Prediction of Vapor Pressure Deficit in Northwest China Based on Exponential Smoothing and ARIMA Models (Postprint)

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Abstract

Saturated vapor pressure deficit is a key influencing factor in the water transfer process of the soil-vegetation-atmosphere continuum. Under the background of global climate change, predicting saturated vapor pressure deficit in Northwest China is of great practical significance for vegetation restoration and risk assessment of agroforestry meteorological disasters. Based on monthly saturated vapor pressure deficit values in five northwestern provinces (regions) from 1990 to 2019, this study investigated the interannual variation characteristics and periodic variation patterns of saturated vapor pressure deficit in Northwest China using methods such as trend analysis and wavelet analysis; and simulated and predicted saturated vapor pressure deficit in Northwest China using exponential models and ARIMA models, screening for optimal sample step length and prediction step length. The results show that: (1) Among the five northwestern provinces (regions), Xinjiang has the highest annual average saturated vapor pressure deficit, followed by Ningxia, Shaanxi, Gansu, and Qinghai; over the past 30 years, saturated vapor pressure deficit in Northwest China has shown an overall upward trend, with Ningxia and Xinjiang experiencing the largest increases at 0.036 kPa $\cdot$ $(10a)^{-1}$ and 0.033 kPa $\cdot$ $(10a)^{-1}$, respectively, followed by Gansu [0.026 kPa $\cdot$ $(10a)^{-1}$], Qinghai [0.021 kPa $\cdot$ $(10a)^{-1}$], and Shaanxi [0.012 kPa $\cdot$ $(10a)^{-1}$]; (2) For all northwestern provinces (regions), the 16-year scale period contributes most to wavelet variance, representing the dominant period of saturated vapor pressure deficit variation. Additionally, Shaanxi, Gansu, and Xinjiang also exhibit periodic characteristics of 24–27 years with smaller variance contributions; (3) Compared with the exponential model, the ARIMA model reduces root mean square error by an average of 42.3%, increases the coefficient of determination R^2 by an average of 11.1%, and improves the Nash-Sutcliffe efficiency coefficient by an average of 17.7%, effectively improving the prediction accuracy of saturated vapor pressure deficit; (4) In the near future, saturated

vapor pressure deficit in all regions of Northwest China will show varying degrees of increasing trend, with the most pronounced increases in Ningxia and Xinjiang at 9.5% and 8.9%, respectively.

Full Text

Prediction of Vapor Pressure Deficit in Northwest China Based on Exponential Smoothing and ARIMA Models

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Abstract

Vapor pressure deficit (VPD) is a key factor influencing water transport in the soil-plant-atmosphere continuum. Under the background of global climate change, predicting VPD in Northwest China holds important practical significance for vegetation restoration and risk assessment of meteorological disasters in agriculture and forestry. Based on monthly VPD data from five provinces (regions) in Northwest China from 1990 to 2019, this study investigated interannual variation characteristics and periodic patterns using trend analysis and wavelet analysis methods. Exponential smoothing models and Autoregressive Integrated Moving Average (ARIMA) models were employed to simulate and predict VPD, with optimal sample and prediction steps selected through comparative analysis.

The results show that: (1) Among the five provinces (regions), Xinjiang exhibited the highest annual mean VPD (0.61 kPa), followed by Ningxia (0.54 kPa), Shaanxi (0.48 kPa), Gansu (0.46 kPa), and Qinghai (0.36 kPa). Over the past 30 years, VPD in Northwest China showed an upward trend, with Ningxia and Xinjiang displaying the largest increases at 0.036 $\text{kPa} \cdot (10\text{a})^{-1}$ and 0.033 $\text{kPa} \cdot (10\text{a})^{-1}$, respectively, followed by Gansu [0.026 $\text{kPa} \cdot (10\text{a})^{-1}$], Qinghai [0.021 $\text{kPa} \cdot (10\text{a})^{-1}$], and Shaanxi [0.012 $\text{kPa} \cdot (10\text{a})^{-1}$]. (2) All provinces (regions) exhibited periodic oscillation characteristics, with a 15–20 year cycle representing the dominant period that contributed most significantly to wavelet variance. Additionally, Shaanxi, Gansu, and Xinjiang showed 24–27 year cycles, though with smaller variance contributions. (3) Compared with exponential smoothing models, the ARIMA models reduced root mean square error (RMSE) by an average of 42.3%, increased the coefficient of determination (R^2) by 11.1%, and improved the Nash-Sutcliffe efficiency coefficient by 17.7%, effectively enhanc-

ing VPD prediction accuracy. (4) Predictions indicate that VPD in Northwest China will continue to increase in the coming years, with the most pronounced rises in Ningxia (9.5%) and Xinjiang (8.9%).

