Spatiotemporal Evolution Characteristics of Atmospheric Precipitable Water in Xinjiang and Its Relationship with Precipitation Conversion: Postprint

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Abstract

Precipitable Water Vapor (PWV) is an important indicator characterizing atmospheric water vapor content, and clarifying the conversion mechanism between PWV and precipitation is of great significance for the efficient utilization of water resources. This study takes Xinjiang as the research area, calculates PWV based on multi-source data, evaluates the advantages and disadvantages of calculating PWV using ERA5 global atmospheric reanalysis data with radiosonde data as reference, and reveals the conversion relationship between PWV and precipitation through Precipitation Conversion Efficiency (PCE). The results show that: (1) The PWV calculated by ERA5 has high accuracy, with correlation coefficient and root mean square error of 0.98 and 2.6 mm respectively compared with PWV determined by traditional radiosonde data. (2) From 1960 to 2020, PWV in Xinjiang shows an overall increasing trend with an increase rate of 0.1 $\mathrm{mm} \cdot (10a)^{-1}$; wavelet spectrum analysis shows that the variation periods of PWV in the study area are dominated by short periods, namely 2.6 years and 6 years. (3) At the point scale, PCE increases with the increase of station precipitation; at the linear scale, the variation pattern of PCE exhibits a "U"-shaped pattern in the longitude direction and approximately an "L"-shaped pattern in the latitude direction; at the area scale, high-value areas of PCE are mainly distributed in forest land, slope gradients of 25°–35°, and regions above 5000 m in altitude, with values of 7.17%, 5.8%, and 5.1% respectively. (4) PCE differs significantly in typical years of precipitation abundance and deficit anomalies; extremely wet years with strong convergence and intense water vapor upward motion induce higher PCE, while normal and dry years have lower PCE. (5) The Arctic Oscillation Index and Pacific Decadal Oscillation are the main factors affecting PCE across the entire Xinjiang region; due to differences in climate and topography among different regions, there are certain variations in the controlling factors of PCE. The research results can provide theoretical reference for atmospheric water resources utilization and precipitation conversion assessment in Xinjiang.

Full Text

Spatial and Temporal Evolution Characteristics of Atmospheric Precipitable Water Vapor in Xinjiang and Its Relationship with Precipitation Conversion

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Abstract

Atmospheric Precipitable Water Vapor (PWV) is a crucial indicator characterizing water vapor content in the atmosphere, and clarifying the conversion mechanism between PWV and precipitation is of great significance for efficient water resource utilization. This study takes Xinjiang as the research area, calculates PWV based on multi-source data, evaluates the accuracy of ERA5 reanalysis data for PWV calculation using radiosonde data as reference, and reveals the conversion relationship between PWV and precipitation through Precipitation Conversion Efficiency (PCE). The results demonstrate that: (1) PWV calculated from ERA5 data exhibits high accuracy, with correlation coefficients and root mean square errors of 0.98 and 2.6 mm, respectively, compared to PWV determined from traditional radiosonde-dependent methods. (2) From 1960 to 2020, PWV in Xinjiang shows an overall increasing trend of 0.1 mm $\cdot$ $(10a)^{-1}$; wavelet spectrum analysis indicates that the variation period of PWV is dominated by short cycles of 2.6 years and 6 years. (3) At the point scale, PCE increases with station precipitation; at the linear scale, PCE variation patterns show a "U" -type distribution along longitude and an "L" -type distribution along latitude; at the surface scale, high PCE values are mainly distributed in forested land, slopes of 25°–35°, and areas above 5000 m altitude, with values of 7.17%, 5.8%, and 5.1%, respectively. (4) Precipitation abundance anomaly years show significant PCE differences, with exceptionally wet years exhibiting strong convergence and vigorous upward water vapor motion leading to higher PCE, while normal and dry years show lower PCE. (5) The Arctic Oscillation Index and Pacific Decadal Oscillation are the main factors influencing PCE across Xinjiang, though controlling factors vary among different regions due to differences in climate and topography. These findings provide theoretical references for atmospheric water resource utilization and precipitation conversion assessment in Xinjiang.

