Comparison and Evaluation of Interpolation Methods for Meteorological Elements in Loess Hilly Regions Based on ANUSPLIN (Postprint)

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Abstract

Meteorological elements are key factors reflecting Earth's hydrothermal processes, and accurate acquisition of meteorological data holds great significance for ecological protection and agricultural production research. The Loess Hilly Region is a typical hilly-gully area where terrain significantly influences the interpolation results of meteorological elements, limiting data accuracy. To acquire the spatial distribution of temperature and precipitation in the Loess Hilly Region and investigate the influence of topographic variation on meteorological spatial interpolation results, this study utilized the professional meteorological interpolation software ANUSPLIN, using daily temperature and precipitation data from 105 meteorological stations in the Yanhe River Basin and its surrounding areas from 2010 to 2021, with three Digital Elevation Models of different resolutions (25 m, 90 m, and 1 km) as covariates for interpolation, to generate raster data of temperature and precipitation in the Loess Hilly Region, reveal the spatiotemporal variation patterns of precipitation in this region, and assess the suitability of the ANUSPLIN interpolation method in the Loess Hilly Region. Results demonstrate: (1) Temperature is higher in the Yanchang area of the eastern Yanhe River Basin and lower in the west; precipitation interpolation reveals lower values in the central and northwestern parts and higher values in the east, with both temperature and precipitation patterns aligning with historical meteorological station observations, and the ANUSPLIN model exhibits good applicability for spatial interpolation of temperature and precipitation in the loess hilly-gully region. (2) Across three DEM resolution scenarios, the ranking of temperature interpolation accuracy is: 25 m > 90 m > 1 km; the ranking of precipitation interpolation accuracy is: 90 m > 25 m > 1 km. This study provides a reference for meteorological distribution and interpolation in hilly regions.

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Comparative Analysis and Evaluation of Meteorological Element Interpolation Methods Based on ANUSPLIN in Loess Hilly Regions

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Abstract

Meteorological elements are key factors reflecting Earth's hydrothermal processes, and accurate acquisition of meteorological data is of great significance to ecological protection and agricultural production research. Loess hilly areas are typical hilly-gully regions where terrain seriously affects the interpolation results of meteorological elements, restricting data accuracy. To obtain the spatial distribution of temperature and precipitation in the loess hilly region and explore the influence of terrain variation on meteorological spatial interpolation results, this study used the professional meteorological interpolation software ANUSPLIN, based on daily temperature and rainfall data from 105 meteorological stations in and around the Yanhe River Basin from 2010 to 2021, introducing digital elevation models of three different resolutions (25 m, 90 m, and 1 km) as covariables for interpolation. This approach generated raster data of temperature and precipitation in the loess hilly region to reveal spatiotemporal variation patterns and evaluate the applicability of the ANUSPLIN interpolation method in this terrain. The results show that: (1) Temperatures in the eastern extension area of the Yanhe River Basin were higher, while western areas had lower temperatures; rainfall interpolation showed lower values in the central and northwestern regions and higher values in the eastern region, both temperature and rainfall conforming to previous meteorological station data patterns, and the ANUSPLIN model demonstrated good adaptability for temperature and rainfall spatial interpolation in the loess hilly-gully region. (2) Under three different resolution simulation scenarios, the accuracy ranking for temperature interpolation was: 25 m > 90 m > 1 km, and for rainfall interpolation: 90 m > 25 m > 1 km. The results of this study provide a reference basis for meteorological distribution and interpolation in hilly regions.

Keywords: ANUSPLIN model; meteorological elements; loess hilly region; digital elevation data; evaluation

Introduction

Meteorological factors are critical elements affecting agricultural production, human activities, and ecological environments, particularly in arid and semi-arid regions. Meteorological elements have been extensively studied in agriculture and environmental research, primarily applied in model prediction and crop production [1]. Initially, meteorological research relied on rain gauge monitoring at meteorological stations. However, due to the limited number of stations, incomplete spatial coverage, and poor timeliness, this approach was insufficient for comprehensively capturing climate events and describing spatial variations. With the development of spatial processing and analysis technologies, spatial interpolation methods have been employed to describe the spatial distribution of meteorological factors, achieving a certain degree of spatial coverage and improving understanding of meteorological spatial variation.

