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The Relationship between Reference Crop Evapotranspiration Change Characteristics and Meteorological Factors in Typical Areas of the Middle of the Dry-Hot Valley of Jinsha River

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Abstract: Reference crop evapotranspiration (ET_0) is a key factor in ecohydrological processes. Studying the variation trend of ET_0 in arid river valleys and its influencing factors is not only helpful to understanding the response of dry and hot river valleys to hydrological processes under the background of climate change but also has important guiding significance for the efficient allocation of soil and water resources and the stable maintenance of the ecosystem in this area. Based on the daily meteorological data of three representative meteorological stations in the middle Dry-hot Valley of the Jinsha River from 1988 to 2019, the ET_0 variation and its influencing factors in the middle Dry-hot Valley of the Jinsha River are analyzed by quantitative and qualitative methods. The results showed that (1) the ET_0 in the middle and middle of the Dry-hot Valley of Jinsha River showed a significant fluctuating trend ($Z > 1.98$), and the linear change rates were examined in Huaping, Yuanmou, and Panzhihua. (2) Grey correlation analysis and principal component analysis mutually verify that daily mean temperature is the most influential meteorological factor. (3) The sensitivity of ET_0 to the change in meteorological factors in the middle section and its sub-sections is as follows: daily average temperature, daily relative humidity, daily average wind speed, and sunshine hours. ET_0 is the most sensitive to the change in daily average temperature, followed by the strengthening of daily average wind speed and the reduction in daily relative humidity, and the sensitivity of ET_0 to the change in sunshine hours is the least. (4) Among the regions, the meteorological factors that contributed the most to the increase in ET_0 in Huaping, Panzhihua, and Yuanmou were daily average wind speed (6.086%), daily average wind speed (8.468%) and daily average temperature (3.869%), respectively. The meteorological factors that contributed the least were sunshine hours.

Keywords: reference crop evapotranspiration; principal component analysis; sensitivity analysis; Jinsha River Dry-hot Valley

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1. Introduction

Evapotranspiration (ET) is an essential component of the water cycle and a key process in plant physiology [1]. It represents the total water vapor flux from vegetation and the Earth's surface to the atmosphere, primarily consisting of transpiration (T), soil evaporation (Es), and canopy interception (Ec), reflecting the movement of water among soil, vegetation, and the atmosphere [2]. Extensive research indicates that transpiration plays a critical role in the global water cycle and water resource management. Approximately two-thirds of the water evaporated into the atmosphere annually is attributed to transpiration, with this proportion potentially higher in arid regions. Furthermore, studies have shown a close relationship between extreme hydrological events such as droughts and floods and *ET* [3].

At present, there are various methods for calculating *ET*, and many scholars at home and abroad have also made certain discussions on the applicability of different estimation methods in the study area [4–7]. Based on the Food and Agriculture Organization of the United Nations (FAO)'s Penman–Monteith model [8], the mainstream model was developed, which comprehensively considers the changes in crop physiological characteristics and meteorological factors and therefore has high calculation accuracy and a wide application range. The reference crop evapotranspiration (ET_0) in this model is regarded as the theoretical upper limit of actual vegetation transpiration. It plays a key role in monitoring the change in meteorological factors and the dry and wet state of climate [9]. Therefore, an in-depth understanding of ET_0 trends and their potential causes is essential to effectively manage regional water resources, develop agricultural irrigation systems, and accurately predict climate change.

According to the latest report of the Intergovernmental Panel on Climate Change (IPCC) of the United Nations [10], the global average temperature has risen by 1.1 °C compared with that before the industrial revolution, which confirms that the global climate is experiencing a warming trend, and this global warming trend has an important impact on ET_0 and its related meteorological elements [11]. As a key indicator for estimating vegetation transpiration and agricultural water management, the change trend of ET_0 reflects the change in crop water demand under future climate change. Therefore, it is of great significance to study the change trend of ET_0 and its influencing factors, which can provide a scientific basis for water resources management and coping with climate change.

In recent years, the analysis of the relationship between the change trend of ET_0 and meteorological factors has become a hot topic for many researchers at home and abroad, and some achievements have been made. For example, Matteo Ippolito et al. [12] used sensitivity analysis to identify the influencing factors of ET_0 changes in Sichibi Island, Italy, and determined that the main influencing factors were daily minimum temperature and daily maximum temperature. Ippolito et al. [13] adopted the fuzzy cluster analysis method and found that the main factor affecting the change in ET_0 in the Fars province of Iran was temperature. Lv Xiaorong et al. [14] used the principal component analysis method to find that the main factor affecting the change in ET_0 in Hubei Province was the annual mean temperature. By using the correlation analysis method, Yan et al. [15] found that daily relative humidity, daily average wind speed, sunshine duration, and daily average temperature were the dominant factors affecting the change in ET_0 in Guangxi Province. Although a variety of methods have been applied to relevant studies, these research methods are often limited to specific analytical means. Considering the numerous and interwoven factors affecting ET_0 and the complex interactions among meteorological factors, the application of a single method may be difficult to fully reveal the influence mechanism. Therefore, the comprehensive application of multiple analysis methods to quantitatively study the impact of meteorological factors on ET_0 and explore the sensitivity of ET_0 to changes in different meteorological factors are crucial for understanding the response of the hydrological cycle to climate change [16]. More importantly, the current research on the trend of ET_0 change and its influencing factors in specific regions is still relatively limited, especially in the fragile ecosystem areas, such as the Dry-hot Valley of the Jinsha River; the relevant research is still in the stage of few, so in-depth research on this region will help to understand the mechanism of ET_0 change more comprehensively. And provide a scientific basis for taking effective countermeasures in the future.