Keywords: precipitable water vapor; precipitation conversion efficiency; conversion relationship; Xinjiang

Introduction

Precipitation is a key indicator for assessing regional climate change and significantly impacts water resource utilization, crop growth, and socioeconomic activities. Water vapor serves as the prerequisite for precipitation, and its distribution and movement in the atmosphere influence the spatiotemporal patterns of precipitation and their response to climate change. Water vapor content is typically represented by Atmospheric Precipitable Water Vapor (PWV), which reflects the abundance of water vapor. Although water vapor accounts for only 0.1%-3% of global water resources, it is the most active component of the atmospheric hydrological cycle and plays a crucial role in global water cycling and energy balance. Traditional PWV calculation methods primarily rely on radiosonde data, which offers high accuracy for individual stations and is often used to evaluate other methods. However, radiosonde stations are sparsely distributed with poor spatial representativeness, making them inadequate for large-scale, real-time monitoring requirements.

To overcome these limitations, scholars have developed alternative methods using surface meteorological data. Since meteorological stations significantly outnumber radiosonde stations, this approach provides much higher spatial resolution, and the accuracy of PWV calculated from surface meteorological data differs little from that determined by radiosonde data, gaining certain recognition. However, in Xinjiang—an arid and semi-arid region with scarce and unevenly distributed observation stations mostly located in low-altitude plains—understanding of PWV variation patterns remains constrained. In recent years, with scientific and technological advances, increasingly abundant atmospheric reanalysis data with high spatiotemporal resolution have been widely applied in PWV research. Previous studies have evaluated the suitability of ERA5 reanalysis data for PWV calculation across China, confirming its feasibility at large scales. Nevertheless, further research is needed to examine its performance under complex terrain and climate conditions for refined PWV assessment.

Over the past several decades, Northwest China has experienced significant climate change, gradually shifting from warm-dry to warm-wet conditions, with precipitation showing a clear increasing trend. However, due to rising temperatures and increased evaporation, the net effect on available water resources remains limited, and water scarcity persists. To clarify the relationship between PWV and precipitation, researchers have proposed the concept of Precipitation Conversion Efficiency (PCE), enabling a shift from qualitative to quantitative analysis of the PWV-precipitation relationship. This is crucial for understanding hydrological cycles, artificial precipitation enhancement, and extreme weather response. While previous studies have analyzed PWV spatiotemporal characteristics using station data, providing good understanding at point scales, the sparse distribution of observation stations has limited comprehension of regional-scale patterns. Although some researchers have employed atmospheric reanalysis and multi-source data to investigate regional PWV distribution, the relatively coarse spatial resolution of currently available datasets poses limitations for fine-scale regional PWV assessment and constrains understanding of PWV-precipitation conversion mechanisms. Meanwhile, with intensifying water resource supply-demand conflicts, atmospheric cloud water resource potential has become a research hotspot, all of which is closely related to PWV. Therefore, this study takes Xinjiang as the research area, uses radiosonde data as reference to evaluate ERA5 data accuracy, analyzes PWV-precipitation conversion mechanisms from multi-scale perspectives, and employs random forest modeling to explore relationships between large-scale climate factors and PCE, providing theoretical references for water resource potential exploitation and atmospheric water resource utilization in Xinjiang.

1.1 Study Area Overview

Xinjiang is located in northwestern China (Fig. 1), deep in the interior of the continent, and features a typical continental arid climate. Its total area is approximately 166×10^{4} km^2, accounting for one-sixth of China' s landmass. Xinjiang has complex terrain, with the Altai Mountains, Junggar Basin, Tianshan Mountains, Tarim Basin, and Kunlun Mountains distributed sequentially from north to south, forming a "three mountains 夹 two basins" pattern. The Tianshan Mountains divide Xinjiang into northern and southern regions, creating distinct mountain-desert systems with different arid climate conditions. Far from the ocean and limited by moisture sources, Xinjiang experiences scarce precipitation and strong evaporation, with an average annual precipitation of approximately 157.7 mm. Available water resources are scarce and unevenly distributed spatiotemporally.