Currently, numerous interpolation methods exist with varying applications in system simulation and inversion. Common methods include local polynomial interpolation, spline function (Spline), and inverse distance weighting (IDW) [2]. Hutchinson developed ANUSPLIN, a method for interpolating meteorological and hydrological data at different spatial and temporal scales. Its main feature is the ability to incorporate linear covariables such as terrain variables, making it widely applicable in mountainous and hilly regions with significant topographic variation [3]. Additionally, ANUSPLIN offers a simple operational process that does not require separate pre-calibration of parameters, generating temperature and precipitation time series surfaces with high precision and reliability [4]. In recent years, the ANUSPLIN interpolation method has been widely applied by domestic and international scholars for climate data interpolation [5].

The loess hilly region is located in the central Loess Plateau and represents a key area for ecological restoration in China. This region is characterized by crisscrossing gullies and variable terrain, where meteorological factors such as temperature and precipitation are significantly influenced by topography [6]. Traditional interpolation methods primarily estimate values based on spatial distances between meteorological stations. However, the loess hilly region is predominantly mountainous, and terrain variation is sufficient to affect the differential distribution of spatial temperature and precipitation [7]. Obtaining meteorological data based solely on distance cannot truly reflect meteorological changes in this region, thus failing to meet the needs of vegetation restoration and reconstruction efforts. Therefore, exploring meteorological interpolation methods that incorporate terrain variation at different resolutions is of great significance for improving meteorological spatial data and related research in complex terrain hilly regions.

Based on the ANUSPLIN spatial interpolation method, this study interpolated temperature and precipitation data from 2010 to 2021 in the Yanhe River Basin while selecting three different precision digital elevation models (DEM) as co-variables. The study compared and analyzed the interpolation accuracy of temperature and precipitation at each scale, evaluated the applicability of the ANUSPLIN interpolation method in the loess hilly-gully region, and selected the optimal dataset for regional temperature and precipitation. This research addresses the shortcomings of insufficient interpolation accuracy in hilly regions and provides a theoretical basis and methodological reference for accurately obtaining meteorological spatial interpolation data in topographically complex hilly areas.

1.1 Study Area Overview

This study focused on the Yanhe River Basin (36°23 ~37°17 N, 108°45 ~110°28 E) as a typical loess hilly region, covering an area of 7,687 km^2 with elevations ranging from 454 to 1,765 m. The basin extends sequentially from southeast to northwest through Yanchang, Yan'an, Ansai, and Zhidan, representing a typical hilly-gully area [Figure 1: see original paper]. The climate is relatively dry year-round, with rainy summers and less winter precipitation, situated in a transitional zone between warm temperate continental monsoon semi-humid climate and temperate semi-arid climate. Annual rainfall is 496 mm, and the average annual temperature is 8.8 °C. Rainfall and temperature show obvious gradient changes from southeast to northwest. The soil is primarily loessal soil, and vegetation includes forests, shrublands, and grasslands, with *Robinia pseudoacacia* and *Quercus wutaishanica* as dominant species.

1.2.1 Meteorological Data

Basic meteorological data were obtained from meteorological stations in and around the Yanhe River Basin. The data covered the period from 2010 to 2021 and included daily values such as average temperature, maximum temperature, minimum temperature, and daily precipitation. For this long time series data, some anomalies or missing values existed. Therefore, after screening and removing abnormal data, 105 meteorological stations were retained for the study [Figure 1: see original paper]. The data were processed to calculate annual average temperature and annual cumulative precipitation for interpolation. The three different precision digital elevation model data were derived from: (1) 25 m DEM data obtained from PALSAR data carried by the ALOS satellite, freely downloaded from ASF DAAC (https://search.asf.alaska.edu/#/); (2) 90 m DEM data; and (3) 1 km resolution data from the CGIAR-CSI SRTM China regional dataset.

1.3 Research Methods

1.3.1 Basic Principles of ANUSPLIN ANUSPLIN is a tool for transparent analysis and interpolation of noisy multivariate data using thin-plate smoothing splines. The thin-plate smoothing spline function essentially fits a surface to all meteorological stations, creating a "spline" that passes through the stations to obtain a smooth surface with minimal curvature that approximates all control points. This method uses a two-order polynomial to perform piecewise fitting of curves, employing local thin plates to draw piecewise continuous surfaces. ANUSPLIN extends the spline function method to surfaces, using optimal smoothing parameters to achieve the best balance between fidelity and smoothness, ensuring reliable accuracy while producing smooth and continuous interpolation surfaces [8]. ANUSPLIN also allows transformation of independent and dependent variables and can handle datasets with missing values. When transformations are applied to dependent variables, ANUSPLIN permits reverse transformation of fitted surfaces, calculation of corresponding standard errors, and correction of small biases introduced by these transformations. This feature is particularly convenient when fitting surfaces to precipitation data and other naturally positive or non-negative data [9].

