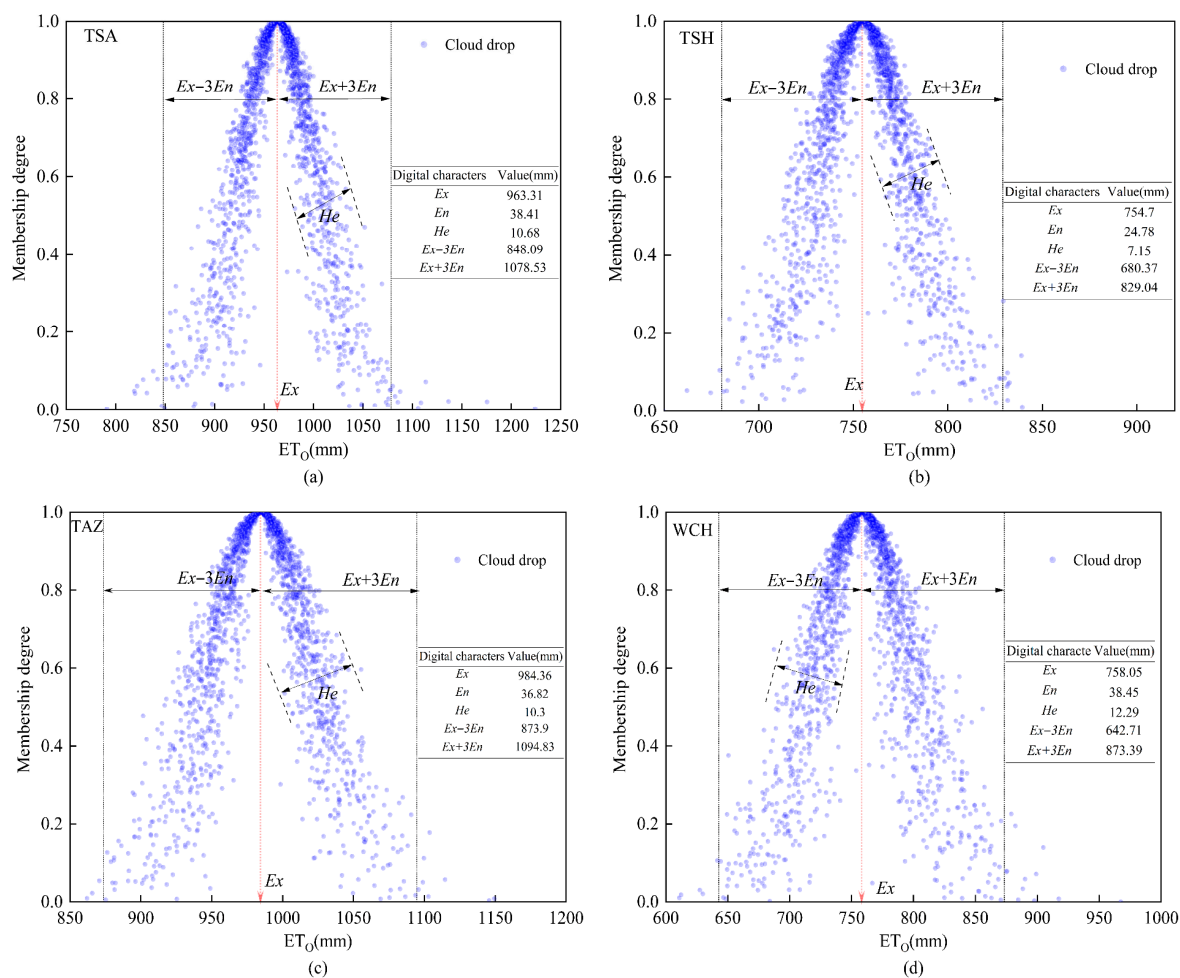


Figure 4. Cloud representations of the temporal distributions of annual ET_0 across four plateau agro-climatic regions in Xizang. This figure presents cloud-model diagrams illustrating the temporal distribution of annual ET_0 for (a) TSA, (b) TSH, (c) TAZ, and (d) WCH. Each cloud comprises numerous cloud drops generated from the expectation (Ex), entropy (En), and hyper-entropy (He). Expectation (Ex) denotes the central tendency of the ET_0 distribution, while the interval $[Ex - 3En, Ex + 3En]$ delineates the primary range of its variability. Hyper-entropy (He) reflects the stability of the uncertainty structure within the annual ET_0 time series.

3.2. Seasonal and Monthly Variation in ET_0

Figure 5a depicts the intra-annual variation in monthly ET_0 across four agro-climatic zones of the Xizang Plateau—TSA, TSH, TAZ, and WCH. The monthly ET_0 series displays a unimodal pattern, with peaks occurring around midyear and minima at the beginning and end of the year. High- ET_0 periods occur mainly from May to August (as indicated by the shaded region in Figure 5a), while minima are observed in December and January of the following year. Among the four zones, TAZ records the highest monthly ET_0 , peaking in June at 128.39 mm, followed by TSA, which peaks in June at 120.40 mm. In contrast, TSH and WCH exhibit substantially lower monthly ET_0 values, with peaks in July. An uncertainty analysis indicates that monthly ET_0 variability rises markedly during high- ET_0 periods (May–August) and remains relatively small during low- ET_0 periods (December–January).

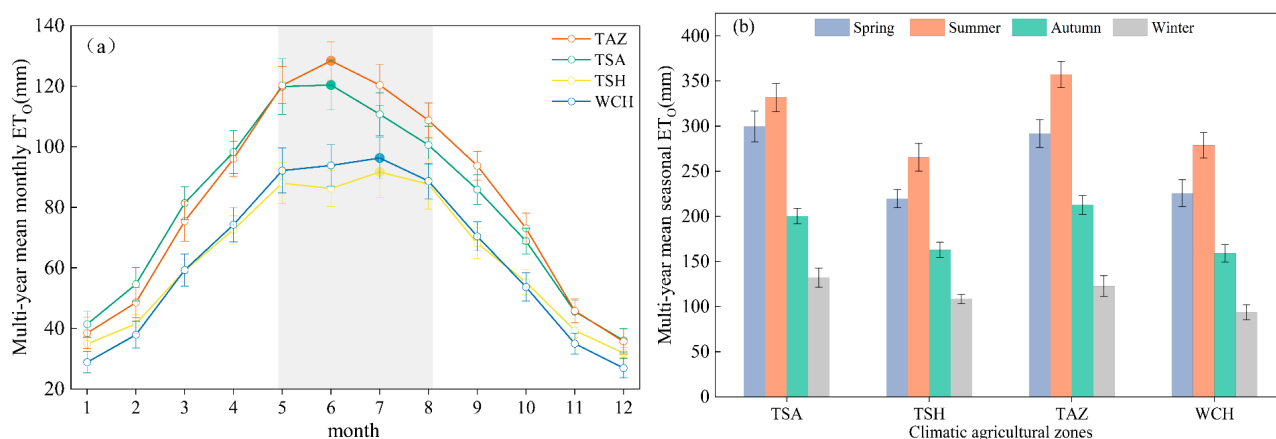


Figure 5. Seasonal characteristics of ET_O across agricultural regions of Xizang. (a) Seasonal variation in the multi-year mean monthly ET_O ; (b) multi-year mean seasonal ET_O for spring, summer, autumn, and winter. Lines with markers denote the mean monthly ET_O , while the error bars indicate interannual variability ($\pm$ SD). The shaded area denotes the high- ET_O season (May–August). Regions are ordered along a gradient from arid to semi-humid climatic conditions.

Cloud-model results (Table 3) show that monthly dispersion and hyper-entropy (En , He) across all zones closely track the seasonal progression of mean ET_O . Specifically, high- ET_O periods correspond to greater dispersion (mean $En = 6.94$ mm), whereas low- ET_O periods exhibit more concentrated distributions (mean $En = 3.20$ mm). Although no significant interregional differences in monthly distribution uniformity were detected ($p = 0.51$), clear differences emerge in stability: TSH shows the highest monthly ET_O stability ($He = 2.03$), whereas WCH shows the lowest stability ($He = 2.62$).