2. Materials and Methods

2.1. Study Area

The middle section of the Jinsha River's Dry-hot Valley is located in the upper reaches of the Yangtze River. It features a hot climate, distinct dry and wet seasons, uneven precipitation distribution, and intense evaporation, making it one of the typical ecologically fragile areas in China [17]. The regions of Panzhihua, Yuanmou, and Huaping in this area are significant production areas for off-season fruits and vegetables in China (Figure 1). However, the scarcity of water resources has consistently been a critical limiting factor for its agricultural development. In order to address this issue, it is crucial to reveal the trends in ET_0 in the middle section of the Jinsha River's Dry-hot Valley, unravel the complex relationship between ET_0 and meteorological factors, and understand the response mechanism of ET_0 under changing meteorological conditions. The aim is to provide a scientific theoretical basis for the rational allocation of irrigation water and the enhancement of water resource utilization in the middle section of the Jinsha River's Dry-hot Valley.

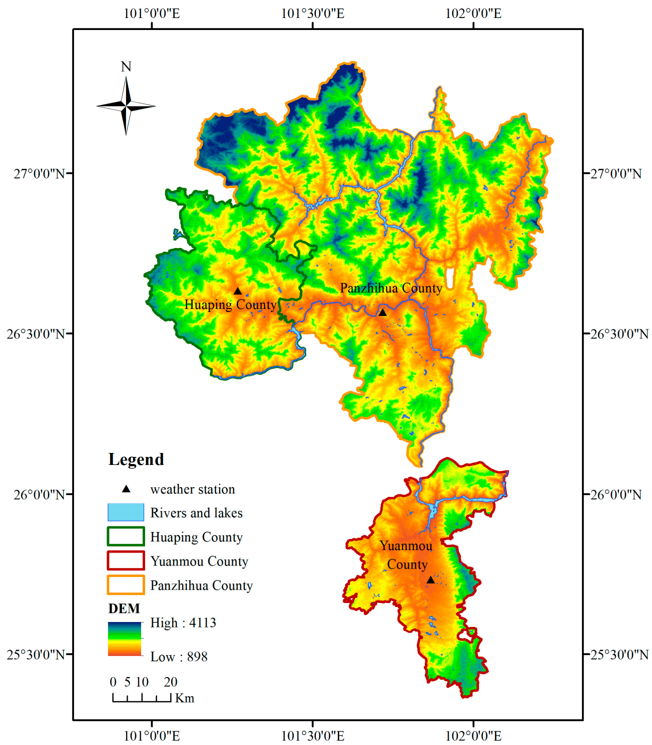

Figure 1. Summary map of the study area.

2.2. Data

The data used in this study were obtained from the China Meteorological Data Network (https://data.cma.cn/, accessed on 15 January 2024), covering three meteorological stations in Panzhihua, Yuanmou, and Huaping during the period of 1988–2019 for day-by-day meteorological element data. The selected meteorological elements include daily relative humidity (RH), sunshine hours (n), daily average temperature (T_{mean}), daily maximum temperature (T_{max}), daily minimum temperature (T_{min}), average wind speed (u), etc.

2.3. Methods

2.3.1. Potential Evapotranspiration Calculation

When calculating ET_0, many factors need to be considered, including surface type, temperature, and humidity. Due to the complex influence of these factors, the calculation results of ET_0 may fluctuate, and the Penman–Monteith formula has practical characteristics which are suitable for climate types in different regions, is simple to operate, and can provide relatively accurate calculation results [8]. Its expression is

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}U_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34U_2)} \quad (1)$$

where ET_0 is the reference crop evaporation amount (mm); R_n is the net radiation [MJ/(m^2·d)]; G is the soil heat flux [MJ/(m^2·d)]; γ is the hygroscopic constant; T is the average daily temperature (°C); U_2 is 2 m wind speed (m/s); e_s and e_a are saturated vapor pressure and actual vapor pressure (kPa), respectively. Δ is the slope of the saturation water vapor pressure curve (kPa/°C). In addition to the meteorological data collected above, other input variables required by Penman–Monteith formula are obtained by deducing and calculating basic meteorological data. For specific methods, please refer to the relevant literature [2].