Keywords: vapor pressure deficit; exponential smoothing; ARIMA model; prediction; Northwest China

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1 Study Area and Research Methods

1.1 Study Area Overview

Northwest China comprises five provincial-level regions: Shaanxi (105°29 -111°15 E, 31°42 -39°35 N), Gansu (92°13 -108°46 E, 32°11 -42°57 N), Ningxia Hui Autonomous Region (104°17 -109°39 E, 35°14 -39°14 N), Qinghai (89°35 -103°04 E, 31°36 -39°19 N), and Xinjiang Uygur Autonomous Region (73°40 -96°18 E, 34°25 -48°10 N). The region covers more than one-third of China' s total land area and is characterized by arid and semi-arid conditions with a temperate continental climate. Annual average temperature is below 8°C, and annual precipitation decreases from east to west, generally below 400 mm. The terrain is dominated by mountains, basins, and plateaus, with sparse vegetation cover, making it a typical ecologically vulnerable zone globally.

1.2 Data and Model Construction

Monthly temperature and relative humidity data from 1990 to 2019 were obtained from 136 meteorological stations across the five provinces (regions). The actual monthly VPD was calculated using the following formula:

$$VPD = 0.611e^{\frac{17.27T}{T+240.97}}(1 - \frac{RH}{100})$$

where T is air temperature (°C) and RH is relative humidity (%).

1.2.1 Model Selection Traditional empirical regression models require numerous parameters and large datasets with complex calculations. While neural networks offer advantages in climate prediction, their outputs are highly sensitive to parameters that are often determined empirically, limiting predictive capability. Grey system theory provides another approach for climate forecasting but shows limited accuracy for oscillating sequences, restricting its application. Exponential smoothing models are commonly used for time series forecasting, offering simple structure and good short-term prediction performance. The ARIMA model can predict future values based on non-stationary time series historical data without relying on external variables, overcoming limitations caused by external parameters. ARIMA models have achieved good results in crop yield forecasting, drought prediction, and temperature prediction. This study introduced exponential smoothing and ARIMA models to simulate and predict VPD in Northwest China by comparing different model structures to establish optimal models for each region. The effects of different sample lengths and prediction horizons on model accuracy were evaluated to select optimal sample and prediction steps, thereby improving model precision for future VPD forecasting.

1.2.2 Verification of Sequence Stationarity and Determination of *d* VPD is a function of temperature and relative humidity, exhibiting periodic variations with seasonal factors and containing trend components and seasonal effects. Therefore, before establishing ARIMA(p,d,q) models, the stationarity of the time series must be verified. Common methods include autocorrelation plot observation and unit root tests. While autocorrelation plots are simple to operate, they lack rigor. Thus, this study employed the Augmented Dickey-Fuller (ADF) test to verify sequence stability and determine the required differencing order (d). Non-stationary sequences require differencing treatment to achieve stationarity.

1.2.3 Determination of *p* and *q* Parameters p and q represent the autoregressive and moving average terms in the ARIMA(p,d,q) model, respectively. To select optimal parameter combinations, this study examined the truncation and tailing characteristics of autocorrelation (AC) and partial autocorrelation (PAC) coefficients after d-order differencing, combined with comparative analysis of models with different parameters to determine the best model structure.

1.3 Model Evaluation Metrics

Adjusted R^2 was used to characterize model goodness-of-fit. The Akaike Information Criterion (AIC) was also employed for model selection, where larger adjusted R^2 and smaller AIC indicate better model performance. The Ljung-Box Q test was used to examine whether residual sequences showed significant autocorrelation; $P > 0.05$ indicates that residuals form a white noise sequence. Mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE) were used to evaluate model parameters. The Nash-Sutcliffe efficiency coefficient (NSE) was used to verify the fit between observed and simulated values, with values closer to 1.0 indicating higher model efficiency and stronger applicability.

The formulas are as follows:

$$AIC = -2\ln(L) + 2k$$

$$MAPE = \frac{1}{N_s}\sum_{i=1}^{N_s}\left|\frac{ETS_i - ETM_i}{ETM_i}\right| \times 100\%$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N_s}(ETS_i - ETM_i)^2}{N_s}}$$

$$NSE = 1.0 - \frac{\sum_{i=1}^{N_s}(ETS_i - ETM_i)^2}{\sum_{i=1}^{N_s}(ETM_i - ET_{AVE})^2}$$

where L is the maximum likelihood function, k is the number of independent parameters, *N_s* is the sample size, *ETS* represents simulated values, *ETM* represents measured values, and *ET_{AVE}* is the mean of measured values.