Table 3. Cloud-model characteristics of monthly ET_O across four plateau agro-climatic regions in Xizang.

Month	TSA			TSH			TAZ			WCH		
	Ex (mm)	En (mm)	He (mm)	Ex (mm)	En (mm)	He (mm)	Ex (mm)	En (mm)	He (mm)	Ex (mm)	En (mm)	He (mm)
1	41.40	4.39	1.20	34.87	2.11	0.27	38.48	6.00	0.48	28.85	3.37	0.93
2	54.61	5.45	1.15	41.54	2.93	1.07	48.54	4.85	1.26	37.92	4.42	0.66
3	81.39	5.73	1.73	59.09	3.58	0.65	75.43	6.30	1.94	59.3	5.08	1.40
4	98.24	7.33	2.01	72.59	4.69	0.85	96.01	5.6	1.68	74.25	5.62	0.92
5	119.88	8.89	2.07	87.97	6.68	0.66	120.3	6.28	1.37	92.15	6.95	2.62
6	120.40	8.18	0.94	86.21	5.72	1.54	128.39	6.51	1.75	93.83	7.21	2.37
7	110.73	7.00	1.14	91.68	8.43	0.66	120.35	6.49	2.14	96.28	6.64	1.38
8	100.56	6.28	0.69	87.65	8.53	2.03	108.71	5.47	1.73	88.71	5.84	0.72
9	85.87	4.72	1.32	68.15	5.00	1.28	93.74	4.54	1.38	70.43	4.90	0.94
10	68.85	4.27	0.53	55.28	4.07	1.16	73.07	4.91	0.96	53.69	4.65	0.47
11	45.60	3.82	0.64	39.33	2.50	0.16	45.78	3.92	0.46	34.98	3.40	0.82
12	36.08	3.78	0.76	31.87	1.76	0.59	35.71	3.92	1.21	26.94	3.15	0.84

Note: The cloud-model characteristics— Ex , En , and He —describe the central tendency, dispersion, and uncertainty of the monthly ET_O distributions, respectively. All values are expressed in millimeters (mm).

At the seasonal scale (Figure 5b), ET_O across the four zones follows a consistent pattern: summer > spring > autumn > winter, with pronounced regional differences ($p < 0.01$). Cloud-model results (Table 4) yield seasonal Ex values of ET_O ranging from 122.73 to 357.45 mm in TAZ, 132.09 to 331.69 mm in TSA, 108.29 to 265.54 mm in TSH, and 93.70 to 278.82 mm in WCH. Among the zones, TSA exhibits the highest summer ET_O (mean $Ex = 331.69$ mm), while WCH records the lowest winter ET_O (mean $Ex = 93.70$ mm). In terms of distribution uniformity, seasonal ET_O displays greater dispersion in spring and

summer and stronger concentration in autumn and winter across all regions. Interregional differences indicate that TSH has the lowest seasonal dispersion (mean $En = 9.59$ mm), while TSA has the highest dispersion (mean $En = 12.97$ mm). Seasonal ET_0 stability exhibits pronounced spatiotemporal heterogeneity. In TSH and TAZ, stability is lowest in summer and autumn and higher in winter and spring, consistent with Figure 6, which shows clustered cloud droplets and thinner cloud layers during these periods. By contrast, TSA and WCH display greater stability in autumn and winter and reduced stability in spring and summer, indicating that these two agro-climatic zones experience greater stability during the cold season.

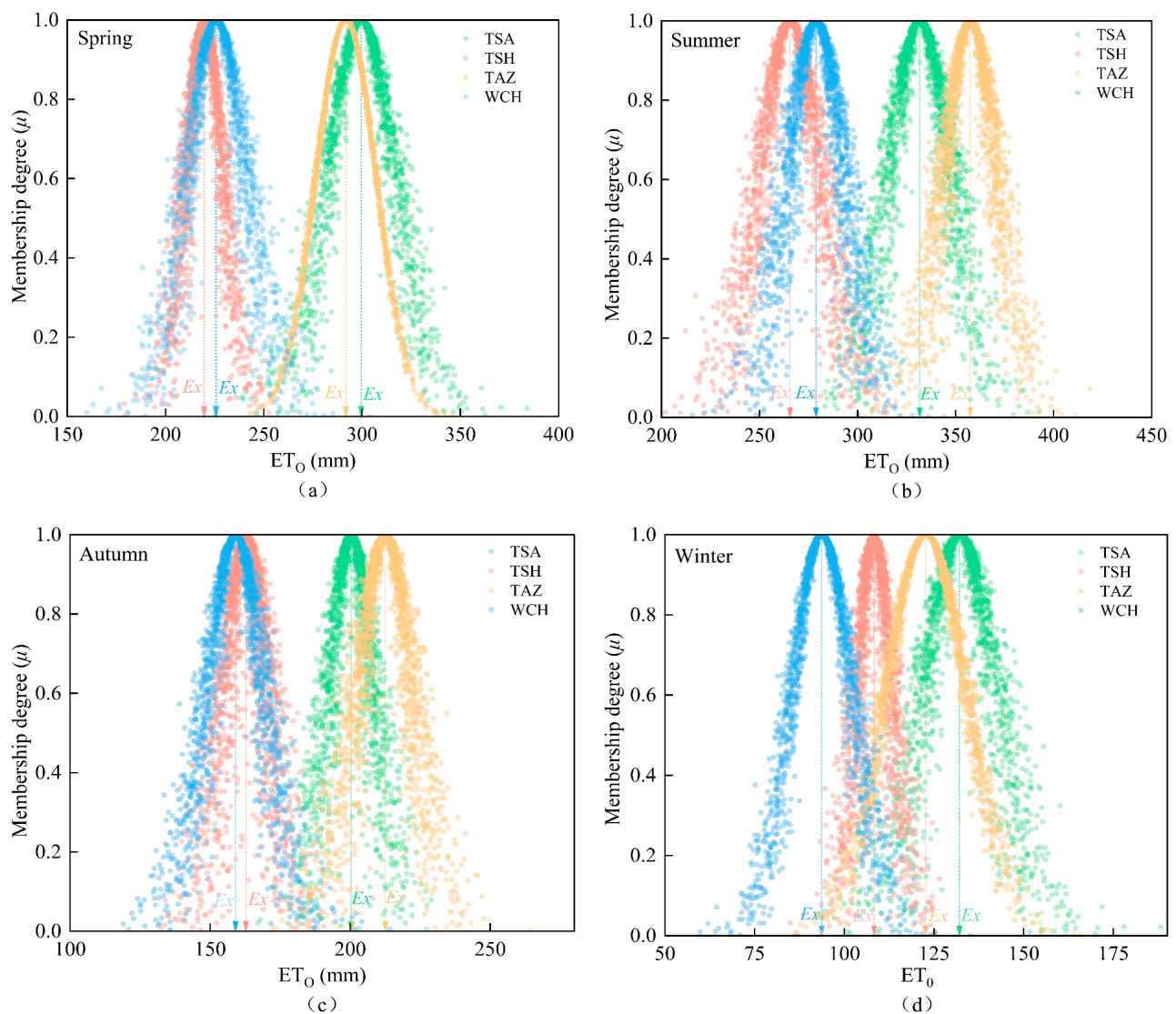


Figure 6. Cloud-model distributions of seasonal ET_0 across four plateau agro-climatic regions in Xizang. The panels show ET_0 distributions for (a) spring, (b) summer, (c) autumn, and (d) winter. In each panel, colored dots represent cloud-model realizations of seasonal ET_0 for each agricultural region. Vertical dashed lines denote the expectation values (Ex) of the ET_0 distributions. Consistent regional color coding across panels facilitates comparisons of seasonal ET_0 characteristics across the four climatic agricultural zones.

Table 4. Cloud-model characteristics of seasonal ET_O across four plateau agro-climatic regions in Xizang.