2.3.2. Climate Propensity Rate and ET_0 Propensity Rate

Generally, it is represented by the tilt rate of a linear equation [18]. The calculation formula is

$$X_i = a + bt_i(i = 1, 2, \ldots, n) \quad (2)$$

where x is the factor value; a is a constant term; b is the regression coefficient; i is the year of the time series. The climatic factors and tendency rate are $10b$.

2.3.3. Principal Component Analysis

Principal component analysis is a statistical analysis method that converts multiple variables into a few uncorrelated comprehensive variables by dimensionality reduction. Its mathematical model is as follows: for k observed variables $X_1 \ldots X_k$, a data matrix of n observed samples [19].

$$X = \begin{bmatrix} X_{11} & X_{12} & \ldots & X_{1k} \\ X_{21} & X_{22} & \ldots & X_{2k} \\ \vdots & \vdots & \ldots & \vdots \\ X_{n1} & X_{n2} & \ldots & X_{\mathrm{nk}} \end{bmatrix} = (X_1, X_2, \ldots, X_k) \quad (3)$$

Synthesize k predictors into p new variables (synthetic variables):

$$\begin{cases} F_1 = a_{11}X_1 + a_{12}X_2 + \cdots + a_{1k}X_k \\ F_2 = a_{21}X_1 + a_{12}X_2 + \cdots + a_{2k}X_k \\ \ldots \\ F_p = a_{p1}X_1 + a_{p1}X_2 + \cdots + a_{pk}X_k \end{cases} \quad (4)$$

The model satisfies the following: (1) Fi and Fj are not correlated ($i \neq j$, i, j = 1, 2, . . ., p); (2) Variance of F_1 > variance of F_2 > variance of F_3, and so on; (3) In the model F_1 is called the first principal component, F_2 is the second principal component, and so on.

2.3.4. Grey Relational Degree Analysis

Gray relational analysis is a new theory and method put forward by Deng [20]; its core is to measure the degree of correlation between factors by comparing the development trend of factor curves. Different from traditional methods, it does not require a large sample size and does not rely on typical distribution laws. Grey relational degree analysis transforms the development trend curve of factors into a grey series, calculates the relational degree, and reveals the main influencing factors and their influencing degree in the development of the system. Grey correlation degree is defined as follows: Let the system main behavior sequence $X_0 = (x_0(1), x_0(2), \ldots, x_0(n))$, related behavior sequence $X_0 = (x_0(1), x_0(2), \ldots, x_0(n))$ and then for $\varepsilon \in (0, 1)$.

$$\gamma(x_0(k),)x_i(k) = \frac{\underset{i}{\min}\ \underset{k}{\min}\ |x_0(k)-x_i(k)|\,\varepsilon\ \underset{i}{\max}\ \underset{k}{\max} + |x_0(k)-x_i(k)|}{|x_i(k)-x_i(k)|+\varepsilon\ \underset{i}{\max}\ \underset{k}{\max} + |x_0(k)-x_i(k)|} \tag{5}$$

$$\gamma(X_0, X_i) = \frac{1}{n}\sum_{k=1}^{n} \gamma(x_0(k), x_i(k)) \tag{6}$$

$\gamma(X_0, X_\mathrm{i})$ is called the grey correlation degree of X_0 and X_i, where ε is called the resolution coefficient; its role is to improve the significance of the difference between the grey correlation coefficients, $\varepsilon \in (0, 1)$; the experience value is generally $\varepsilon = 0.5$.

2.3.5. Path Analysis

Path analysis is a multivariate statistical analysis method. The independent variable $x_i(I = 1, 2, \ldots, n)$ The simple correlation coefficient with the dependent variable y is divided into the direct effect of x_i on y (direct path coefficient) and x_i. Through the indirect effect of other independent variables on y (indirect path coefficient), the relative importance of each factor is directly compared, which makes the analysis results more consistent with the actual situation [21].

The dependent variable y receives multiple factors (x_1, x_2, $\ldots$, x_n), and then the multiple regression equation can be applied:

$$y = a_0 + a_1x_1 + a_2x_2 + \ldots + a_nx_n \tag{7}$$

According to the principle of path analysis, the equation of using a correlation coefficient to solve the path coefficient is as follows:

$$\begin{cases} b_1 + r_{12}b_1 + \ldots r_{1n}b_n = r_{1y}, \\ r_{12}b_1 + b_2 + \ldots r_{2n}b_n = r_{2y}, \\ \vdots \\ \mathrm{r}_{n1}b_1 + r_{n2}b_2 + \ldots + r_{nn}b_n = r_{ny}, \end{cases} \tag{8}$$

where r_{ij} is the correlation coefficient between x_i and x_j; r_{iy} is the simple correlation coefficient between x_i and y; b_i is a direct path coefficient, which reflects the direct effect of independent variable x_i on dependent variable y. $r_{ij}b_j$ is the indirect path coefficient, which reflects the indirect effect of independent variable x_i on dependent variable y through x_j.