1.2 Data Sources

Radiosonde Data. Eight operational radiosonde stations within the study area were selected, providing data from 2002 to 2020 at 12-hour intervals with 37 standard pressure levels. Data were obtained from the China Meteorological Data Network (https://data.cma.cn/).

Meteorological Station Data. Monthly precipitation data from 105 meteorological stations across the study area were collected for the period 1960–2020, also sourced from the China Meteorological Data Network.

ERA5 Reanalysis Data. ERA5 atmospheric reanalysis data from the European Centre for Medium-Range Weather Forecasts were obtained for 1960–2020, with a horizontal resolution of $0.25°\times0.25°$ and 37 pressure levels (https://cds.climate.copernicus.eu/).

Large-Scale Climate Indices. Monthly climate factor datasets from 1960 to 2020 were collected from the NOAA Physical Sciences Laboratory (https://psl.noaa.gov/gcos_{wgsp}/Timeseries/), including the Atlantic Multidecadal Oscillation (AMO), Arctic Oscillation Index (AO), North Atlantic Oscillation (NAO), El Niño-Southern Oscillation (ENSO), Pacific Decadal Oscillation (PDO), and sunspot numbers.

Land Use and Terrain Data. Land use data (30 m resolution) were obtained from the Chinese Academy of Sciences Resource and Environmental Science Data Center (http://www.resdc.cn/). Digital Elevation Model (DEM) data (30 m$×$30 m resolution) were sourced from the Geospatial Data Cloud Platform (https://www.gscloud.cn/).

1.3 Research Methods

PWV Calculation from Radiosonde Data. PWV was calculated using meteorological factors measured by radiosondes at different atmospheric layers:

$$\mathrm{PWV} = \frac{1}{\rho_w g}\int_0^{p_s} q(p)\,dp$$

where PWV is atmospheric precipitable water vapor (mm), _w is liquid water density ($\mathrm{kg \cdot m^{-3}}$), g is gravitational acceleration ($9.8\ \mathrm{m \cdot s^{-2}}$), p_s is surface pressure (hPa), and q(p) is specific humidity at each pressure level ($\mathrm{kg \cdot kg^{-1}}$). For computational convenience, Eq. (1) was discretized to obtain:

$$\mathrm{PWV} = -\frac{1}{g}\sum_{p_s}^{p_{\mathrm{top}}} q_i (p_{i+1} - p_i)$$

PWV Calculation from ERA5 Data. PWV was calculated from ERA5 reanalysis data using:

$$\mathrm{PWV} = \sum_{i=1}^{n} \frac{q_i}{\rho_w g}(p_{i+1} - p_i)$$

where g is latitude-dependent gravitational acceleration:

$$g = 9.780325 \times \frac{1 + 0.00193185 \times \sin^2(\phi)}{\sqrt{1 - 0.00669435 \times \sin^2(\phi)}}$$

with n representing the total number of atmospheric layers, q_i and p_i the mixing ratio ($\mathrm{kg \cdot kg^{-1}}$) and pressure (hPa) at layer i, respectively, and ϕ representing latitude.

Precipitation Conversion Efficiency (PCE). PCE represents the ratio of precipitation to PWV, indicating the efficiency of water vapor conversion to precipitation. Monthly PCE was calculated using observed station precipitation and ERA5-PWV data interpolated to corresponding stations via bilinear interpolation.

Driver Factor Analysis. PCE is influenced by multiple large-scale climate factors including AO, PDO, AMO, NAO, ENSO, and sunspots. Random forest regression models, which are robust against overfitting and capable of handling multi-type data, were employed to quantify the relative contributions of each climate factor to PCE and identify primary influencing factors.