Season	TSA			TSH			TAZ			WCH		
	Ex (mm)	En (mm)	He (mm)	Ex (mm)	En (mm)	He (mm)	Ex (mm)	En (mm)	He (mm)	Ex (mm)	En (mm)	He (mm)
Spring	299.50	17.50	3.63	219.65	9.76	2.42	291.74	15.43	0.48	225.70	15.34	3.65
Summer	331.69	16.21	4.18	265.54	15.86	4.03	357.45	14.07	3.48	278.82	14.58	3.86
Autumn	200.32	7.97	2.88	162.76	7.84	2.92	212.59	10.00	2.88	159.10	10.13	2.53
Winter	132.09	10.23	2.80	108.29	4.91	1.72	122.73	11.45	1.19	93.70	8.56	1.51

Note: The cloud-model characteristics—*Ex*, *En*, and *He*—represent the central tendency, dispersion, and uncertainty of seasonal ET_O distributions, respectively. All values are expressed in millimeters (mm).

3.3. Variation in the Mean Values of Meteorological Factors

Table 5 summarizes the variation trends and cloud-model characteristics (*Ex*, *En*, and *He*) of the major meteorological variables across Xizang's four agro-climatic zones (TSA, TSH, TAZ, and WCH), with the corresponding cloud maps presented in Figure 7.

Table 5. Annual changes and cloud-model characteristics of meteorological factors across four plateau agro-climatic regions in Xizang.

Meteorological Factors	Agricultural Regionalization	Tendency Rate		Statistic	Cloud-Model Digital Characters		
		Slope	R ²		Ex	En	He
T _{min}	TSA	0.02	0.31	5.64 *	−0.04	0.67	0.12
	TSH	0.02	0.50	6.62 *	3.86	0.66	0.13
	TAZ	0.09	0.83	9.22 *	−3.24	1.81	0.63
	WCH	0.03	0.38	6.92 *	−3.20	1.01	0.38
T _{max}	TSA	0.01	0.04	3.06 *	14.79	0.66	0.14
	TSH	0.01	0.10	2.90 *	16.12	0.50	0.20
	TAZ	0.05	0.62	6.88 *	12.11	1.07	0.40
	WCH	0.05	0.35	5.76 *	10.06	1.60	0.68
T _{mean}	TSA	0.01	0.09	3.70 *	6.70	0.53	0.10
	TSH	0.02	0.31	4.86 *	8.81	0.52	0.08
	TAZ	0.07	0.79	8.19 *	3.98	1.42	0.52
	WCH	0.03	0.36	5.98 *	2.58	1.18	0.51
U	TSA	−0.01	0.18	−7.04 *	2.10	0.32	0.05
	TSH	−0.00	0.37	−6.07 *	1.66	0.24	0.17
	TAZ	−0.01	0.38	−6.76 *	2.68	0.33	0.08
	WCH	−0.00	0.00	−3.55 *	2.15	0.45	0.17
SH	TSA	−0.00	0.26	−6.20 *	7.81	0.19	0.07
	TSH	−0.01	0.14	−3.53 *	4.78	0.31	0.05
	TAZ	−0.01	0.42	−6.12 *	8.76	0.29	0.11
	WCH	0.01	0.18	3.05 *	6.85	0.33	0.04
RH	TSA	0.00	0.05	4.79 *	0.47	0.03	0.004
	TSH	0.00	0.01	2.38 *	0.67	0.02	0.005
	TAZ	−0.00	0.19	−3.15 *	0.42	0.03	0.007
	WCH	0.00	0.00	0.05	0.58	0.04	0.016

Note: The slope and the coefficient of determination (*R*²) denote the linear trend and the proportion of variance explained, respectively; the Mann–Kendall statistic (*Z*) assesses trend significance, with significance at the $\alpha = 0.05$ level indicated by an asterisk. The cloud-model characteristics—*Ex*, *En*, and *He*—describe, respectively, the distribution center, dispersion, and stability (fuzziness) of the distributions. Values are provided for each region (TSA, TSH, TAZ, and WCH). Units are provided for each variable; *En* and *He* are dimensionless or scale with the corresponding variable, as indicated in the table.

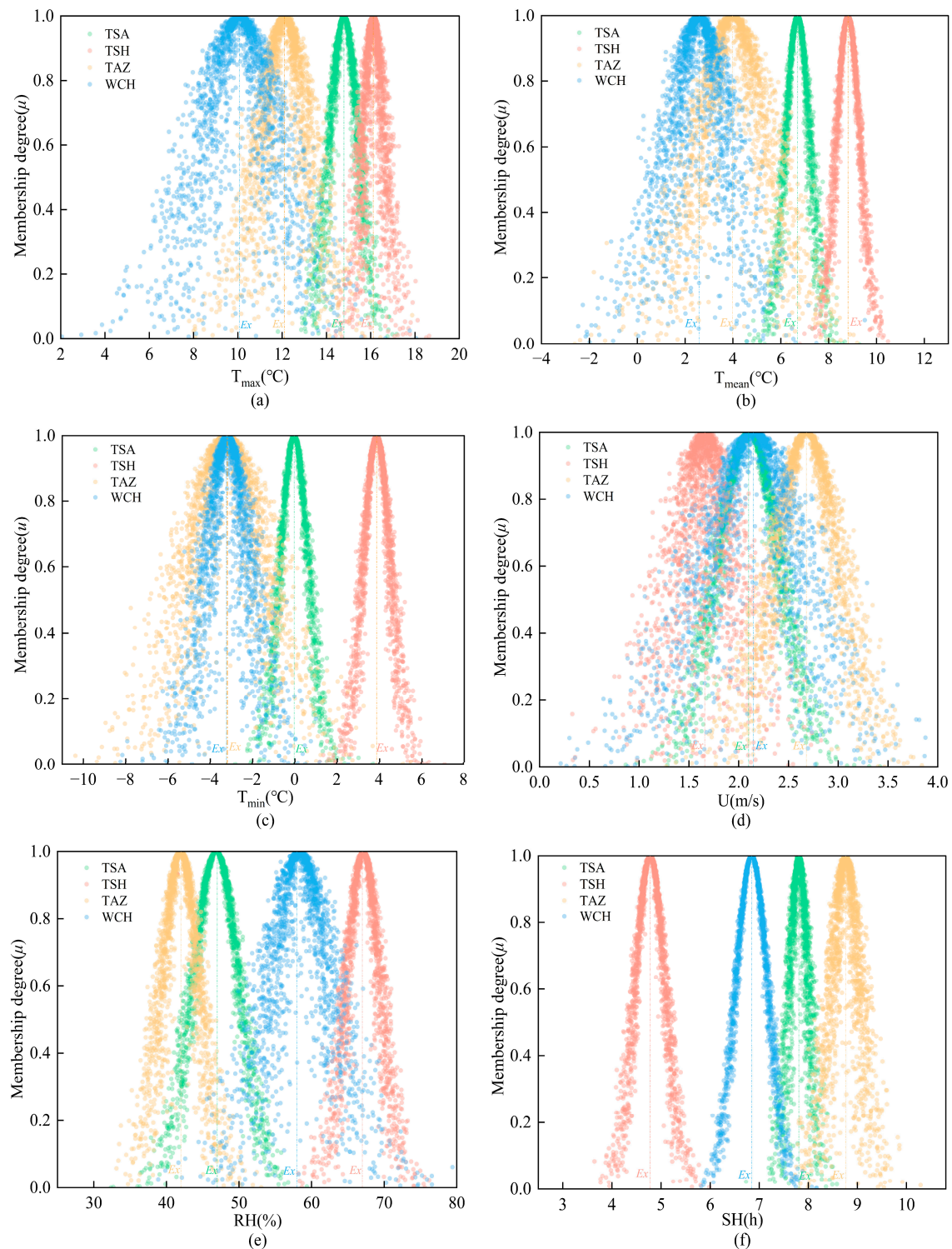


Figure 7. Cloud-model distributions of meteorological factors across four plateau agro-climatic regions in Xizang. This figure presents cloud distributions of meteorological factors across the four agro-climatic zones on the Xizang Plateau (TSA, TSH, TAZ, and WCH), with cloud-model features *Ex*, *En*, and *He*, and the membership degree μ . Subplots (a) $T_{\max}$, (b) T_{mean} , (c) $T_{\min}$, (d) U , (e) RH , and (f) SH . Colors denote the regions TSA, TSH, TAZ, and WCH. The x-axis shows the variable value, and the y-axis shows the membership degree μ . *Ex*, *En*, and *He* reflect the central tendency, dispersion, and stability (fuzziness) of the cloud-model distribution, respectively. μ indicates the cloud membership probability. *Ex* lines and cloud shapes should be consistent with Table 5 values to facilitate cross-reference.