2.3.6. Sensitivity Analysis

This study uses the sensitivity coefficient defined by McCuen [22] to determine the sensitivity of potential evapotranspiration changes to meteorological elements:

$$S_x = \lim_{\Delta x \to 0}\left(\frac{\Delta ET_0/ET_0}{\Delta x/x}\right) = \frac{\partial ET_0}{\partial x}\cdot\frac{|x|}{ET_0} \tag{9}$$

where ET_0 is potential evapotranspiration (mm/d); S_x is the sensitivity coefficient of potential evapotranspiration with respect to meteorological factor x, dimensionless quantity.

2.3.7. Contribution Rate Analysis

By multiplying the sensitivity coefficient of the meteorological factor with the relative change rate of the meteorological factor for many years, the change in ET_0 caused by the meteorological factor is obtained, that is, the contribution of the factor to the change in ET_0. If the contribution rate is positive (negative), it indicates that the factor causes the increase (decrease) of ET_0, and if the absolute contribution rate is large (small), it indicates that the meteorological factor has a large (small) influence on ET_0. The contribution rate is calculated as follows [23–26]:

$$Con_x = S_x \cdot RC_x \tag{10}$$

$$RC_X = \frac{n \cdot b_x}{|V_x|} \times 100\% \tag{11}$$

3. Results

3.1. Analysis of PET Changes

Table 1 and Figure 2 are the results of the annual ET_0 dynamic process in the middle and subsections of the Jinsha River Dry-hot Valley. There are significant differences in the annual average ET_0 value, stability, propensity rate, and correlation, showing obvious geographical differences and trends. In the past 32 years, ET_0 in the middle of the dry and hot valley of Jinsha River and in the subregions of Panzhihua, Yuanmou, and Huaping showed a significant upward trend (Z > 1.98), with an increase rate of 38.336, 47.696 mm, 16.257 mm and 51.055 mm per 10 years, respectively. The growth rate was shown as Huaping > Yuanmou > Panzhihua. The annual average ET_0 in the Panzhihua area is about 1462.731 mm, which is relatively slightly lower than that in the middle part of the Jinsha River Dry-hot Valley (1495.522 mm) and Huaping (1415.706 mm) but significantly lower than that in Yuanmou area (1608.128 mm). In the middle part of the Jinsha River Dry-hot Valley, the maximum value of annual ET_0 reached 1681.433 mm, and the minimum value was 1337.500 mm, with the maximum value occurring in 2012 and the minimum value in 1990. On the other hand, in the Panzhihua area, the annual ET_0 is as follows: the maximum value is 1604.900 mm, the minimum value is 1279.200 mm, the maximum value occurs in 2019, while the minimum value occurs in 2002, and the standard deviation is 85.135 mm. For the Yuanmou area, the data of the annual ET_0 show that the maximum value is 1905.300 mm, the minimum value is 1397.700 mm, with the maximum value occurring in 2012 and the minimum value in 2008, and presenting a significance level of 0.135 ** in terms of correlation. Finally, in the Huaping area, the annual ET_0 was 1594.000 mm as the maximum value and 1268.200 mm as the minimum value, with the maximum value occurring in 2004 and the minimum value occurring in 1990. The discrete coefficient of Yuanmou is 7.030%, with the worst stability, followed by Huaping and Panzhihua, with increased stability of fluctuation changes. Overall, the data indicate that the annual ET_0 values in the middle part of the Jinsha River Dry-hot Valley and its different subsections generally show an upward trend; however, the magnitude of the change, the significance of the change trend, and the level of correlation among the regions are somewhat different.

Table 1. Interannual trends of ET_0 in the middle part of the Jinsha River Dry-hot Valley and its subsections.

Station	Maximum Value/mm	Minimum Value/mm	Maximum Year/Year	Minimum Year/Year	Mean ± Standard Deviation/mm	Coefficient of Variation (CV)	Inclination Rate/mm.(10a)$^{-1}$	Mann–Kendall Z Value	Variation Trend	Correlation/r
Whole region	1681.433	1337.500	2012	1990	1495.522 ± 88.749	5.934%	38.336	2.11	↑	0.405 *
Panzhihua	1604.900	1279.200	2019	2002	1462.731 ± 85.135	5.820%	47.696	3.28	↑	0.526 **
Yuanmou	1905.300	1397.700	2012	2008	1608.128 ± 113.026	7.030%	16.257	2.56	↑	0.135 *
Huaping	1594.000	1268.200	2004	1990	1415.706 ± 92.551	6.537%	51.055	2.82	↑	0.517 **

Notes: ** and * represent significance tests passing 0.01 and 0.05 confidence levels, respectively.↑ Indicates an upward trend.