2.1 Accuracy Assessment of ERA5 PWV

Using eight radiosonde stations as benchmarks, ERA5 datasets were bilinearly interpolated to station locations. Monthly PWV from both radiosonde and ERA5 data show consistent unimodal distribution trends, though with some magnitude differences. ERA5-PWV exhibits larger errors in summer and smaller errors in winter, likely due to intense precipitation and volatile water vapor changes in summer versus stable moisture conditions during the long, dry winters. Statistical metrics including correlation coefficient (r), root mean square error (RMSE), and mean absolute error (MAE) were calculated (Table 1). ERA5-PWV demonstrates high correlation with radiosonde-PWV ($r = 0.98$), with relatively small errors averaging 2.6 mm for both RMSE and MAE. Notable biases exist among different stations, possibly because ERA5 is generated from numerical weather prediction models whose accuracy is affected by input data quality and model parameters. Overall, ERA5-PWV shows high precision and stability in Xinjiang, adequately capturing PWV variation trends.

2.2 Spatiotemporal Variation of PWV

Based on the high accuracy of ERA5 data, the spatiotemporal variation of PWV in Xinjiang was analyzed. Temporally, PWV shows an increasing trend from 1960 to 2020 at a rate of $0.1\ \text{mm} \cdot (10\text{a})^{-1}$, with an abrupt change detected around 1987 using cumulative anomaly methods. Wavelet spectrum analysis reveals multiple periodicities, with significant cycles of 1–3 years and 4–6 years. Under 95% confidence intervals (within red dashed lines in Fig. 3), dominant periods are short cycles of 2.6 years and 6 years, indicating increased uncertainty and more frequent variations in PWV under changing environmental conditions.

Spatially, PWV distribution shows significant heterogeneity, generally decreasing from plains to mountains (Fig. 4). High PWV values occur in plains with scarce precipitation and strong evaporation (Tarim and Turpan-Hami basins), while mountainous areas with abundant precipitation and major runoff formation (Altai, Tianshan, and Kunlun Mountains) show low values. Northern Xinjiang generally exhibits higher PWV than southern Xinjiang, with a negative correlation between elevation and PWV. This pattern occurs because Xinjiang's plains are mainly basins with low terrain and thick air columns, concentrating atmospheric moisture in the lower troposphere and resulting in richer water vapor compared to surrounding mountainous areas.

The spatial trend of PWV (Fig. 4b) shows an overall increasing trend with notable spatial differences. Plains exhibit significant increases, with the largest 增幅 in the Tarim Basin (0.15-0.23 mm · a^{-1}). Mountainous areas show non-significant increases (0.02-0.06 mm · a^{-1}), with 增幅 gradually increasing from peripheries to central regions.

2.3 Variation Characteristics of PCE

2.3.1 Multi-scale Variation Characteristics of PCE At the point scale, PCE increases with station precipitation, ranging from 0.31% to 13.88%. Using the Tianshan Mountains as a boundary, PCE differences between northern and southern slopes are minimal, though northern stations (6.05% on average) are slightly higher than southern stations (5.83%). Plain areas show higher PCE than mountainous regions, but plains have far lower precipitation amounts. For the extremely arid Turpan-Hami Basin with precipitation below 50 mm, PCE is notably low (0.31%-8.61%, averaging 2.26%), contributing to severe drought and fragile ecological conditions.

To clarify the relationship between precipitation magnitude and PCE, stations were categorized by precipitation level: <50 mm, 50-100 mm, 100-150 mm, 150-200 mm, 200-250 mm, and >250 mm (Fig. 5). Average PCE values are 3.02%, 6.44%, 7.87%, 9.83%, and 0.78%, respectively, demonstrating a close relationship between precipitation amount and PCE, where increased precipitation contributes to higher PCE.

At the surface scale, spatial PCE patterns were derived using co-kriging interpolation with ERA5-PWV data (Fig. 6). Overall, PCE shows marked spatial differences, with higher values in mountains than plains. The Altai, Tianshan, and Kunlun Mountains are typical high-value zones, while the Tarim and Turpan-Hami basins are low-value zones. Analysis by land use type (Fig. 7) reveals that forest land has the highest PCE (7.17%), followed by water bodies, construction land, grassland, cropland, and unused land, with relatively small differences among types.

