Postprint: Reference Crop Evapotranspiration Prediction in the Xilingol Grassland Based on Multivariate Time Series Models

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Abstract

To investigate the influence of various meteorological factors on reference crop evapotranspiration (ET0) in the Xilingol Grassland and to predict ET0, meteorological data obtained from six national-level surface meteorological stations in the Xilingol Grassland of Inner Mongolia and the corresponding calculated PM-ET0 were subjected to grey relational analysis. CAR-ET0 models based on multivariate time series CAR (Controlled Auto-regressive) were established respectively according to the ranking of grey relational coefficients from highest to lowest. The results indicate that: (1) The grey relational coefficients between meteorological factors and PM-ET0 exhibit a decreasing distribution transitioning from the desert steppe region through the typical steppe region to the meadow steppe region. Daily minimum temperature and average temperature show the lowest correlation with PM-ET0, while average sunshine duration demonstrates the highest correlation with PM-ET0, with a value of 0.7293. (2) For the meadow steppe region and desert steppe region, CAR-ET0 models established using sunshine duration and temperature as the two input factors achieve relatively high accuracy; for the typical steppe region, wind speed is additionally required as the third factor of the model. (3) Through verification of model prediction accuracy, the CAR-ET0 model demonstrates overall higher prediction accuracy than the HS-ET0 and PMT-ET0 methods. Combined with grey relational analysis, meteorological factors that exert significant influence on local reference crop evapotranspiration can be identified, which can provide a theoretical basis for meteorological monitoring network layout schemes, ET0 determination, and grassland ecological restoration in the Xilingol Grassland.

Full Text

Prediction of Reference Crop Evapotranspiration in Xilinguole Grassland Based on Multivariate Time Series Model

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Abstract

This study was conducted to explore the influence of various meteorological factors on reference crop evapotranspiration (ET_0) and to predict ET_0 in Xilinguole grassland. Meteorological data obtained from six national ground meteorological stations in Xilinguole, Inner Mongolia, were analyzed for their correlation with PM-ET_0 calculated using the FAO-56 Penman-Monteith method. Based on the correlation coefficients, multivariate time series Controlled Autoregressive (CAR) models were established for each meteorological factor and ET_0. Results demonstrated that the correlation coefficients between meteorological factors and PM-ET_0 exhibited a decreasing trend from desert steppe areas to typical steppe areas and then to meadow steppe areas. Daily minimum temperature and average temperature showed the weakest correlation with ET_0, while average sunshine hours displayed the strongest correlation, with a maximum value of 0.7293. In meadow and desert steppe regions, the CAR model achieved high prediction accuracy when sunshine hours and temperature were used as input factors. In typical steppe regions, wind speed was required as a third input factor. Validation of model prediction accuracy revealed that the CAR-ET_0 model generally outperformed the HS-ET_0 and PMT-ET_0 models in terms of precision. Combined with correlation analysis, this approach can identify meteorological factors that significantly influence local reference crop evapotranspiration, thereby providing a theoretical basis for designing meteorological monitoring schemes, determining reference crop evapotranspiration, and guiding ecological restoration efforts in Xilinguole grassland.

Keywords: reference crop evapotranspiration; grey correlation analysis; multivariate time series model; Xilinguole grassland

1.1 Study Area Overview

Xilinguole is located in central-eastern Inner Mongolia, on the southern part of the Mongolian Plateau, covering a total area of approximately 203,000 km^2, of which natural grassland accounts for about 87%. This region represents a significant livestock production base and ecological protection barrier in China, comprising roughly 26% of Inner Mongolia's total grassland area. Situated in the mid-latitude westerly belt, Xilinguole experiences a mid-temperate semi-arid to arid continental monsoon climate characterized by strong winds, drought, and cold conditions. The terrain slopes downward from south to north, with low mountains and hills in the east and south, and relatively flat terrain in the west and north. The predominant soil type is silt loam. Based on differences in natural geographical conditions, the pastoral area can be divided into three vegetation zones: meadow steppe in the east, typical steppe in the center, and desert steppe in the west.

1.2 Data Sources

The Xilinguole Meteorological Bureau operates meteorological stations in each banner (county, city, district), but only national-level ground stations provide the comprehensive meteorological data required for this study. The meteorological data were obtained from the National Meteorological Science Data Center for six national ground stations in Xilinguole. The meteorological factors included daily maximum temperature, daily minimum temperature, average relative humidity, sunshine hours, and average wind speed. The geographical distribution of these stations is shown in [Figure 1: see original paper], and the average climatic data for each station from 1980 to 2019 are summarized in .