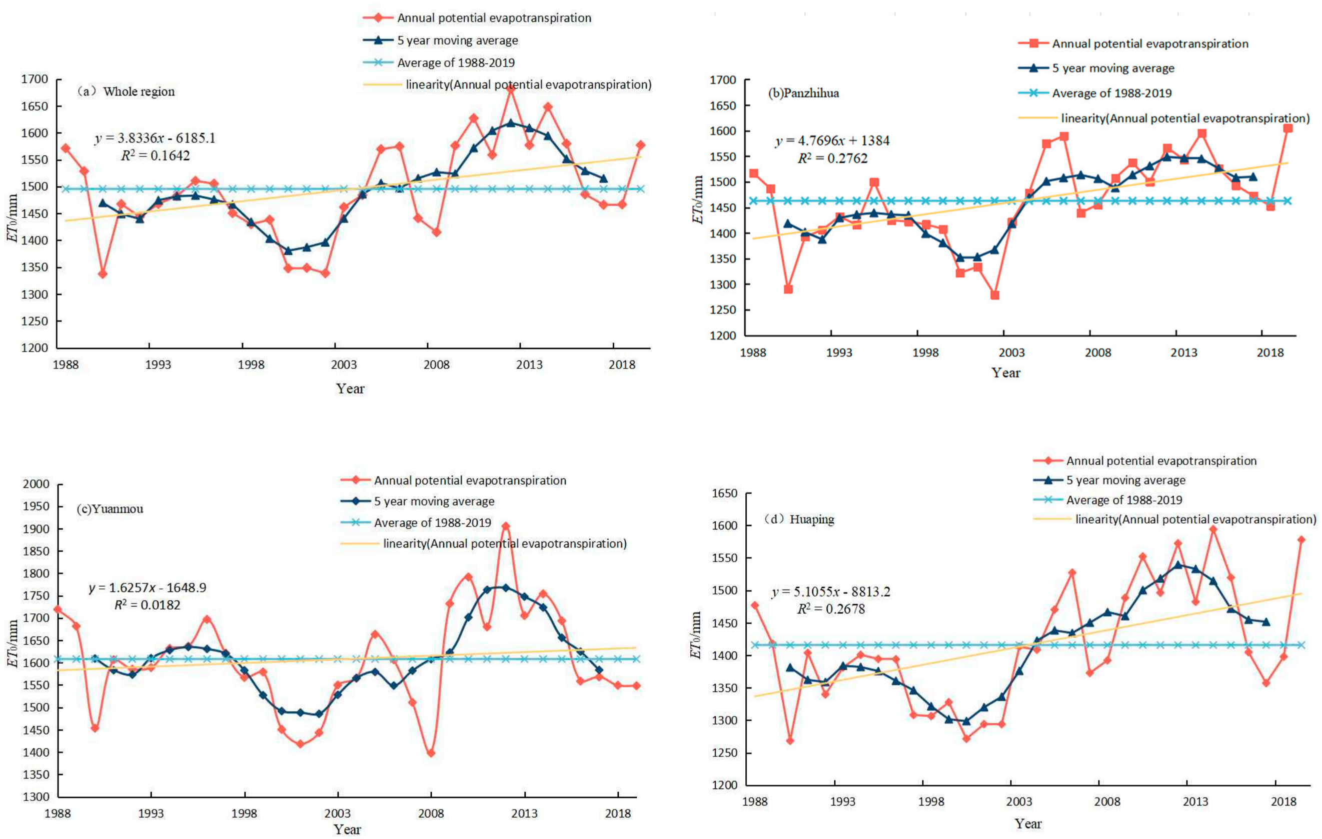

Figure 2. Process of interannual variation in ET_0 in the middle region of the Jinsha River Dry-hot Valley and its segments, 1988–2019.

3.2. Principal Component Analysis of Meteorological Factors

ET_0 size is affected by complex factors, and various meteorological factors are interrelated and affect each other. The six meteorological factors T_{mean}, T_{max}, T_{min}, RH, n, and u affecting the change in ET_0 were subjected to principal component analysis, and the results were as follows. Table 2 shows KMO > 0.6, indicating that there is a correlation between the variables, in line with the requirements of principal component analysis, and through Bartlett's test, $p < 0.05$ is significant and can be carried out the principal component analysis. The first three principal components were extracted, and their cumulative variance explained accounted for 94.97%, of which the first principal component accounted for 70.09% (expression: $F_1 = 0.156u - 0.208RH + 0.158n + 0.229T_{\text{mean}} + 0.203T_{\text{min}} + 0.227T_{\text{max}}$), and the variables with larger absolute values of loadings were T_{mean}, T_{min}, and T_{max}, mainly reflecting the effect of temperature. The second principal component accounts for 14.53% (expression: $F_2 = -0.78u + 0.246RH + 0.651n + 0.113T_{\text{mean}} + 0.002T_{\text{min}} + 0.197T_{\text{max}}$), mainly reflecting the effect of wind speed, the component loadings of the largest meteorological factors is u. The third principal component accounts for 10.36% (expression: $F_3 = -0.358u + 0.477RH - 0.714n + 0.353T_{\text{mean}} + 0.776T_{\text{min}} + 0.127T_{\text{max}}$), mainly reflecting the influence of radiation, and the largest meteorological factor of component loadings is n. Overall, the principal component analysis reveals the relationship between ET_0 and meteorological factors more deeply, and the change in ET_0 is mainly affected by temperature and less affected by humidity.