Temperature variables display significant upward trends across all zones, with Mann–Kendall Z values ranging from 2.90 to 9.22 and decadal warming rates from 0.1 to 0.9 °C. The greatest warming rate is observed in TAZ, followed by WCH, while TSA and TSH warm more slowly. Cloud-model characteristics indicate that TAZ has the lowest $T_{\min}$ Ex (−3.24 °C); $T_{\max}$ and the En and He values for T_{mean} are the highest among the four regions, implying more pronounced cold-season conditions, greater temperature dispersion, and poorer interannual stability, as evidenced by dispersed cloud droplets and thicker cloud layers in Figure 7. In contrast, TSA and TSH show lower En and He values, with more aggregated cloud droplets and thinner cloud layers, indicating more uniform and stable temperature distributions. Overall, TAZ exhibits the greatest temperature variability and distributional uncertainty, whereas TSA shows comparatively greater thermal stability.

Across the four regions, the annual mean wind speed ranges from 1.66 to 2.68 m·s^{−1} and exhibits a general downward trend over time. Statistically significant declines occur in TSA, TSH, TAZ, and WCH ($Z = -7.04, -6.07, -6.76$, and -3.55). Cloud-model results indicate that TAZ exhibits the highest Ex (2.68 m·s^{−1}), while TSH exhibits the lowest (1.66 m·s^{−1}). Although TAZ records the greatest mean wind speed, its En is the smallest (0.11 m·s^{−1}), suggesting limited interannual fluctuations and a more concentrated distribution. By contrast, WCH shows the largest En (0.45 m·s^{−1}), indicating greater interannual variability. In terms of stability, TSA has the smallest He (0.05 m·s^{−1}), corresponding to highly aggregated cloud droplets and thinner cloud layers in Figure 7, indicating the highest interannual wind speed stability. By contrast, TSH and WCH exhibit weaker stability.

Sunshine duration shows marked regional differentiation, with significant decreases in TSA, TSH, and TAZ (TSA: $Z = -6.20$) and a significant increase in WCH ($Z = 3.05$). Cloud-model analysis reveals that WCH has the largest En (0.33 h), indicating greater interannual variability, while the remaining regions show En values between 0.19 and 0.31 h, reflecting relatively concentrated distributions. With regard to stability, WCH exhibits the smallest He value (0.04 h). Figure 7 shows highly aggregated cloud droplets and the thinnest cloud layer, indicating a more stable interannual sunshine distribution, despite its greater amplitude of variability.

Relative humidity increased significantly in TSA and TSH ($Z = 4.79$ and 2.38) and decreased significantly in TAZ ($Z = -3.15$), whereas WCH showed no significant change ($Z = 0.05$). Cloud-model metrics indicate that the RH Ex is highest in TSH (67%) and lowest in TAZ (42%), reflecting pronounced regional differences in annual mean atmospheric moisture conditions. WCH exhibits the largest En (0.04) and He (0.016), indicating greater dispersion and higher structural uncertainty in RH distribution, while the other regions show En values from 0.02 to 0.03 and He values from 0.004 to 0.007, suggesting more uniform and stable interannual distributions. Cloud maps in Figure 7 further confirm higher cloud-droplet aggregation and thinner cloud layers in TSA, TSH, and TAZ, supporting their relatively stronger RH stability.

3.4. Sensitivity and Contribution of Meteorological Factors Controlling ET_O Across Climatic Agricultural Zones

3.4.1. Sensitivity of ET_O to Meteorological Factors

Table 6 presents the sensitivity coefficients (Se) of ET_O to $T_{\max}$, $T_{\min}$, T_{mean} , U , SH , and RH across the four agro-climatic zones. Pronounced regional differentiation is evident in both the direction and magnitude of these sensitivities, indicating that ET_O 's responses to climatic drivers vary spatially.

Across all regions, $T_{\max}$ shows positive sensitivity, with $Se_{T_{\max}}$ values of 0.28 (TSA), 0.51 (TSH), 0.34 (TAZ), and 0.35 (WCH), indicating that higher $T_{\max}$ promotes ET_O . T_{mean} also exhibits positive sensitivity across regions, although $Se_{T_{\text{mean}}}$ values are smaller. $T_{\min}$ shows clear regional differentiation, being positively sensitive in TSH ($Se_{T_{\min}} = 0.09$) and negatively sensitive in TSA, TAZ, and WCH ($Se_{T_{\min}} = -0.06$ to -0.001). The overall

sensitivity of ET_O to wind speed is weak: WCH shows a marginal negative response ($Se_U = -0.01$), whereas the other regions show positive Se_U . RH exhibits negative sensitivity across all regions ($Se_{RH} = -0.62$ to -0.30), indicating that declines in RH promote ET_O . SH exhibits positive sensitivity across all regions ($Se_{SH} = 0.34$ – 0.69), reflecting the significant influence of radiative conditions on ET_O .

Table 6. Sensitivity coefficients of ET_O changes to climate factors across four plateau agro-climatic regions in Xizang.

Agricultural Regionalization	Se_{Tmin}	Se_{Tmax}	Se_{Tmean}	Se_U	Se_{SH}	Se_{RH}
TSA	−0.001	0.281	0.152	0.084	0.686	−0.306
TSH	0.087	0.513	0.292	0.013	0.341	−0.621
TAZ	−0.050	0.342	0.108	0.069	0.566	−0.302
WCH	−0.063	0.351	0.120	−0.008	0.465	−0.416

Note: T_{max} , T_{min} , and T_{mean} are temperature-related variables, but they influence ET_O through distinct physical pathways in the FAO 56 Penman–Monteith equation. Consequently, their sensitivities are analyzed separately to avoid double-counting temperature effects. Se_{Tmax} , Se_{Tmin} , Se_{Tmean} , Se_U , Se_{RH} , and Se_{SH} denote the sensitivity coefficients of T_{max} , T_{min} , T_{mean} , U, RH, and SH to ET_O , respectively.

Figure 8 contrasts the composite sensitivities of temperature factors (Se_{Tem} , defined as the mean of Se_{Tmax} , Se_{Tmin} , and Se_{Tmean}) with those of non-temperature factors ($Se_{Non-Tem}$, defined as the mean of Se_U , Se_{SH} , and Se_{RH}). Se_{Tem} is positive across all regions, ranging from 0.13 to 0.30, with TSH the highest at 0.30 and TSA the lowest at 0.13, indicating that ET_O in TSH is most responsive to temperature changes. For non-temperature factors, $Se_{Non-Tem}$ is positive in TSA, TAZ, and WCH (0.01–0.15) but negative in TSH (−0.09), implying that in the TSH climate, the combined marginal effect of wind speed, sunshine duration, and RH suppresses ET_O growth. This counterintuitive result stems from the mixed influence of non-temperature factors on TSH. RH contributes the strongest negative effect (−0.62) among the regions, while U contributes a small positive effect (0.01) and SH contributes a moderate positive effect (0.34). Averaging these effects shows that the negative RH impact dominates the positive contributions from wind and radiation, yielding a net negative composite sensitivity.