The thin-plate spline estimation z(xi) is calculated by a suitably smooth function that minimizes:

$$J_m(f) = \sum_{i=1}^{n} w_i \left(\frac{y_i - f(x_i)}{\delta_i} \right)^2 + \lambda J_m(f)$$

where y_i is the observed data value at observation i; f is the estimated spline function; λ is a positive number called the smoothing parameter; and $J_m(f)$ is a measure of the roughness of function f defined using m-order partial derivatives (also called the roughness order) [10]. In the formula, the function f and coefficient b are obtained through least squares estimation.

The theoretical statistical model formula for local thin-plate smoothing splines is:

$$Z_i = f(x_i) + b^T y_i + e_i$$

where Z_i is the dependent variable at spatial point i; T is the number of iterations; f is the unknown smooth function estimated for x_i; x_i is the independent variable; y_i is the p-dimensional independent covariable; b is the p-dimensional coefficient of y_i; and e_i is random error [11].

1.3.2 Interpolation Accuracy Evaluation Metrics This study selected data from 20 meteorological stations as a validation set using random sampling. Cross-validation was used to compare the interpolated data with actual observations to assess the accuracy and bias of meteorological simulation [12]. The interpolation accuracy under the three resolutions was compared using cross-validation. The root mean square error (RMSE) was used to evaluate interpolation performance, expressed as:

$$\mathrm{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(Z_x-Z_y)^2}$$

where Z_x and Z_y represent the measured and interpolated climate data values, respectively, and n is the length of the calculation sequence. Smaller RMSE values indicate better meteorological simulation performance.

Additionally, correlation analysis was performed between measured and predicted values, with the coefficient of determination (R^2) used to represent the goodness-of-fit of the univariate polynomial regression equation. R^2 values range between 0 and 1, with larger values indicating better simulation performance.

2 Results and Analysis

2.1 Interpolation Results

The interpolation surfaces for annual average temperature and cumulative precipitation in the study area from 2010 to 2021 were obtained using ANUSPLIN [Figure 2: see original paper]. Compared with the 1 km resolution, the 25 m and 90 m resolution interpolation results showed more prominent details and could reflect local terrain features while maintaining good smoothness. The results indicated that the daily annual average temperature was higher in Yanchang County in the eastern part of the basin and lower in Jingbian and Zhidan in the west, as well as in Ansai District in the central region. The daily annual average temperature across all three resolutions showed an overall trend of "high in the east, low in the west."

The temperature interpolation range was 7.872–13.313 °C for 25 m resolution, 7.786–13.329 °C for 90 m resolution, and 7.725–13.354 °C for 1 km resolution. The rainfall interpolation range was 1.046–1.852 mm for 25 m resolution, 1.062–1.847 mm for 90 m resolution, and 1.117–1.847 mm for 1 km resolution. The minimum rainfall values for 25 m and 90 m resolutions differed by only 0.016 mm, which is relatively close, but the 1 km resolution result differed significantly, with both lower and upper limits being 0.071 mm and 0.055 mm higher, respectively, narrowing the interpolation range.

The spatial distribution of low rainfall was mainly concentrated in Jingbian in the western part of the basin, Baota District in the central region, and a small portion of Yanchang in the east. The interpolation results showed prominent detail characteristics with obvious "mosaic" patterns. Compared with previous studies in arid regions, no large patches or "bulls-eyes" appeared, indicating that ANUSPLIN effectively fitted terrain features, consistent with the research conclusions of Liu Lin et al. [13]. The interpolation results also showed relatively good smoothness. Furthermore, the results indicated lower rainfall in the central and northwestern parts of the Yanhe River Basin and higher rainfall in the east, which was validated in the research of Liu Chunli et al. [14]. Soil moisture changes were also consistent with these patterns [15], and temperature interpolation characteristics conformed to previously published meteorological station data patterns. The northwestern part of the Yanhe River Basin is a grassland zone [16] with generally low precipitation and low temperatures, while the eastern part is a forest-grassland and forest zone with high precipitation and high temperatures, consistent with the interpolation results. This indicates that the ANUSPLIN model can better adapt to the loess hilly-gully region.