1.4 Data Processing

Data preprocessing was conducted using Excel 2010. Data analysis and modeling were performed using EViews 7.2 and SPSS 19.0 software. Origin 9.4 was used for plotting. The Least Significant Difference (LSD) method was applied for multiple comparisons of VPD values. Wavelet variance analysis was used to determine the main periods of sequence variation.

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2 Results

2.1 VPD Variation Characteristics in Northwest China

From 1990 to 2019, the annual mean VPD values across the five provinces (regions) followed the order: Xinjiang (0.61 kPa) > Ningxia (0.54 kPa) > Shaanxi (0.48 kPa) > Gansu (0.46 kPa) > Qinghai (0.36 kPa) [Figure 1: see original paper]. Xinjiang and Ningxia showed relatively large interannual VPD fluctuations, while the other three provinces exhibited smaller variations. Interannual variability rates were 0.32% for Shaanxi, 0.29% for Gansu, 0.19% for Ningxia, 0.32% for Qinghai, and 0.24% for Xinjiang.

Linear trend analysis revealed that Ningxia and Xinjiang had the highest trend slopes at 0.036 kPa $\cdot$ (10a)$^{-1}$ and 0.033 kPa $\cdot$ (10a)$^{-1}$, respectively, followed by Gansu [0.026 kPa $\cdot$ (10a)$^{-1}$], Qinghai [0.021 kPa $\cdot$ (10a)$^{-1}$], and Shaanxi [0.012 kPa $\cdot$ (10a)$^{-1}$]. This indicates that VPD in Ningxia and Xinjiang has shown a more pronounced upward trend over the past 30 years compared to other provinces.

Wavelet analysis revealed periodic oscillation characteristics in VPD evolution across all provinces (regions) [Figure 2: see original paper]. The dominant period was 15-20 years, showing the strongest oscillation signal and most significant periodic variation. This scale remained stable throughout the study period, indicating steady periodic VPD changes in Northwest China over the past 30 years. Wavelet variance analysis confirmed that the 15-20 year cycle contributed most to variance (up to 7.75%), representing the primary period of VPD variation. Additionally, Shaanxi, Gansu, and Xinjiang exhibited 24–27 year cycles, though with smaller variance contributions of 2.80%–3.14%.

Monthly VPD characteristics showed that the highest monthly VPD occurred in July at 2.34 kPa, while the lowest appeared in January at 0.78 kPa [Figure 3: see original paper]. Annual mean VPD was 1.15 kPa. Multiple comparisons indicated significant differences in monthly VPD within each province ($P < 0.05$), except for Shaanxi. Significant differences in VPD among provinces were found for most months ($P < 0.05$), except during January-February and November-December [Figure 5: see original paper].

2.2 Model Selection and Parameter Calibration

ADF test results showed that the original VPD sequences were non-stationary, with test statistics greater than critical values at the 5% significance level . After first-order differencing, all provincial sequences became stationary, with test statistics smaller than critical values, allowing rejection of the null hypothesis at the 5% level. Therefore, the differencing order d was determined to be 1.

Autocorrelation analysis of first-differenced sequences revealed that AC coefficients decayed abruptly to small fluctuations after lag 1, indicating first-order truncation [Figure 6: see original paper]. Partial autocorrelation coefficients showed large fluctuations after lag 1 but gradually stabilized within confidence intervals, suggesting $p = 1$ and $q = 1$ as potential parameters. Based on these characteristics, preliminary ARIMA(1,1,1), ARIMA(2,1,1), and ARIMA(3,1,1) models were selected for comparison, with ARIMA(1,1,1) ultimately identified as optimal. For exponential smoothing, the Holt-Winters additive model was selected as most suitable.

2.3 Model Simulation and Performance Analysis

Residual testing revealed that exponential smoothing models required a minimum sample step of 4 years, while ARIMA models needed at least 5 years to be effective. Sample steps of 4–30 years were tested for exponential models and 5–30 years for ARIMA models. Comparative analysis identified optimal sample steps for each model . To ensure sequence continuity and predict VPD from 2020 onward, the exponential smoothing model was fitted to 1990–2019 data, while ARIMA models used 1990–2016 (ARIMA(1,1,1) and ARIMA(2,1,1)) and 1990–2014 (ARIMA(3,1,1)) data.

Prediction steps of 1, 3, and 5 years were tested. For exponential smoothing, adjusted R^2 was highest at 1-year prediction steps, decreasing with longer steps . ARIMA(1,1,1) and ARIMA(3,1,1) showed no significant differences across prediction steps, but ARIMA(2,1,1) performed best at 3-year steps with minimal error. Overall, the optimal prediction step was determined to be 1 year for exponential smoothing, 3 years for ARIMA(2,1,1), and 1 year for both ARIMA(1,1,1) and ARIMA(3,1,1).