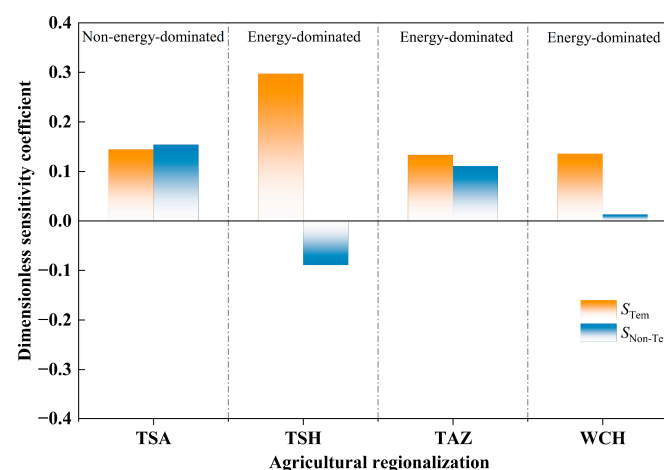


Figure 8. Average sensitivity coefficients of ET_O to temperature and non-temperature factors in four plateau agro-climatic regions in Xizang. The average temperature-sensitivity, S_{Tem} , is defined as $S_{Tem} = (Se_{Tmax} + Se_{Tmin} + Se_{Tmean})/3$, representing ET_O 's average sensitivity to temperature-related factors. The average non-temperature sensitivity, $Se_{Non-Tem}$, is defined as $Se_{Non-Tem} = (Se_{RH} + Se_{SH} + Se_U)/3$, representing ET_O 's average sensitivity to RH, SH, and U (radiation and dynamical factors). Positive values indicate that increasing the factor raises ET_O ; negative values indicate a decrease. If $|Se_{Non-Tem}| > |Se_{Tem}|$, the region is non-temperature-factor-dominant; otherwise, it is temperature-factor-dominant.

3.4.2. Contribution of Meteorological Factors to ET_O Changes

To identify the dominant drivers of ET_O changes across four agro-climatic zones, this study employs the contribution-rate method to quantify the net effect of each meteorological factor. The contribution rate captures the actual change in a meteorological factor over the study period and its net impact on ET_O (increase or decrease). The sign of the contribution rate is determined jointly by the sensitivity direction and the factor-change trend. A positive contribution rate indicates that the factor's change promotes ET_O , whereas a negative rate indicates inhibition of ET_O growth.

The contribution-rate analysis (Table 7) reveals significant spatial heterogeneity in the dominant meteorological drivers of ET_O , demonstrating that the same factor can exhibit distinct directional contributions across different regions. Specifically, T_{max} and T_{mean} exhibit significant positive contributions to ET_O in all four regions, emerging as the factors with the largest individual contribution rates. T_{max} contributions are 5.28% (WCH), 4.82% (TAZ), 2.96% (TSA), and 2.63% (TSH), whereas T_{mean} contributions are 5.31% (WCH), 4.63% (TAZ), 3.16% (TSA), and 3.14% (TSH). T_{min} shows regional differentiation: positive in TSH ($CR_{Tmin} = 2.86\%$), negative in TSA (-0.51%), TAZ (-3.28%), and WCH (-2.96%). The wind speed contribution (CR_U) is positive in WCH (0.68%) but negative in TSA, TAZ, and TSH (-2.71% , -2.30% , and -1.01% , respectively). The sunshine duration contribution (CR_{SH}) is negative in TSA, TSH, and TAZ (-0.73% to -2.63%) and near zero in WCH (0.03%), indicating that SH variations suppress ET_O in most regions, with the strongest inhibition observed in TSH. Across all four regions, the relative humidity contribution (CR_{RH}) remains positive, spanning 1.46–2.88%, indicating that variations in RH consistently promote ET_O .

Table 7. Contribution rates of different meteorological factors to ET_O across four plateau agro-climatic regions in Xizang.

Agricultural Regionalization	CR_{Tmin} (%)	CR_{Tmax} (%)	CR_{Tmean} (%)	CR_U (%)	CR_{SH} (%)	CR_{RH} (%)
TSA	−0.506	2.960	3.157	−2.711	−0.721	1.463
TSH	2.862	2.627	3.143	−1.010	−2.629	2.364
TAZ	−3.276	4.824	4.626	−2.300	−0.604	2.761
WCH	−2.958	5.280	5.307	0.678	0.034	2.883

Note: T_{max} , T_{min} , and T_{mean} are temperature-related variables, but they influence ET_O through distinct physical pathways in the FAO 56 Penman–Monteith equation. Accordingly, their contribution rates were analyzed separately to avoid double-counting temperature effects. The contribution rates of meteorological factors in the TSH, TSA, WCH, and TAZ regions are composite contribution rates. They are obtained by summing the contribution rates of meteorological stations within each region (see Table 1) during calculation, with the sign determined by the resulting total.

Figure 9 shows that the combined contribution of temperature factors (CR_{Tem} ; T_{max} , T_{min} , T_{mean}) is positive in all four regions, ranging from 5.61% to 8.63%, indicating a consistent temperature-driven direction across the study area. In contrast, the combined contribution of non-temperature factors ($CR_{Non-Tem}$; SH, RH, U) exhibits distinct regional differentiation: it suppresses ET_O in TSA, TSH, and TAZ ($CR_{Non-Tem}$ between -1.97% and -0.14%) but promotes ET_O in WCH ($CR_{Non-Tem} = 3.60\%$). Across all regions, temperature factors contribute more strongly in absolute terms than non-temperature factors, identifying temperature as the primary driver of ET_O changes.

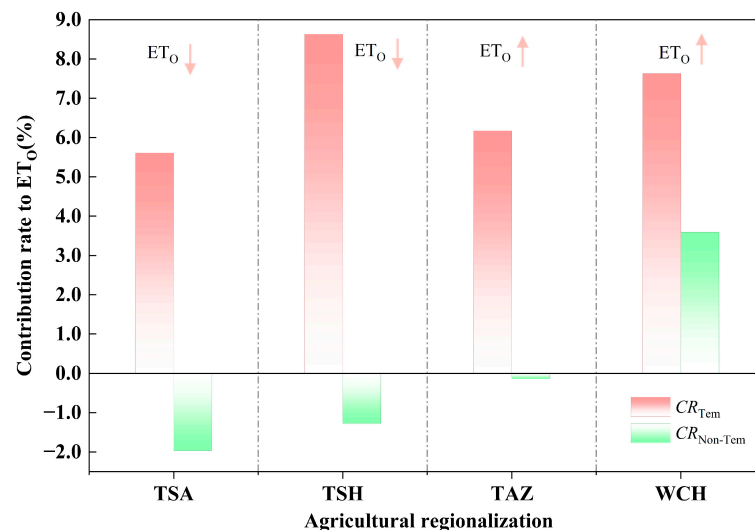


Figure 9. Contribution rates of temperature-related and non-temperature factors to ET_O across four plateau agro-climatic regions in Xizang. The temperature-related composite contribution, CR_{Tem} , equals the sum of the contributions from T_{max} , T_{min} , and T_{mean} , while the non-temperature composite contribution, $CR_{Non-Tem}$, equals the sum of the contributions from RH, SH, and U.

3.5. Integrated Assessment of ET_O Stability and Dominant Meteorological Drivers

Table 8 quantifies the correspondence between ET_O stability and that of its dominant meteorological factors across four agro-climatic zones, using cloud-model hyper-entropy (He) and a stability-difference index (ΔHe). Dominant factors are identified through a contribution-rate analysis; ET_O stability is represented by the cloud-model parameter He , and ΔHe quantifies the relative stability difference between ET_O and its dominant driver.

Table 8. Integrated stability characteristics of ET_O and its dominant meteorological factors across four plateau agro-climatic zones in Xizang.

Climatic Zone	Integrated Information on Dominant Meteorological Factors			He_{ETO} (mm)	ΔHe
	Dominant Factor	Contribution Rate (%)	He_{dom} (mm)		
TSA	T_{mean}	3.16	0.10	10.68	0.99
TSH	T_{mean}	3.14	0.08	7.15	0.98
TAZ	T_{max}	4.82	0.40	10.30	0.96
WCH	T_{mean}	5.31	0.51	12.29	0.93

Note: For each zone, the dominant meteorological factor is defined as the variable with the highest contribution rate to ET_O . The hyper-entropy of ET_O and that of the dominant factor are denoted as He_{ETO} and He_{dom} , respectively. The stability difference index, ΔHe , is defined as $\Delta He = (He_{ETO} - He_{dom}) / He_{ETO}$. Higher ΔHe values indicate a larger relative disparity in stability between ET_O and its dominant driver. Contribution rates represent the relative importance of each meteorological factor in explaining ET_O variability, as described in Section 3.4.2.