Terrain factors significantly influence PCE. Statistical analysis by slope grade shows PCE initially increasing then decreasing with slope, peaking at 25°-35° (5.79%). PCE values for slopes of 0°-5°, 5°-15°, and 15°-25° are 5.28%, 4.88%, and 5.79%, respectively, showing minimal variation. By elevation band, PCE first decreases then increases with altitude: <500 m (3.16%), 500-1000 m (3.11%), 1000-1500 m (2.69%), 1500-2000 m (3.95%), 2000-2500 m (6.68%), 2500-3000 m (7.41%), and >3000 m (9.37%). The highest PCE occurs above 5000 m (averaging 5.1%), with little difference between 3000-5000 m (3.79%) and <500 m (3.16%).

At the linear scale, PCE variation patterns differ along longitude and latitude (Fig. 8). Along longitude, PCE shows a "U" -shaped pattern, becoming more pronounced closer to moisture sources where water vapor is abundant. Along latitude, PCE exhibits an "L"-shaped distribution, with northern Tianshan areas higher than southern areas and more dramatic variations influenced by complex terrain. Although PCE variation patterns align with topographic fluctuations along both axes, local high and low altitude areas show opposite relationships between PCE change and terrain relief, likely due to interactions with moisture intensity, wind direction, wind speed, and surface cover that require further investigation.

2.3.2 PCE Variation in Different Typical Years Using observed precipitation data, typical years were selected including extremely wet years (P > 95th percentile), normal years (45th–55th percentile), and extremely dry years (P < 5th percentile) to explore PCE variation mechanisms. Considering moisture source direction, Tianshan Mountain blocking, and energy dissipation during moisture transport, latitudinal profiles along northern and southern Tianshan slopes and longitudinal profiles along moisture pathways were selected as typical cross-sections to analyze PCE patterns (Fig. 8).

Comparisons of water vapor content, water vapor flux, and water vapor flux divergence among typical years (Table 2) show that extremely wet years have significantly higher water vapor content and flux, providing abundant moisture conditions favorable for precipitation conversion. Water vapor flux divergence in extremely wet years is notably lower, indicating strong convergence and enhanced upward motion that facilitates precipitation formation and results in higher PCE. In contrast, normal and extremely dry years show higher divergence values, indicating weak convergence and moisture accumulation capacity that is unfavorable for precipitation generation, leading to lower PCE. Overall, sufficient moisture conditions and strong water vapor convergence are the primary causes of PCE differences among typical years.

2.3.3 Impact of Large-Scale Climate Factors on PCE To better understand PCE drivers, random forest models were used to analyze relationships between large-scale climate factors (AO, PDO, AMO, NAO, ENSO, sunspots) and PCE. Considering Xinjiang' s precipitation patterns and terrain characteristics, the entire region, northern Xinjiang, southern Xinjiang, and three typical river basins (Irtysh, Tarim, and Ili) were analyzed to determine climate factor contributions (Fig. 9).

For the entire Xinjiang region, AO and PDO show relatively high contributions at 25.7% and 22.2%, respectively, with other climate factors having minimal impact. Regionally, southern Xinjiang is primarily influenced by PDO (27.4%) and AO (25.3%). Northern Xinjiang shows high contributions from all climate factors except sunspots, with AO contributing 24.3%. At the basin scale, PDO dominates PCE in the Ili River Basin (32.2%) and Tarim River Basin (32.1%), while AO overwhelmingly controls the Irtysh River Basin (41.4% contribution). These regional differences in controlling factors are attributed to variations in terrain and climate conditions. Previous studies have identified PDO as an important factor affecting dry-wet changes in Northwest China, with positive PDO phases associated with increased precipitation in northwestern, northeastern, and Tibetan Plateau regions. This aligns with our findings. PDO may influence precipitation in the Ili and Tarim River Basins by modulating atmospheric circulation systems through sea surface temperature anomalies during PDO events. The dominant AO influence in the Irtysh River Basin may relate to AO' s impact on mid-high latitude climates in the Northern Hemisphere.