From the temperature interpolation results at different resolutions, based on the calculated RMSE values, the 25 m resolution interpolation data showed the best accuracy, followed by the 90 m resolution, with the 1 km resolution showing the poorest accuracy. In terms of the coefficient of determination (R^2), the R^2 for 25 m resolution was 0.833, indicating good fitting performance, followed by 90 m resolution, with 1 km resolution showing slightly poorer fitting performance. In summary, under the three different precision simulation scenarios, the accuracy ranking for temperature interpolation was: 25 m > 90 m > 1 km. Research by Jia Yang et al. [17] showed that higher resolution DEM data as covariables yield higher ANUSPLIN model interpolation accuracy, and the temperature interpolation results in this study follow this pattern. High-precision terrain data can effectively reflect spatial differences and improve the accuracy of temperature spatial interpolation.

2.2 Comparison of Interpolation Results

The accuracy of rainfall interpolation results was tested following the same method as for annual average temperature. The accuracy ranking for rainfall interpolation under the three resolution scenarios was: 90 m > 25 m > 1 km. The 90 m resolution showed the highest interpolation accuracy, while the 1 km resolution showed the lowest accuracy. Simultaneously, when comparing the interpolation results of 90 m resolution with measured results, the R^2 value was also the largest among the three resolutions at 0.833, indicating good fitting performance, followed by 25 m resolution, with 1 km resolution showing the poorest fitting performance. This pattern differs from temperature interpolation, and the authors speculate that the reason may be related to the abundance of mountains in the loess hilly region [18], where precipitation tends to accumulate in gullies, leading to errors in station data. The spatial precision of 70–200 m is exactly consistent with terrain variation, though deterministic testing requires further verification in subsequent work. However, this result also indicates that meteorological station placement in hilly regions must consider terrain variation.

High-resolution climate datasets, including remote sensing data and long time series data, are urgently needed for related research in the loess hilly region. In recent years, climate change in arid regions has been significant [19], and real-time meteorological data are valuable for climate, vegetation research, and human activities. The spatiotemporal variation trend of evapotranspiration is basically consistent [20]. The area around Yan'an City in this study had relatively less rainfall, possibly due to human interference causing errors in meteorological station data. Previous research has also indicated that Yan'an City in the Yanhe River Basin is an area with frequent human activity [21]. Zhao Meiliang et al. [22] demonstrated in their study of hydrological spatial distribution in Northwest China that land use changes affect the distribution of hydrological elements. Overall, the ANUSPLIN model shows good adaptability for temperature and rainfall spatial interpolation in the loess hilly-gully region.

3 Conclusions and Discussion

This study selected the Yanhe River Basin, a typical loess hilly region on the Loess Plateau, as the research area. Based on daily meteorological data from 2010 to 2021 and using three DEM resolutions (25 m, 90 m, and 1 km) as covariables, the ANUSPLIN interpolation method was applied to perform spatial interpolation of meteorological data at different topographic resolutions. Through cross-validation using meteorological station data, the interpolation accuracy levels of each DEM resolution were compared and analyzed. The study found that DEM resolution affects meteorological spatial interpolation results, with specific findings as follows:

(1) Temperature interpolation showed that the eastern Yanchang area of the Yanhe River Basin had higher temperatures, while the western area had lower temperatures, consistent with previous meteorological station data patterns [23]. Rainfall interpolation showed lower values in the central and northwestern regions, consistent with the basic characteristics of spatiotemporal evapotranspiration trends in this area [24]. The area around Yan'an City in this study had relatively less rainfall, possibly due to human interference causing errors in meteorological station data. Previous research has also indicated that the Yanhe River Basin around Yan'an City is an area with frequent human activity [25]. Overall, the ANUSPLIN model demonstrates good adaptability for temperature and rainfall spatial interpolation in the loess hilly-gully region.

(2) Under three different resolution simulation scenarios, the accuracy ranking for temperature interpolation was: 25 m $>$ 90 m $>$ 1 km, consistent with the conclusion that higher DEM resolution yields higher interpolation accuracy [26]. However, the rainfall interpolation accuracy ranking was: 90 m $>$ 25 m $>$ 1 km, indicating that rainfall data spatial interpolation has an optimal DEM resolution related to regional terrain characteristics. Field observations revealed that slope lengths in the loess hilly region mountains are mostly between 60–300 m, which is consistent with this result. Terrain data such as slope and slope length may be more suitable for describing rainfall data information than elevation alone.

This study conducted spatial accuracy verification across multiple scales based on the ANUSPLIN interpolation method combined with DEM data. The good fit between results and observations demonstrates reliability. The conclusions can provide references for interpolation applications in hilly regions. However, this study only considered elevation data as a covariable, while other terrain factors such as aspect and slope position also affect interpolation results. Incorporating multiple covariables into the ANUSPLIN interpolation method could provide more meaningful references for optimizing meteorological interpolation accuracy.

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