Across all four agro-climatic zones, He_{ETO} consistently surpasses He_{dom} , indicating that ET_O instability exceeds that of its dominant meteorological factor. Figure 10 reveals spatial discrepancies in stability rankings: ET_O stability follows the order TSH > TSA > TAZ > WCH, whereas the stability of the dominant factors follows TSH > TAZ > TSA > WCH. This demonstrates that the correspondence between ET_O stability and dominant-factor stability is not consistent across regions.

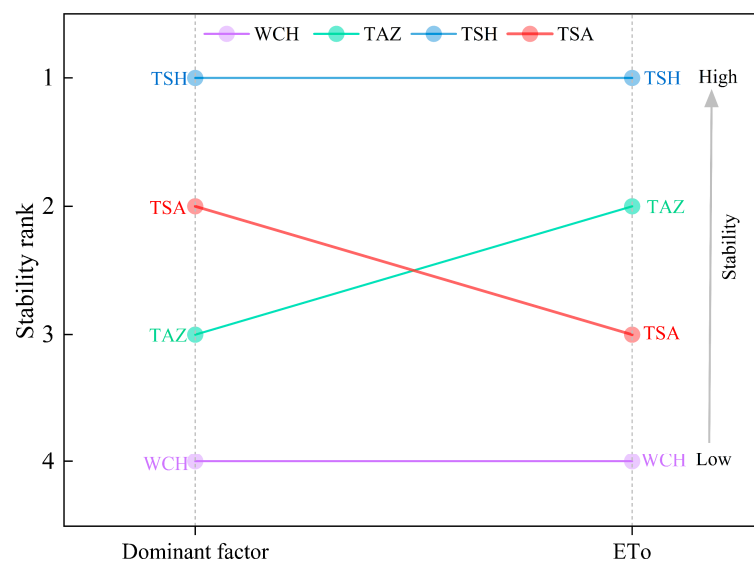


Figure 10. Rank correspondence of stability (He) between ET_O and its dominant meteorological factors across four plateau agro-climatic zones in Xizang. Stability is expressed as the rank of He , with lower ranks indicating higher stability. Parallel lines indicate consistent stability rankings between ET_O and the dominant factor, whereas rank crossovers indicate divergence in the stability structure.

For instance, in the TSH region, the dominant-factor stability (T_{mean}) exhibits the highest stability ($He_{dom} = 0.08$ mm), and the corresponding ET_O also shows the highest stability ($He_{ETO} = 7.15$ mm). Similarly, in the WCH region, the dominant-factor stability shows the lowest stability ($He_{dom} = 0.51$ mm), with the corresponding ET_O also displaying the lowest stability ($He_{ETO} = 12.29$ mm). In these two regions, a consistently positive relationship is observed, in which greater stability of the dominant factor corresponds to greater ET_O stability (Figure 10).

In the TSA region, although the dominant-factor stability ranks second ($He_{dom} = 0.10$ mm, second only to TSH), its corresponding ET_O stability is comparatively low ($He_{ETO} = 10.68$ mm), ranking second to last, just above the least stable WCH. In the TAZ region, the dominant-factor stability ranks third ($He_{dom} = 0.40$ mm), yet its corresponding ET_O stability is higher than that of TSA, ranking second overall. This highlights that higher stability of the dominant factor does not necessarily guarantee higher ET_O stability.

These findings indicate that the stability of the ET_O time series cannot be predicted from the stability of a single dominant factor alone, and that the relationship between the two varies across regions.

4. Discussion

4.1. Methodological Advantages of the Cloud Model in Characterizing ET_O Stability and Physical-Mechanism Analysis

ET_O is governed by nonlinear interactions among multiple meteorological factors [63], and its spatiotemporal evolution exhibits substantial randomness, uncertainty, and stability [64]. The analysis of ET_O uncertainty currently relies primarily on classical statistical methods, such as linear regression and trend tests, as well as time–frequency analysis techniques, including wavelet analysis and empirical mode decomposition [65–67]. However, these approaches are constrained by stationarity assumptions and struggle to characterize multi-scale heterogeneity under nonstationary conditions [68]. In contrast, the cloud model—which integrates randomness and fuzziness—offers a new perspective for analyzing such problems [69]. Compared with single statistical indicators, the cloud model simultaneously characterizes the core value (Ex), dispersion (En), and dispersion stability

(*He*), thereby providing a more comprehensive portrait of uncertainty under multi-factor drivers [70]. Specifically, hyper-entropy (*He*)—a second-order measure of entropy (*En*)—quantifies the credibility and volatility of the uncertainty representation, providing a novel tool for probing higher-order features of system randomness.

The Tibetan Plateau, a region highly sensitive to global climate change, exhibits significant non-stationarity and pronounced variability in hydrometeorological elements amidst a warming climate, primarily owing to its intricate topography and distinctive atmospheric circulation, including monsoon influences [71,72]. The cloud model, with its unique capacity to quantify the coupled “randomness-fuzziness”, effectively captures the inherent uncertainty structure within such complex systems. This provides a robust analytical framework for profoundly elucidating the evolutionary characteristics of ET_O in the region and its higher-order driving mechanisms, thereby transcending the limitations of conventional approaches that solely focus on means or basic measures of dispersion [33,73]. This study utilizes the cloud model to quantify the uniformity and stability of ET_O distributions across the agro-climatic zones of the Xizang Plateau, demonstrating substantial spatiotemporal differentiation. Spatially, cloud-model parameters indicate that the WCH and TSA agro-regions exhibit the greatest annual nonuniformity in ET_O distribution and the poorest system stability (maximum *He*). Conversely, the TSH agro-region exhibits the most uniform and stable ET_O distribution (minimum *He*). This pronounced spatial differentiation corresponds to the transition of climate zones across the Tibetan Plateau from south to north and from low to high altitudes. Specifically, the low-altitude, high-humidity, semi-humid southern region (TSH) exhibits optimal ET_O stability, whereas the high-altitude, low-humidity, semi-arid region (TSA) and the transitional zone (WCH), situated at the monsoon edge and susceptible to frequent extreme climatic events, demonstrate the greatest ET_O instability. This pattern aligns with observations of increased inter-annual variability in plateau monsoons [74] and the frequent occurrence of extreme precipitation and drought events [75,76] amidst global climate change, thereby underscoring the cloud model’s efficacy in delineating the spatial distribution of regional climate sensitivity. Temporally, ET_O discreteness across regions is scattered in summer and clustered in winter. On a monthly timescale, nonuniformity and instability peak from May to August (the warm season), while the cold season (December–January) exhibits high system stability. This pattern is seasonally reinforced: ET_O discreteness is dispersed in spring–summer and concentrated in autumn–winter, with winter showing the lowest discreteness. These results are corroborated by the cloud model’s numerical characteristics and its intuitive cloud maps, confirming the method’s applicability in complex-terrain climates.

The cloud model’s characterization of ET_O stability is not confined to a single numerical level. Rather, it overcomes the limitations of traditional statistics—which describe dispersion solely by the standard deviation or the coefficient of variation—by providing a synergistic analysis based on *En* and *He* [77,78]. Traditional methods often equate large ET_O dispersion with large fluctuations; by contrast, the cloud model distinguishes between regular wide-range fluctuations (high *En* and low *He*) and irregular random oscillations (high *En*, high *He*) [78–80]. In this study, the thin-cloud features (low *En* and low *He*) observed in winter ET_O cloud maps suggest that this period is likely shaped by reduced radiation, lower temperatures, and weakened vapor-pressure deficit activity [81], yielding a highly ordered and relatively stable hydrothermal-driving mechanism dominating ET_O changes [82]. Conversely, thick-cloud features (high *En* and high *He*) observed in summer indicate that, under the Plateau monsoon climate, intense water vapor transport and energy-dissipation processes introduce strong random perturbations. This deconstruction of the uncertainty structure demonstrates that the cloud model, when applied to non-linear, non-stationary hydrological time series in the Tibet region [83], can extract second-order

random information masked by traditional smoothing, thereby transforming qualitative concepts into quantitative values [84]. This approach provides a more granular and robust methodological basis for identifying sensitive time windows (e.g., summer) and vulnerable regions (e.g., WCH and TSA) within the regional water cycle.