1.3 Reference Crop Evapotranspiration Calculation Models

1.3.1 FAO-56 Penman-Monteith Method

The FAO-56 Penman-Monteith (PM) method was used to calculate reference crop evapotranspiration (ET_0). The equation is expressed as:

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}$$

where ET_0 is reference crop evapotranspiration ($\mathrm{mm \cdot d^{-1}}$); Δ is the slope of the saturation vapor pressure curve ($\mathrm{kPa \cdot °C^{-1}}$); G is soil heat flux density ($\mathrm{MJ \cdot m^{-2} \cdot d^{-1}}$); T is mean daily air temperature (°C); R is net radiation at the crop surface ($\mathrm{MJ \cdot m^{-2} \cdot d^{-1}}$); γ is the psychrometric constant ($\mathrm{kPa \cdot °C^{-1}}$); e is saturation vapor pressure (kPa); e is actual vapor pressure (kPa); and u_2 is wind speed at 2.0 m height ($\mathrm{m \cdot s^{-1}}$).

1.3.2 Multivariate Time Series (CAR) Model

The Controlled Autoregressive (CAR) model combines one-dimensional time series analysis with multivariate regression methods. It considers both the inherent dynamics of the system and the influence of environmental factors, effectively avoiding errors caused by complex time series problems. The CAR model has been widely applied in hydrological forecasting, groundwater dynamics, and meteorology with significant results.

For a general case with m variable time series constructing an n-order CAR model, the form is:

$$y_t = a_{1y_{t-1}} + a_{2y_{t-2}} + \cdots + a_{ny_{t-n}} + b_{11}x_{1,t-1} + \cdots + b_{mn}x_{m,t-n} + \varepsilon_t$$

Model parameter estimation employs the recursive least squares method. Letting $z_t = [y_{t-1}, y_{t-2}, \cdots, y_{t-n}, x_{1,t-1}, \cdots, x_{m,t-n}]^T$ and $\theta = [a_1, a_2, \cdots, a_n, b_{11}, \cdots, b_{mn}]^T$, the model can be expressed as $y_t = z_t^T\theta + \varepsilon_t$. The recursive least squares estimate is:

$$\hat{\theta}_t = \hat{\theta}_{t-1} + K_t(z_t - z_t^T\hat{\theta}_{t-1})$$

$$P_t = \frac{1}{\alpha}(I - K_{tz}t^T)P_{t-1}$$

where α is the forgetting factor (typically 0.9–1.0). A smaller α (closer to 0) causes faster forgetting of historical data, while α closer to 1 retains historical data longer.

Model order determination uses F-tests on adjacent CAR models to judge whether increasing the order significantly improves fit, thereby determining the true model order and time lag.

1.3.3 Grey Correlation Analysis

Grey correlation analysis differs from traditional statistical correlation analysis. Based on grey system theory, it compares time series between factors, requires less data, and focuses on dynamic processes rather than static relationships. This method has been widely applied in agriculture, hydrology, and meteorology. The correlation degree reveals the relative impact of different meteorological factors on ET_0.

1.4 Data Analysis

Data were organized using Excel 2016, with input factors placed in left columns and the output factor (ET_0) in the rightmost column. The DPS7.05 data processing system was used to define data blocks for analysis. Grey correlation analysis and multivariate time series modeling were performed under the grey system method and time series modules, respectively. QGIS 3.14 software with inverse distance weighting interpolation was applied to spatially interpolate the correlation coefficients across the study area, and Origin 2018 was used for figure preparation.

2.1 Correlation Analysis Between Reference Crop Evapotranspiration and Meteorological Factors

The spatial distribution of correlation coefficients between multi-year average PM-ET_0 and meteorological parameters at each station is shown in [Figure

2: see original paper]. The correlation coefficients exhibit a decreasing trend from northwest to southeast across the study area, transitioning from desert steppe to typical steppe to meadow steppe. The weakest correlations were found between ET_0 and daily minimum temperature and average temperature, while the strongest correlation was with average sunshine hours (maximum correlation coefficient of 0.7293).