3 Conclusions

This study evaluated the accuracy and applicability of ERA5 reanalysis data for PWV calculation in Xinjiang, analyzed spatiotemporal variation trends of PWV, investigated PWV-precipitation conversion mechanisms through PCE calculation, and explored relationships between PCE and large-scale climate factors using random forest models. The main conclusions are:

1. ERA5-PWV demonstrates high accuracy and stability in Xinjiang, with average correlation coefficients and RMSE of 0.98 and 2.6 mm, respectively, compared to radiosonde-derived PWV.

2. Temporally, PWV in Xinjiang increased from 1960 to 2020 at a rate of 0.1 $\mathrm{mm} \cdot (10\mathrm{a})^{-1}$, with an abrupt change occurring in 1987. Wavelet frequency spectra reveal dominant short periods of 2.6 years and 6 years. Spatially, PWV decreases with increasing altitude, with higher values in plains and lower values in mountainous areas.

3. At the point scale, PCE increases with station precipitation. At the surface scale, high PCE values are distributed in forest land and water bodies; PCE increases with slope up to 25°–35°; and PCE increases with altitude above 1000 m. At the linear scale, PCE shows a "U" -type pattern along longitude and an "L" -type pattern along latitude.

4. Water vapor content, water vapor flux, and water vapor flux divergence are the main causes of PCE differences among typical years. Extremely wet years have abundant moisture and strong convergence, resulting in significantly higher PCE than other years.

5. AO and PDO are the main factors affecting PCE across Xinjiang, though controlling factors vary by region: PDO dominates in the Ili and Tarim River Basins, while AO overwhelmingly controls the Irtysh River Basin.

These results provide theoretical references for atmospheric water resource utilization and precipitation conversion assessment in Xinjiang.

References

[7] Alshawaf F, Fuhrmann T, Knopfler A, et al. Accurate estimation of atmospheric water vapor using GNSS observations and surface meteorological data[J]. *Geoscience and Remote Sensing*, 2015, 53(7): 3765-3775.

[8] Yang Jingmei, Qiu Jinhuan. The empirical expression of the relation between precipitable water and ground water vapor pressure for some areas in China[J]. *Chinese Journal of Atmospheric Sciences*, 1996, 20(5): 620-626.

[9] Wang Z, Chen P, Wang R, et al. Performance of ERA5 data in retrieving precipitable water vapor over Hong Kong[J]. *Advances in Space Research*, 2023, 71(10): 4055-4071.

[10] Zhang W, Zhang H, Liang H, et al. On the suitability of ERA5 in hourly GPS precipitable water vapor retrieval over China[J]. *Journal of Geodesy*, 2019, 93: 1897-1909.

[11] Shi Y, Shen Y, Li D, et al. Discussion on the characteristics and trend of present climate change from warm dry to warm wet in Northwest China[J]. *Quaternary Sciences*, 2003, 23(2): 152-164.

[12] Wang Y, Shen Y, Li D, et al. Fused downscaling framework and spatiotemporal characteristics of TRMM 3B43 precipitation product in the Qinghai region[J]. *Arid Land Geography*, 2024, 47(7): 1136-1146.

[13] Pan F, He W, Xie Y, et al. Multiple branches of water vapor transport over the Nujiang River Basin in summer and its impact on precipitation[J]. *Acta Geographica Sinica*, 2023, 78(1): 87-100.

[14] Dong H, Wang D, Cao J, et al. Climate dry wet conditions, changes, and their driving factors in Xinjiang[J]. *Arid Zone Research*, 2023, 40(12): 1875-1884.

[15] Qiang A, Wei J, Xie H, et al. Spatial temporal characteristics and changes of atmospheric water vapor in the Three River Headwaters region[J]. *Advances in Water Science*, 2019, 30(1): 14-23.

[16] Li J, Li D, Zhang J. Research on summer effective precipitation conversion rate over the Yellow River Basin[J]. *Advances in Water Science*, 2012, 23(3): 346-354.

[17] Wang N, Gu W, Qiu C, et al. Characteristics of atmospheric water vapor distribution and transport during summer over Shandong Province[J]. *Plateau Meteorology*, 2021, 40(1): 159-168.