Model performance comparison showed that ARIMA models achieved higher goodness-of-fit and efficiency than exponential smoothing models [TABLE:2, TABLE:3]. Specifically, ARIMA models reduced RMSE by an average of 42.3%, increased R^2 by 11.1%, and improved Nash-Sutcliffe efficiency by 17.7% compared to exponential smoothing models.

2.4 Model Prediction

Based on optimal prediction steps, forecasts were generated for 2020–2025 (exponential smoothing) and 2020–2021 (ARIMA models) . Results indicate that VPD in Shaanxi and Xinjiang will increase by 4.5% and 8.9%, respectively, while Gansu, Ningxia, and Qinghai will show slight decreases by 2021. Over the longer term (2020–2025), VPD in Shaanxi, Gansu, Qinghai, and Xinjiang will increase by 4.5%, 1.8%, 1.9%, and 8.9%, respectively, while Ningxia will see the highest increase at 9.5%.

Comparison of predicted and observed VPD levels (1990–2019) revealed that exponential smoothing predictions were generally lower than ARIMA predictions, tending to underestimate actual VPD levels . ARIMA model predictions were closer to observed values, demonstrating better accuracy.

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3 Discussion

VPD is a crucial meteorological parameter in ecological models for simulating vegetation stomatal conductance and estimating evapotranspiration, and serves as a primary reference variable in ecosystem carbon and water flux studies. Recent research indicates that global VPD has increased dramatically, possibly due to reduced ocean evaporation and lower atmospheric water content over land. Against the backdrop of global warming, Northwest China has experienced rising temperatures and increased frequency of extreme high-temperature events, which may contribute to VPD increases. Elevated VPD can limit plant carbon uptake and water use efficiency in terrestrial ecosystems, potentially reducing crop yields and causing forest mortality.

Our results show that Ningxia and Xinjiang experienced the most significant VPD increases from 1990 to 2019, likely related to regional temperature rises and increased frequency of dry events. Precipitation affects VPD primarily through its influence on air temperature and humidity, while VPD changes can impact actual evapotranspiration and consequently regional precipitation patterns. Recent studies have reported decreasing precipitation trends in eastern Northwest China, which may partially explain the observed VPD increases.

Predictions based on optimal models suggest that VPD in Northwest China will continue rising in the coming years. The persistent VPD increase may indicate that the warming and drying trend in Northwest China will continue for an extended period. This aligns with previous research showing that under the combined effects of temperature and precipitation, the entire Northwest China region is becoming drier. The predicted VPD increases, particularly in Xinjiang (8.9% by 2025), suggest potential risks of soil drought and vegetation degradation, necessitating adaptive measures such as adjusting agricultural and forestry structures and optimizing water resource allocation.

ARIMA models demonstrated superior performance compared to exponential smoothing, with average RMSE reduction of 42.3%, R^2 increase of 11.1%, and Nash-Sutcliffe efficiency improvement of 17.7%. The ARIMA model structure is concise, accurate, and highly applicable, providing a valuable reference for VPD prediction in Northwest China. However, factors influencing VPD are complex, including not only directly related atmospheric temperature and humidity but also latitude, longitude, elevation, solar radiation, and human activities. Future research should explore more optimized and combined models to further improve prediction accuracy and enhance the ability to identify VPD trend changes.

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4 Conclusions

1. From 1990 to 2019, VPD in Northwest China showed an overall upward trend. Ningxia and Xinjiang exhibited the most significant increases at 0.036 $\mathrm{kPa} \cdot (10\mathrm{a})^{-1}$ and 0.033 $\mathrm{kPa} \cdot (10\mathrm{a})^{-1}$, respectively, followed by Gansu [0.026 $\mathrm{kPa} \cdot (10\mathrm{a})^{-1}$], Qinghai [0.021 $\mathrm{kPa} \cdot (10\mathrm{a})^{-1}$], and Shaanxi [0.012 $\mathrm{kPa} \cdot (10\mathrm{a})^{-1}$]. All provinces (regions) displayed periodic oscillations with a dominant 15-20 year cycle contributing up to 7.75% of variance.
2. Based on current observations, VPD in Northwest China is projected to continue increasing. By 2025, VPD in Shaanxi, Gansu, Qinghai, and Xinjiang will increase by 4.5%, 1.8%, 1.9%, and 8.9%, respectively, while Ningxia will show the highest increase at 9.5%.
3. Compared with exponential smoothing models, ARIMA models reduced RMSE by 42.3% on average, increased R^2 by 11.1%, and improved Nash-Sutcliffe efficiency by 17.7%. The ARIMA models exhibited smaller errors, better fit, higher variable explanation, and stronger applicability, effectively improving VPD prediction accuracy in Northwest China.

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