The spatial pattern reflects the influence of both parameter characteristics and geographical location. Erenhot City in the west, affected by the Mongolian High, experiences a mid-temperate continental monsoon climate with arid desert steppe conditions, strong evapotranspiration potential, and low precipitation, making ET_0 highly sensitive to solar radiation. In contrast, East Ujimqin Banner in the northeast, influenced by both southeastern oceanic warm-moist airflow and northwestern dry-cold airflow, has lower average temperatures and relatively less sunshine, yet still shows strong correlation between sunshine hours and ET_0.

2.2 CAR Model Construction and Validation Under Different Meteorological Factors

The meteorological dataset from 1980–2019 was divided into calibration (1980–2013) and validation (2014–2019) periods. CAR models were established by sequentially adding meteorological factors in descending order of their correlation coefficients with ET_0. The forgetting factor for recursive least squares was set at 0.98, and the significance level was 0.05. Model performance was evaluated using the coefficient of determination (R^2), root mean square error (RMSE), and Nash-Sutcliffe efficiency coefficient (NSE):

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N}(Q_{m,t} - Q_{o,t})^2}{N}}$$

$$NSE = 1 - \frac{\sum_{t=1}^{N}(Q_{m,t} - Q_{o,t})^2}{\sum_{t=1}^{N}(Q_{o,t} - \bar{Q}_o)^2}$$

where $Q_{m,t}$ and $Q_{o,t}$ are predicted and observed values, respectively.

Model performance improved with additional meteorological factors during calibration, while during validation, R^2 initially increased then decreased with more inputs, indicating optimal model complexity. The CAR model generally achieved $R^2 > 0.75$ and NSE > 0.70 in both periods across stations, demonstrating satisfactory performance.

Comparative analysis revealed that: - In meadow steppe regions (East and West Ujimqin Banners), the CAR model using only sunshine hours and maximum temperature (CAR_2) outperformed the Hargreaves-Samani (HS) and PMT methods. - In typical steppe regions (Abag Banner, Xilinhot, Duolun County), adding wind speed as a third factor (CAR_3) was necessary for highest accuracy. - In desert steppe region (Erenhot), the CAR_2 model with sunshine and temperature showed superior performance.

The CAR-ET_0 model prediction accuracy was generally higher than both HS-ET_0 and PMT-ET_0 models across all grassland types [FIGURE:3, FIGURE:4].

3 Discussion

Accurate ET_0 prediction is essential for regional water resource evaluation, irrigation scheduling, water balance calculations, and climate analysis. While the FAO-56 PM method is considered the standard, it requires comprehensive meteorological data that are often unavailable in extensive regions like Xilinguole grassland, where national stations are sparse. Alternative methods such as Hargreaves-Samani and PMT require fewer parameters but may sacrifice accuracy.

Machine learning and deep learning approaches have shown promise but often require large datasets and face challenges with the stationary assumptions of time series data. The multivariate time series CAR model offers advantages by combining time series analysis with multivariate regression, considering both system dynamics and environmental influences while avoiding errors from complex time series processing.

This study demonstrates that the correlation between meteorological factors and ET_0 varies significantly across grassland types in Xilinguole. Sunshine hours consistently emerge as the most influential factor, yet this parameter is not routinely measured at all regional stations. The spatial variability of wind speed in this windy, semi-arid region further complicates ET_0 prediction.

The CAR model approach, using correlation analysis to select input factors, provides a robust framework for ET_0 prediction using data from regional meteorological stations. This strategy enables more accurate ET_0 forecasting beyond the coverage of national stations, supporting climate analysis, water resource management, and irrigation decisions. Future work should focus on optimizing meteorological monitoring networks to capture key parameters like sunshine duration, thereby improving model performance and supporting ecological restoration efforts.

4 Conclusions

1) Across the study area, correlation coefficients between meteorological factors and ET_0 decrease from desert steppe through typical steppe to meadow steppe. Daily minimum and average temperatures show the weakest correlation, while average sunshine hours show the strongest correlation (maximum coefficient of 0.7293).

2) The CAR-ET_0 model generally achieves higher prediction accuracy than HS-ET_0 and PMT-ET_0 methods. For meadow and desert steppe regions, the highest accuracy is obtained using sunshine hours and maximum temperature as inputs. For typical steppe regions, wind speed must be included as a third factor.

3) Due to Xilinguole grassland's unique geographical conditions and climate characteristics, temperature-only methods (HS and PMT) show lower accuracy than approaches incorporating sunshine and wind speed. A tailored meteorological monitoring scheme based on local characteristics should be developed to support CAR model implementation for precise ET_0 prediction, providing data support for ecological restoration and scientific research in Xilinguole grassland.

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