Post-print of a Soil Water Erosion Prediction Model for Artificial Grasslands in the Loess Hilly and Gully Region of Central Gansu

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Abstract

To address the issue that soil water erosion processes are complex and difficult to effectively predict in the Loess Hilly and Gully Region of Central Gansu, this study utilized experimental data from artificial grassland runoff plots at the Anjiagou Soil and Water Conservation Experimental Station in Dingxi City from 2005 to 2016 (January to December). Eight factors—including monthly rainfall, monthly erosive rainfall, monthly runoff, monthly rainfall intensity, runoff plot area, runoff plot slope, soil sand content, and soil clay content—were employed as input variables, with monthly soil water erosion amount as the output. Partial Least-Squares Regression (PLSR) and Long Short-Term Memory (LSTM) recurrent neural network were applied to establish a prediction model for soil water erosion in artificial grassland, and the model' s effectiveness was evaluated against common neural network models including BP (Back Propagation) and RNN (Recurrent Neural Network). The results indicated that PLSR reduced the eight input factors to four, thereby effectively resolving the problem of excessive sample size requirements for LSTM neural network models. The integration of PLSR and LSTM neural network models could effectively enhance the prediction accuracy and convergence speed for artificial grassland soil water erosion processes, with prediction results showing an average relative error of less than 4% and a correlation coefficient higher than the other three neural network models, while the number of iterations, root mean square error, and mean absolute error were all lower than those of the other three models. The study revealed that slope exerted a relatively pronounced influence on the soil water erosion process of artificial grassland; when rainfall was less than 25 mm, soil water erosion amount in artificial grassland did not increase significantly with slope, but when rainfall exceeded 25 mm, soil water erosion amount in artificial grassland increased significantly with slope. The PLSR-LSTM neural network soil water erosion prediction model can accurately predict soil water erosion amounts for artificial grassland in the Loess Hilly and Gully Region of

Central Gansu, providing novel ideas and methods for accurate forecasting of soil erosion in this region.

Full Text

Testing a Soil Water Erosion Predictive Model in an Artificial Grassland in the Hill-Gully Loess Plateau

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Abstract

Soil water erosion is widespread in the hill-gully Loess Plateau of central Gansu, China, but it is difficult to observe and predict. The objectives of this study were to establish a predictive model for soil water erosion based on a partial least squares algorithm (PLSR) and long short-term memory (LSTM), and to evaluate the model' s effectiveness using a back-propagation neural network, a recurrent neural network, and a LSTM neural network. The results were verified with experimental data from a runoff field of artificial grassland in the soil and water conservation experimental stations in Anjiagou, Dingxi City, from 2005 to 2016 (1–12 months). Input factors for the model were monthly precipitation, monthly erosive precipitation, monthly runoff, monthly rainfall intensity, runoff area, slope of runoff field, sand content, and clay content, from which the model predicted monthly soil water erosion. The results revealed that the original eight input factors could be reduced to four by the PLSR algorithm in the prediction model, alleviating the requirement of the LSTM neural network model for a large number of samples. Our method improved both the prediction precision and the convergence rate of the soil water erosion model in artificial grassland by combining a PLSR algorithm with a LSTM neural network. The average relative error of our prediction results was less than 4%, and the correlation coefficients were higher for our model than for the three neural network models used for comparison. In addition, iteration times, root mean square error, and mean absolute error were lower than for the other neural network models. We found that slope had a significant effect on soil water erosion, but only when the monthly rainfall was more than 25 mm. Our PLSR-LSTM neural network model could be used to accurately predict soil water erosion in artificial grassland in the hill-gully Loess Plateau of central Gansu, and it could provide a new path toward accurate prediction of soil erosion in this area.

Keywords: hill-gully loess plateau; artificial grassland; long short-term memory (LSTM) recurrent neural network; soil water erosion prediction

2.4 PLSR-LSTM Model Validation

The PLSR-LSTM neural network model was validated using data from 2014 to 2016 (1–12 months), including monthly precipitation, erosive precipitation, runoff, and rainfall intensity. The validation results showed that the average relative error between measured and predicted values was 4%, with RMSE values of 0.234, 0.294, 0.321, and 0.368; MAE values of 0.246, 0.318, 0.348, and 0.381; and R^2 values of 0.985, 0.982, 0.977, and 0.965 for the four runoff fields respectively.

The PLSR-LSTM model demonstrated superior performance compared to BP, RNN, and LSTM neural networks. The prediction accuracy was highest for runoff field 1 and decreased progressively for fields 2, 3, and 4, consistent with the observed soil erosion patterns. The model's relative error remained below 4% across all validation periods, confirming its reliability for predicting soil water erosion in artificial grassland.

[Figure 4: see original paper]

Analysis of Soil Erosion Patterns

Monthly average soil water erosion from 2014 to 2016 showed distinct patterns across the four runoff fields, with erosion rates following the order: field 4 > field 3 > field 2 > field 1. This ranking corresponded to differences in slope gradient and vegetation coverage among the experimental plots.

[Figure 5: see original paper]

The comparison between measured and predicted soil water erosion values for 2014–2016 demonstrated strong agreement, with the PLSR-LSTM model accurately capturing seasonal variations and peak erosion events. The model performed particularly well during high-rainfall months, maintaining prediction accuracy even under extreme conditions.

[Figure 6: see original paper]

Relationship Between Slope and Soil Water Erosion

Analysis revealed that slope gradient significantly influenced soil water erosion, but this effect was contingent on rainfall amount. When monthly rainfall was less than 10 mm, slope had minimal impact on erosion rates. For rainfall between 10 mm and 25 mm, erosion increased moderately with slope, particularly on gradients of 5°–20°. However, when monthly rainfall exceeded 25 mm, the slope effect became pronounced, with erosion rates increasing substantially on steeper slopes. Under heavy rainfall conditions (>50 mm monthly), slope became the dominant factor controlling erosion magnitude.

[Figure 7: see original paper]

The PLSR-LSTM model effectively captured these complex interactions between rainfall intensity, slope gradient, and soil erosion. By reducing the eight original input variables to four principal components, the model achieved faster convergence and higher prediction accuracy than conventional neural network approaches. This dimensionality reduction, combined with LSTM' s ability to process temporal sequences, provided a robust framework for predicting soil water erosion in the Loess Plateau' s artificial grassland ecosystems.

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