Table 2. Results of principal component loading of meteorological factors.

Component	Kaiser-Meyer-Olkin (KMO) Value	p-Value	Eigenvalue	Variance Explained Rate	T_{mean}	T_{min}	T_{max}	n	RH	u
1	0.744	0.001	4.205	70.09%	0.962	0.875	0.955	0.663	−0.855	0.656
2			0.872	14.53%	0.098	0.002	0.172	0.566	0.215	−0.682
3			0.621	10.36%	0.22	0.443	0.079	−0.483	0.296	−0.222

3.3. Cluster Analysis and Gray Correlation Analysis of Meteorological Factor Systems

Systematic cluster analysis is the process of combining the most similar objects based on the degree of closeness between observations or variables, categorizing observations in an aggregation-by-aggregation fashion until finally, all samples are clustered into one class [27]. As Table 3 shown, the cluster analysis divides the six meteorological elements into four classes, and T_{men}, T_{max}, and T_{min} are categorized as Type I according to the role of temperature on the change in ET_0; n and u are Type II and Type III, respectively, reflecting the influence of radiation and wind speed; and RH is Type IV, reflecting the influence of humidity on the change in ET_0. The gray correlation method takes ET_0 as the reference series, and the six meteorological indicators as the comparison series, and the correlation degree is calculated and ranked; the higher the ranking, the greater the influence of meteorological indicators on ET_0, and vice versa, the lesser the influence on ET_0. The correlation degree of ET_0 and meteorological indicators is ranked as follows: $T_{mean} > T_{max} > T_{min} > n > u > RH$, the influence of T_{mean} on ET_0 is the greatest, with 0.809, and the influence of RH on ET_0 is the least, with 0.643. T_{mean}, T_{max}, $T_{min,}$ and n are thermal factors, u is the dynamic factor, and RH is the humidity factor. The gray correlation results verified that the first principal component loadings of the largest meteorological factors, T_{mean}, T_{min}, and $T_{max,}$ were closely related to ET_0. Considering the results of cluster analysis and gray correlation degree analysis, in order to simplify the problem and eliminate the repeated correlation factors, a total of four meteorological factors, T_{mean}, RH, n, and u, were selected as the key factors to carry out the subsequent pathway analysis [16].

Table 3. Results of grey correlation degree analysis and clustering analysis of meteorological factors.

	Evaluation Unit	T_{mean}	T_{max}	T_{min}	n	u	RH
Relevance Results	relatedness	0.809	0.804	0.793	0.779	0.714	0.643
	rankings	1	2	3	4	5	6
cluster analysis		I	I	I	II	III	IV

3.4. Flux Analysis of ET_0 by Meteorological Factors

According to the results of the systematic cluster analysis and gray correlation analysis of meteorological factors, four meteorological factors, RH, u, T_{mean}, n, were identified for the pathway analysis, and the results were as follows. The results are shown in Table 4. Changes in ET_0 were correlated with all four meteorological factors in the table ($p < 0.01$), but there were differences in the direct and indirect effects of each meteorological factor on ET_0. The pathway coefficients reflect the magnitude of the direct effect of meteorological factors on the changes in ET_0, and the order is as follows: $T_{mean} > u > RH > n$, except for the negative value of RH, all other values are positive, which indicates that RH is inversely related to the changes in ET_0 and that u, T_{mean}, and n are in a positive direction to ET_0, i.e., with the decrease in RH, the trend of ET_0 is to increase, and with the increase in u, T_{mean}, and n, the trend of ET_0 is to increase. The factor that has the largest direct effect on ET_0 is RH, and the smallest effect is n. The indirect pathway coefficient reflects the indirect effect of other meteorological factors on ET_0 changes through a certain meteorological factor, and the ranking is $RH > u > T_{mean} > n$, with RH as the main factor indirectly affecting ET_0 changes and n as the least indirectly affecting factor. The correlation coefficients represent the combined effects, and the ranking is $T_{mean} > u > RH > n$. T_{mean} has the greatest effect on ET_0 changes, n has the least effect, and the increase in T_{mean}, u, n, and the decrease in RH contribute to the increase in ET_0 changes.

Table 4. Flux analysis of meteorological factors on ET_0.

Meteorological Factor	Path Coefficient	Indirect Passage Coefficient					Correlation Coefficient
		RH	***n***	T_{mean}	***u***	$\sum$	
RH	−0.294		0.178	0.508	0.155	0.841	−0.686 **
n	0.226	0.191		−0.095	0.153	0.249	0.589 **
T_{mean}	0.680	0.141	0.138		0.068	0.347	0.747 **
u	0.303	0.199	0.092	0.211		0.502	0.689 **

Note:** and * indicate significance tests passing 0.01, 0.05 confidence, respectively.