[18] Yang H, Ge R, Xu B. Analysis of total water vapor in tropospheric gas column using single station sounding data[J]. *Meteorology*, 1998, 24(9): 9-12.

[19] Li S, Xie G, He Q, et al. Research on precipitation, precipitable water and the precipitation conversion efficiency of Altay Prefecture[J]. *Journal of Glaciology and Geocryology*, 2008, 30(4): 675-680.

[20] Zhou S, Wu P, Wang C, et al. Spatial distribution of atmospheric water vapor and its relationship with precipitation in summer over the Tibetan Plateau[J]. *Acta Geographica Sinica*, 2011, 66(11): 1466-1478.

[21] Li X, Zhang G. Research on precipitable water and precipitation conversion efficiency around Tianshan Mountain Area[J]. *Journal of Desert Research*, 2003, 23(5): 33-37.

[22] Fan X, Liu H, Zhao W, et al. Analysis of precipitation conversion in Xinjiang based on NCEP data[J]. *Journal of Shihezi University (Natural Science)*, 2016, 34(3): 372-378.

[23] Yao J. Change in atmospheric and surface water resource in Xinjiang[J]. *Arid Zone Research*, 2024, 41(2): 181-190.

[24] Xu C, Dou Y, Meng Q. Prediction of the standardized precipitation evapotranspiration index in the Xinjiang region using the EMD-LSTM model[J]. *Arid Zone Research*, 2024, 41(4): 527-539.

[25] Yu J, Zhang J, Zhang M, et al. SAPEI-Based spatial and temporal variation characteristics of drought in Xinjiang[J]. *Agricultural Research in the Arid Areas*, 2023, 41(4): 275-288.

[26] Wang P, He J, Zheng Y, et al. Inter-decadal relationships between summer Arctic Oscillation and aridity-wetness feature in Northwest China[J]. *Journal of Desert Research*, 2007, 27(5): 883-889.

[27] Ma Z. The interdecadal trend and shift of dry/wet over the central part of North China and their relationship to the Pacific Decadal Oscillation (PDO)[J]. *Chinese Science Bulletin*, 2007, 52(15): 2120-2124.

[28] Jia Y, Zhang B. Relationship of dry-wet climate changes in Northern China in the past 57 years with Pacific Decadal Oscillation (PDO)[J]. *Acta Pedologica Sinica*, 2019, 56(5): 1085-1097.

[29] Cong J, Zhao T, Ma Y. Multi-decadal variability of precipitation in arid and semi-arid region of Northern China and its relationship with Pacific Decadal Oscillation index[J]. *Climatic and Environmental Research*, 2017, 22(6): 643-657.

[30] Zhao L, An S, Yang L, et al. Study on precipitable water and precipitation conversion efficiency in Urumqi during the period of 1976-2007[J]. *Arid Zone Research*, 2010, 27(3): 433-437.

[31] Tian J, Zhang Z, Zhao T, et al. Warmer and wetter climate induced by the continual increase in atmospheric temperature and precipitable water vapor over the arid and semi-arid regions of Northwest China[J]. *Journal of Hydrology: Regional Studies*, 2022, 42: 101151.

[32] Zhang Y, Ma X, Han H, et al. Analysis of spatial and temporal distribution characteristics of cloud water resources in Qinghai Province from 2014 to 2018[J]. *Arid Zone Research*, 2021, 38(5): 1254-1262.

[33] Liu R, Yang Q, Wang M. Intercomparison and analysis of the result about atmospheric precipitable water calculated by NCEP reanalysis and empirical formula[J]. *Journal of Arid Land Resources and Environment*, 2010, 24(4): 77-85.

[34] Wang Q, Wang X, Zhou Y, et al. The dominant factors and influence of urban characteristics on land surface temperature using random forest algorithm[J]. *Sustainable Cities and Society*, 2022, 79: 103722.

[35] Liu K, Xu K, Zhu C, et al. Diversity of marine heatwaves in the South China Sea regulated by ENSO phase[J]. *Journal of Climate*, 2022, 35(2): 877-893.

Note: Figure translations are in progress. See original paper for figures.