4.2. Regional Differentiation of the “Evaporation Paradox” in Xizang: The Complex Regulatory Role of Aerodynamic Factors in ET_O Changes

Classical theory predicts that global warming, by elevating temperatures and consequently increasing the vapor-pressure deficit (VPD), will heighten atmospheric evaporative demand [85]. Nonetheless, empirical analyses across diverse agro-climatic zones in Xizang reveal substantial regional differentiation: the WCH and TAZ agro-regions manifest a positive warming-evaporation enhancement, whereas the TSA region demonstrates the classic evaporation paradox (Figure 3 and Table 5). This apparent contradiction reflects the complex nonlinear mechanisms by which plateau climate change drives the water cycle, indicating that temperature rise is not the sole driver. Aerodynamic weakening, represented by decreasing wind speeds [86], and reduced radiative input, represented by declining sunshine duration [87], together constitute key regulatory mechanisms.

Specifically, although TSA experienced significant warming at $0.3\text{ }^{\circ}\text{C}$ per decade (Mann–Kendall statistic $Z = 3.70$), ET_O declined significantly by 6.58 mm per decade ($Z = -4.39$). Contribution-rate analysis (Table 7) shows that reductions in mean wind speed (U) and sunshine duration (SH) in this region contributed -2.71% and -0.62% to ET_O , respectively. This phenomenon of decreasing wind speed is highly consistent with the “Global Stilling” characteristic proposed by McVicar et al. [88], which may be attributed to a reduction in the thermal differences between the plateau and surrounding regions, alongside atmospheric circulation adjustments [89]. Conversely, the reduction in sunshine duration reflects a “Solar Dimming” trend in certain parts of the plateau, as confirmed by studies by You et al. [90] and Yang et al. [91,92], potentially associated with increased cloud cover or alterations in aerosol concentrations [93]. In this multifactorial interplay, the negative effects of aerodynamic and radiation terms counterbalance the positive contribution of temperature increase ($CR_{Tem} = 2.19\%$), thereby culminating in a downward trend for ET_O . These results suggest that aerodynamic and radiative factors critically govern ET_O in Xizang’s semi-arid agro-regions. The evaporation paradox is activated at the local scale when its adverse influences outweigh the warming contribution [94]. This finding is highly consistent with the established understanding regarding the causes of the “evaporation paradox” in global semi-arid regions, which are primarily driven by non-temperature factors such as wind speed, sunshine duration, and relative humidity [95,96].

By contrast, in WCH, wind speed declines did not produce the evaporation paradox. This region’s sunshine duration increased significantly ($Z = 3.05$), offsetting wind speed reductions. In addition, positive contributions from relative humidity ($CR_{RH} = 2.88\%$) and the thermal term ($CR_{Tem} = 7.63\%$) jointly produced a hydrothermal synergistic enhancement. Consequently, aerodynamic and thermal effects together increased ET_O by 10.74 mm per decade (Figure 3). This finding indicates that the evaporation paradox is highly context-dependent, arising from the net interplay of hydrothermal factors under regional climatic conditions [97].

In summary, the dynamics of ET_O in Xizang are primarily governed by the interaction of thermal (temperature-driven) and non-thermal factors (e.g., wind speed and sunshine). The direction and magnitude of these non-thermal components, especially wind speed and sunshine, act as key determinants for the local occurrence of the evaporation paradox [98]. In TSA, wind speed and sunshine reductions attenuate evaporative demand, alleviating warming-induced water deficits. In WCH, increased sunshine and temperature intensify atmospheric water demand. These findings suggest that predicting future agricultural

water demand requires considering wind speed, cloud cover, and aerosol effects on surface energy balance and water transport [99], in addition to temperature alone.

4.3. Non-Linear Transmission Mechanisms of Meteorological Perturbations: Exponential Amplification and Wind Speed Anchoring Effects of the FAO 56 Penman–Monteith Equation in Plateau Environments

Traditionally, hydro-meteorological analyses have emphasized how mean changes in meteorological factors influence ET_O , whereas the effects of the magnitude of fluctuations in input variables on ET_O have received comparatively less attention [100,101]. In response, this study, based on cloud-model excess entropy (He) quantification (Table 8, Figure 10), finds that ET_O stability in several agricultural regions of the Xizang Plateau does not align with the stability of the dominant meteorological factors: in the TSA agro-region, input factors are highly stable while ET_O fluctuates markedly; in the TAZ agro-region, the pattern is reversed. This phenomenon, termed stability decoupling, suggests that meteorological perturbations, when transformed into ET_O via the FAO 56 Penman–Monteith equation, undergo nonlinear modulation that is closely related to the local climatic background [102,103].

- (1) Perturbation amplification in semi-arid contexts: the exponential response mechanism of saturation vapor pressure

The TSA region exhibits a typical “stable input—unstable output” pattern: although the dominant factors display high interannual stability ($He_{dom} = 0.10$), ET_O stability is poor ($He_{ETO} = 10.68$). The physical root of this decoupling lies in the nonlinear slope Δ of the saturation vapor-pressure curve within the FAO 56 Penman–Monteith equation [104]. According to the Clausius–Clapeyron relation, Δ increases approximately exponentially with temperature [105,106]. Under this type of TSA semi-arid background, this characteristic amplifies the temperature perturbation through the pathway shown in Figure 11.

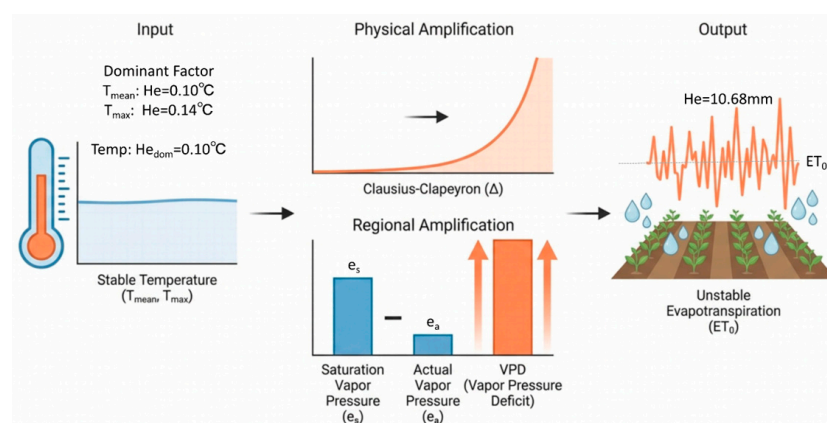


Figure 11. Schematic of the nonlinear amplification mechanism of temperature disturbances transmitted to evapotranspiration in TSA agricultural areas.

- i. Exponential amplification of saturation vapor pressure in response to temperature perturbations: small temperature perturbations are transformed into significant changes in e_s via the exponential term in the Clausius–Clapeyron equation [105,107,108].
- ii. VPD amplification in low-humidity environments: because the actual vapor pressure (e_a) is low, fluctuations in e_s are transmitted almost entirely to the vapor-pressure deficit (VPD) [109,110]. VPD is a key driver of the aerodynamic term in the FAO 56 Penman–Monteith equation, and the resulting sequence of processes amplifies ET_O in response to a weak temperature signal.

- (2) Perturbation suppression in arid and strong wind contexts: regulatory effect of wind speed stabilization on product-term fluctuations

In contrast to the TSA agro-region, the TAZ agro-region presents an “unstable input—stable output” pattern (Figure 12). Despite its dominant factor, exhibiting the lowest stability among the four agro-regions ($He_{dom} = 0.40\text{ }^{\circ}\text{C}$), its ET_O stability nevertheless surpasses that of TSA. This pattern stems from the product structure within the aerodynamic term of the FAO 56 Penman–Monteith equation. Cloud-model results show that wind speed in the TAZ agro-region is not only greatest in magnitude ($Ex = 2.68\text{ m}\cdot\text{s}^{-1}$) but also highly stable ($He = 0.08\text{ m}\cdot\text{s}^{-1}$; Table 5), indicating an extremely stable strong-wind environment in this area.