3.5. Analysis of the Contribution of Meteorological Factors to Changes in ET_0 and Sensitivity of ET_0 to Changes in Meteorological Factors

As Table 5 shows, the sensitivity of ET_0 to changes in meteorological factors in the middle part of the Jinsha River Dry-hot Valley and its subsections is ranked as T_{mean}, RH, u, n; and the contribution rate of meteorological variables to ET_0 is ranked as u, RH, T_{mean}, n. The influence of meteorological variables with a high degree of sensitivity on ET_0 is different from the order of their contribution rate to ET_0. When the changes in these meteorological variables with a high degree of sensitivity are not significant for many years, it may lead to their lower contribution rate to ET_0. When these highly sensitive meteorological variables do not change significantly over the years, it may lead to their lower contribution to ET_0. In the middle part of the Jinsha River Dry-hot Valley, T_{mean} increases by 5.820% over the years, and the increase in temperature causes an increase in ET_0, with a positive contribution rate of 2.981%; ET_0has a low sensitivity to n, and the increase in n by 4.872% over the years causes an increase in ET_0, with a positive contribution rate of 0.488%; RH changes inversely with ET_0 because the relative rate of change in RH over the years is −9.999%, and the decrease in RH causes an increase in ET_0, with a positive contribution rate of 4.12%; and the decrease in RH causes an increase in ET_0, with a positive contribution rate of 4.12%, with a positive contribution of 4.126%; although ET_0 is relatively insensitive to changes in u, the multi-year changes in u are significant, with a multi-year relative rate of change of 21.475% causing an increase in ET_0 with a positive contribution of 5.519%, and an increase in u is the main factor causing an increase in ET_0 in the middle Jinsha River Dry-hot Valley region.

Table 5. Contributions of meteorological variables to ET_0 in the middle and subsections of the Jinsha River Dry-hot Valley.

Meteorological Factor	Whole Region			Huaping			Panzhihua			Yuanmou		
	Sensitivity Factor	Multi-Year Linear Change Rate/%	Contribution Rate/%	Sensitivity Factor	Multi-Year Linear Change Rate/%	Contribution Rate/%	Sensitivity Factor	Multi-Year Linear Change Rate/%	Contribution Rate/%	Sensitivity Factor	Multi-Year Linear Change Rate/%	Contribution Rate/%
T_{mean}	0.512	5.820	2.981	0.485	6.248	3.027	0.460	4.148	1.907	0.551	7.024	3.869
n	0.100	4.872	0.488	0.097	6.117	0.593	0.101	6.231	0.630	0.097	2.215	0.216
RH	−0.413	−9.999	4.126	−0.466	−12.089	5.630	−0.309	−12.525	3.870	−0.402	−5.344	2.148
u	0.257	21.475	5.519	0.233	26.076	6.086	0.233	36.312	8.468	0.265	6.814	1.808

In each segment, the meteorological factors with the largest contribution to the increase in ET_0 in Huaping, Panzhihua, and Yuanmou were u (6.086%), u (8.468%), and T_{mean} (3.869%), respectively. The meteorological factor with the smallest contribution rate is n. The ordering of the contribution rate of meteorological factors in Huaping is u, RH, T_{mean}, n; the ordering of the contribution rate of meteorological factors in Panzhihua is u, RH, T_{mean}, n; the ordering of the contribution rate of meteorological factors in Yuanmou is T_{mean}, RH, u, n; the ordering of the sensitivity of ET_0 to the changes in meteorological factors in each segment is consistent with the ordering of the sensitivity of the changes in meteorological factors is T_{mean}, RH, u, and n. Due to the difference in changes in the various meteorological factors over the years, the caused inconsistency in the contribution and ranking of ET_0 changes.

4. Discussion

The Jinshajiang River Dry-hot Valley has a very harsh climate due to its special geographic location and unique topography and geomorphology, which makes it one of the most fragile ecological environments in China. The ET_0 in the middle and subsections of the Jinshajiang River Dry-hot Valley showed a significant fluctuating upward trend from 1988–2019 ($p < 0.05$), which was consistent with the results of Liu Qinsuan et al. [28] This is consistent with the results of the ET_0 study on the Yunnan–Guizhou Plateau, but it should be noted that there are also other studies showing a decreasing trend in ET_0 [29–32]. However, it should be noted that other studies have also shown a downward trend in ET_0, indicating that ET_0 changes in different regions are different; that is, ET_0 changes are geographically specific. The linear change rate of ET_0 in the whole region is 38.336 mm every 10 years, and the change rate of Huaping is the most obvious, which is 51.055 mm every 10 years. The correlation between meteorological factors and ET_0 was calculated as T_{mean}, T_{max}, T_{min}, n, u, RH, which indicated that ET_0 was strongly correlated with T_{mean}, T_{max}, and T_{min} and was verified with the results of principal component analysis, which was consistent with the conclusion of Ma Yali et al. [10] The study of Hexi Corridor concluded that ET_0 had the highest degree of association with temperature. The pathway analysis showed that n, T_{mean}, u played a positive role in ET_0 changes, and RH played an inverse role in ET_0 changes, and the increase in n, T_{mean}, u and the decrease in RH contributed to the increase in ET_0 changes, which was consistent with the results of the study on ET_0 in the hilly areas of Sichuan and Central China by Feng Yu et al. [26] The conclusion that the flux coefficients of ET_0 and RH in the hilly area of central Sichuan are negative, and those of n, T_{mean}, and u are positive is consistent with the conclusion of Feng Yu et al. The sensitivities of the middle Jinshajiang River Dry-hot Valley and its subsections were ranked as T_{mean}, RH, u, and n. ET_0 was most sensitive to the increase in T_{mean}, followed by the decrease in RH and the increase in u to increase ET_0, and ET_0 was the least sensitive to the change in n, which was consistent with the findings of Ni Ningqi et al. [33]. This is consistent with the conclusion that ET_0 is the most sensitive to Tmean changes, followed by RH, in the southwestern part of the Yunnan-Guizhou Plateau over the past 56 years. Among the subsections, the meteorological factors with the largest contribution to ET_0 increase in Huaping, Panzhihua, and Yuanmou were u (6.086%), u (8.46%), and T_{mean} (3.869%), and the meteorological factor with the smallest contribution was n. The results of the study are consistent with the findings of Wang Xiao-Jing et al. [34] study, which found that wind speed and temperature had the largest contribution in the ET_0 changes over the past 50 years. The contribution rate and the magnitude of multi-year relative change together determine the difference between the sensitivity factors and the main influencing factors. Although ET_0 is the most sensitive to the change in T_{mean}, the multi-year change in T_{mean} is not significant, which leads to the inconsistency between the contribution rate and the ordering of sensitivity coefficients.

The aim of this study was to investigate the influence of climatic factors on ET_0 change in the middle part of the Jinsha River Dry-hot Valley region, focusing on the interrelationships between four meteorological factors such as T_{mean}, RH, u, and n, and ET_0 change; however, in addition to the meteorological factors, a variety of elements such as the subsurface, moisture conditions, land-use practices, and human activities also have a significant impact on the change in ET_0 [35]. However, to fully understand the mechanism of ET_0 change, it is necessary to explore the effects of various aspects, such as climate change, in greater depth. In this study, principal component analysis (PCA), cluster analysis (CA), and through-trail analysis (TTA) were used to explore the causes of ET_0 changes qualitatively, while sensitivity analysis (SA) and contribution rate calculation (CR) were used to quantitatively assess the sensitivity of ET_0 to climatic variables and the contribution of

ET_0 to climatic variables, and at the same time, the changes in ET_0 under the coupling of quantitative and qualitative effects were taken into account, which provided a new basis for revealing the response mechanism of ET_0 changes to meteorological variables. This provides a new basis for revealing the response mechanism of ET_0 changes to meteorological variables [26]. The study is also based on the study of ET_0 changes under quantitative and qualitative coupling effects. Given global warming, this study helps to scientifically predict the trend of ET_0 change in the middle part of the Jinsha River Dry-hot Valley and provides a scientific basis for the formulation of a rational irrigation water use plan and the improvement in the utilization efficiency of agricultural water resources.

5. Conclusions

(1) The annual ET_0 in the middle part of the Jinsha River Dry-hot Valley and its subsections all showed a significant increase (Z > 1.98), with the increase shown as Huaping > Yuanmou > Panzhihua. The annual average ET_0 of Panzhihua was about 1462.731 mm, which was slightly lower than that of the middle section of the Jinsha River Dry-hot Valley (1495.522 mm) and Huaping (1415.706 mm) but significantly lower than that of Yuanmou (1608.128 mm). The annual maximum and minimum ET_0 values in each region occurred in different years, showing obvious fluctuations. Meanwhile, the Yuanmou area showed a high dispersion coefficient (7.030%) and the worst stability, followed by Huaping and Panzhihua.

(2) The results of the principal component analysis show that the first principal component is temperature, the second principal component is wind speed, and the third principal component is radiation, and the changes in ET_0 are mainly affected by temperature and less by humidity. Cluster analysis divided the six meteorological factors into four categories, and the gray correlation values were calculated as follows in descending order: $T_{mean} > T_{max} > T_{min} > n > u > RH$. Gray correlation and principal component analysis verified each other to verify the meteorological factors with the largest loadings of the first principal component.

(3) The sensitivity of ET_0 to changes in meteorological factors in the middle part of the Jinsha River Dry-hot Valley and its subsections is ranked as T_{mean}, RH, u, n. ET_0 is most sensitive to the increase in T_{mean}, followed by the decrease in RH and the increase in u. ET_0 is prompted to increase in size, and ET_0 is the least sensitive to the change in n. The increase in ET_0 in the middle part of the Jinsha River Dry-hot Valley is the most sensitive to the increase in RH and u. In each segment, the meteorological factors with the largest contribution of ET_0 increase in Huaping, Panzhihua, and Yuanmou were u (6.086%), u (8.468%), and T_{mean} (3.869%), respectively. The meteorological factor with the smallest contribution was n.

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