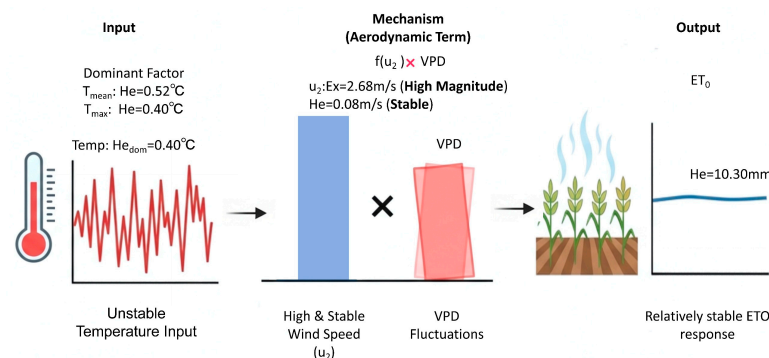


Figure 12. Schematic of the nonlinear damping mechanism of temperature perturbations to ET_O in the TAZ region.

Within a product-structure framework, if a factor (U_2) simultaneously exhibits a large magnitude and high stability, it largely suppresses the variability of the entire product term. In this case, the stable, strong wind acts as a baseline and stabilizing anchor for the aerodynamic term, effectively dampening the transmission of VPD fluctuations to ET_O [111]. Consequently, even with substantial temperature fluctuations in the TAZ region, ET_O remains relatively stable. In this context, perturbation-transmission suppression is exhibited by the FAO 56 Penman–Monteith equation.

- (3) Nonlinear transmission: climate-background dependency and implications.

The preceding comparison indicates that meteorological perturbations propagate through the FAO 56 Penman–Monteith equation in a manner that depends strongly on the local climate context. In semi-arid regions, the exponential response of the saturation vapor-pressure to temperature dominates, producing a tendency toward perturbation amplification in ET_O . In contrast, in arid and windy regions, the stabilizing effect of wind speed within the aerodynamic term dominates, yielding perturbation suppression [112]. The fact that the same mathematical structure can exhibit distinctly different transmission characteristics under different parameter domains reflects a hallmark of nonlinear systems. Notably, this nonlinear behavior is not prominent in the TSH and WCH agro-regions, which still display linear transmission features (stable input leads to stable output) and no evident stability decoupling. This pattern largely arises from (i) higher background humidity (humid or semi-humid climates), which dampens the sensitivity of VPD to es fluctuations [87], and (ii) a relatively balanced contribution from radiation and aerodynamic terms, making it difficult for a single nonlinear component to dominate the overall transmission process [113]. In this context, the transmission of meteorological disturbances is closer to a linear mapping.

In summary, the differences in ET_O stability revealed by the He parameter of the cloud model essentially reflect the spatial distribution of the nonlinear transmission characteristics

of the FAO 56 Penman–Monteith equation under varying climatic backgrounds. This finding implies that, for water-resource risk management in semi-arid regions, stability in temperature forecasts cannot by itself be used to infer the stability of agricultural water demand. Because water vapor pressure responds exponentially to temperature, even small thermal perturbations can trigger large fluctuations in the ET_O system [26]. Such intrinsic nonlinear risks should be fully considered in the formulation of future irrigation systems and in the design of corresponding safety margins.

4.4. Cloud-Model Application Reflections: From Methodological Limitations to ET_O Stability Differentiation and Implications for Irrigation Management

Although the cloud model offers substantial benefits in overcoming the challenge wherein traditional hydrological statistical methods are unable to simultaneously account for sequence randomness and fuzziness, a data-driven theoretical framework that extracts numerical features through a reverse cloud generator inherently possesses certain limitations. Specifically, the convergence and robustness of its theoretical parameter system (particularly the hyper-entropy) are contingent upon the time-series sample size and the time-window resolution. Consequently, its efficacy in accurately characterizing extreme instantaneous meteorological shocks requires further refinement. Moreover, current research primarily employs a one-dimensional cloud model for the independent analysis of a single element's evolutionary structure; consequently, the comprehensive representation of uncertainties under the synergistic influence of multi-dimensional meteorological factors (e.g., moisture, thermal, and dynamic fields) remains an area for further exploration.

Despite these limitations, the findings derived from the cloud model in this study possess significant practical implications. Traditionally, irrigation strategies commonly deduce agricultural water demand from the historical variability of temperature, precipitation, and a limited set of other factors. Nevertheless, by utilizing the He parameter of the cloud model to delineate ET_O stability differences across four agricultural climate zones, this study demonstrates that the TSH agricultural zone exhibits the highest stability ($He = 7.15$ mm), whereas the WCH agricultural zone displays the lowest stability ($He = 12.29$ mm). Consequently, in the highly unstable WCH and TSA (especially the TSA region afflicted by the “evaporation paradox”), irrigation management ought not to solely depend on long-term mean ET_O or historical temperature trends. Instead, it is imperative to incorporate greater uncertainty margins and implement adaptive management strategies, such as “elastic irrigation regimes” or “meteorological service-driven on-demand irrigation” [114,115]. In contrast, the TSH permits a reduction in the frequency of irrigation decision-making, thereby enabling a concentrated focus on medium- to long-term water-resource optimization.

5. Conclusions

Using the FAO 56 Penman–Monteith model, this study computed long-term ET_O time series for 28 meteorological stations across four agro-climatic zones on the Xizang Plateau (TSA, TSH, TAZ, and WCH). We applied Mann–Kendall trend tests, cloud-model analysis of hyper-entropy (He), sensitivity analyses, and contribution-rate decomposition to analyze the spatiotemporal differentiation of ET_O and identify the dominant driving factors, while also exploring nonlinear modulation of meteorological perturbations during transmission. The main conclusions are presented below.

- (1) ET_O changes across the Xizang Plateau agro-climatic zones exhibit pronounced spatial differentiation. Trend analysis indicates that annual ET_O rose significantly by 15.76 and 10.74 mm per decade in the TAZ and WCH, respectively, while it declined by 1.12 and 6.58 mm per decade in the TSH and TSA, respectively. Cloud-model

analysis indicates that the TSH exhibits the greatest annual ET_O uniformity and stability ($He = 7.15$ mm), whereas the WCH shows the poorest uniformity and stability ($He = 12.29$ mm). Regarding intra-annual distribution, ET_O across agro-climatic zones follows a unimodal pattern (high in the middle, low at the ends), with the greatest uniformity and stability occurring in winter and spring and relatively lower stability in summer and autumn.

- (2) The contribution-rate decomposition indicates that temperature factors (T_{max} , T_{min} , and T_{mean}) are the primary drivers of ET_O changes across all zones. Specifically, increases in T_{max} and T_{mean} confer positive contributions to ET_O , with the largest contributions observed across regions. Conversely, wind speed and sunshine duration generally suppress ET_O across most zones. The combined contributions of temperature factors dominate across zones, with absolute contributions ranging from 5.61% to 8.63%, substantially exceeding those of non-temperature factors (−1.97% to −3.60%).
- (3) Cloud-model analysis indicates that the stability of annual ET_O is generally lower than the stability of its key meteorological drivers. The relationship between ET_O stability and the stability of these major drivers shows substantial regional heterogeneity rather than a straightforward linear pattern. This implies that ET_O trends and stability are not determined solely by the amplitude or stationarity of a single factor, such as temperature. Instead, the FAO 56 Penman–Monteith model demonstrates climate-background dependency in transmitting meteorological perturbations, with net effects depending on the combination of local factor-value domains. Therefore, in water-resource management on the Tibetan Plateau, particularly for irrigation scheduling and water-demand forecasting in semi-arid zones, ET_O stability should not be inferred from the historical variability of a few meteorological factors (e.g., temperature).
- (4) The spatio-temporal differentiation of ET_O stability, as characterized by the hyper-entropy (He) of the cloud model, offers distinct irrigation strategies tailored to specific regions: In areas exhibiting lower stability, such as WCH and TSA, the He value can serve as a critical early warning indicator to guide short-term emergency water allocation; conversely, in regions demonstrating greater stability, such as TSH, the frequency of irrigation decision-making can be streamlined, thereby enabling a focus on medium- to long-term water-resource optimization and management. Building upon these findings, future research ought to integrate the cloud model with deep learning methodologies for the construction of probabilistic water-demand forecasting models. This integration aims to culminate in a comprehensive technical system encompassing “stability diagnosis—risk early warning—adaptive management”.

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