A new method for predicting the spatial and temporal distribution of precipitation δ 18 O based on deep learning and spatial and temporal clustering

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Abstract

Predicting precipitation δ ^{18}O accurately is crucial for understanding water cycles, paleoclimates, and hydrological applications. Yet, forecasting its spatio-temporal distribution remains challenging due to complex climate interactions and extreme events. We developed a method combining spatio-temporal clustering and deep learning neural networks to improve multi-site, multi-year precipitation δ ^{18}O predictions. Using a comprehensive dataset from 33 German sites (1978-2021), our model considers precipitation δ ^{18}O and its controlling factors, including precipitation and temperature distribution. We applied the K-means++ method for classification and divided data into training and prediction sets. The CNN[1](#fn-0002) model extracted spatial features, while the Bi-LSTM model focused on temporal features. Spatio-temporal clustering using K-means++ improved forecast accuracy and reduced errors. This study highlights the potential of deep learning and clustering techniques for forecasting complex spatio-temporal data and offers insights for future research on isotope distributions.

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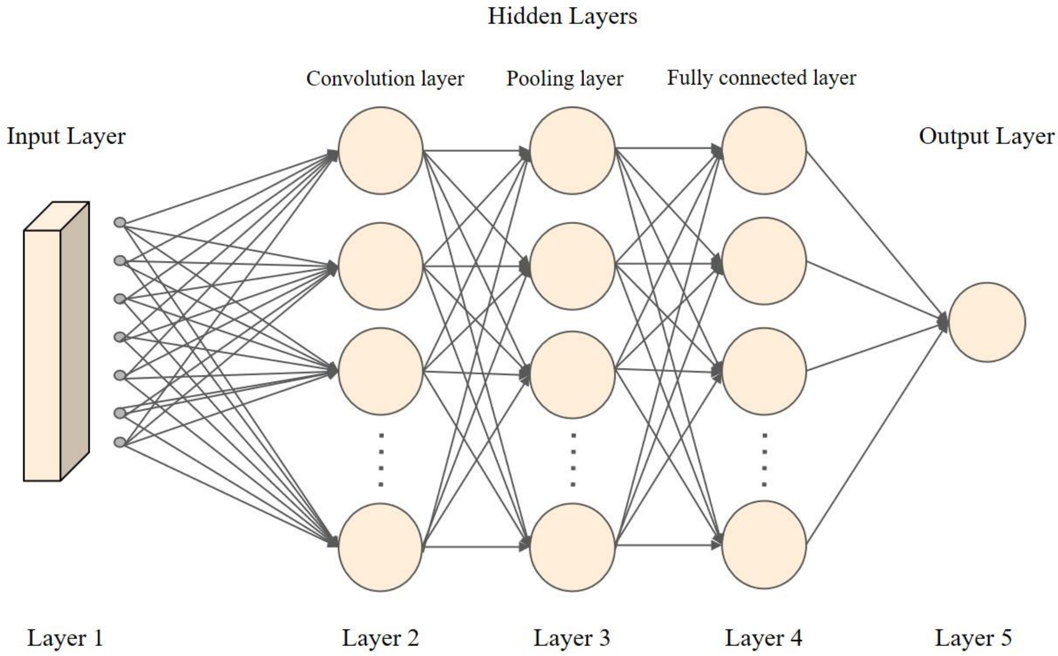
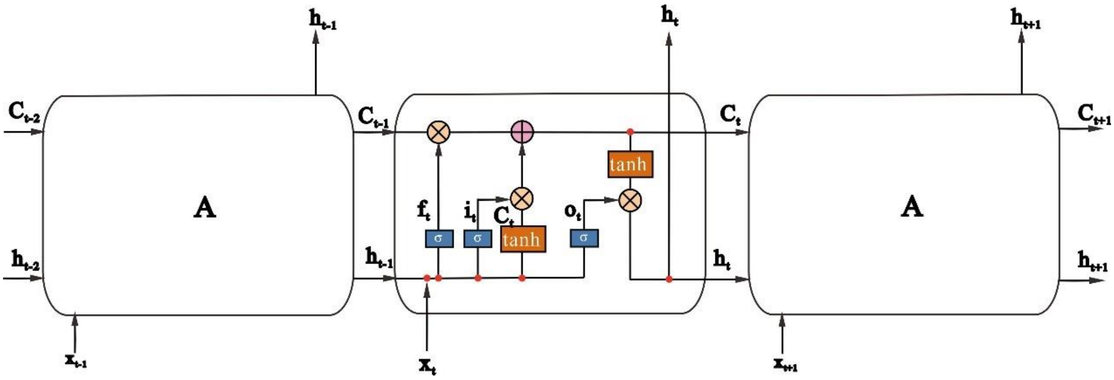
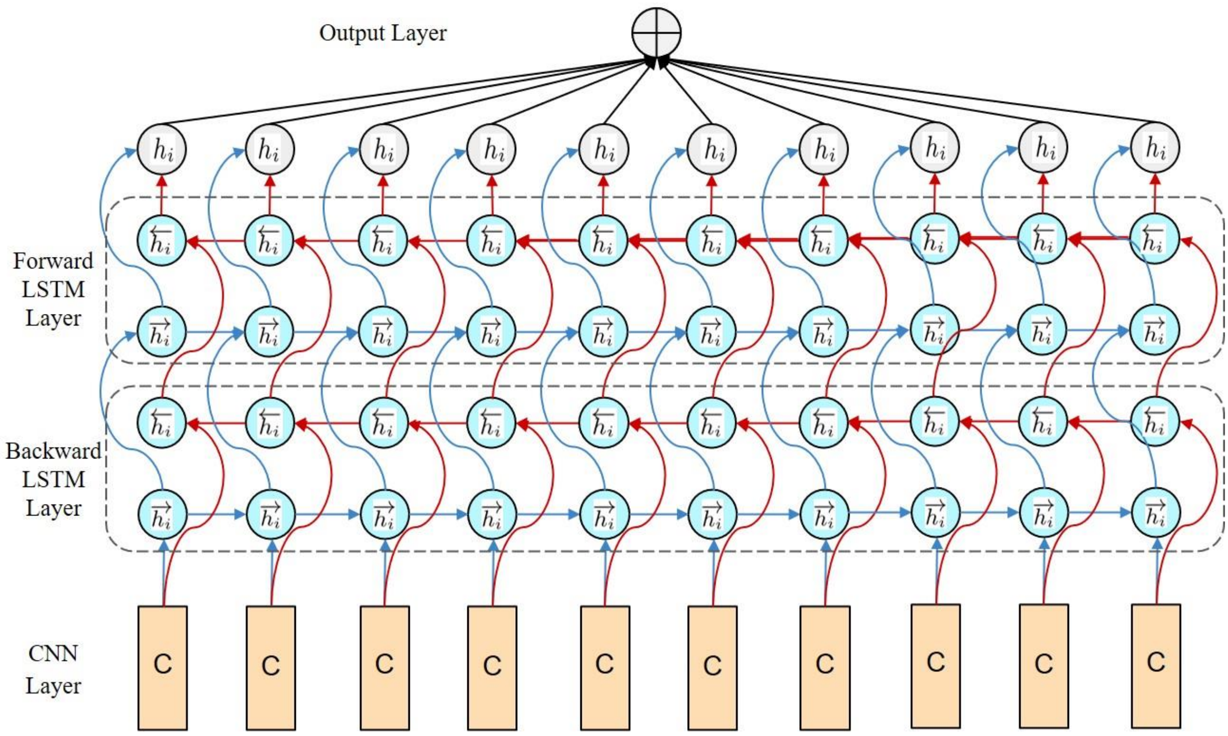


(a) Structure of Convolutional Neural Network.



(b) The memory cell of LSTM.



(c) Schematic diagram of CNN-Bi-LSTM forecasting model.

Fig. 1 The internal structure of the prediction model.

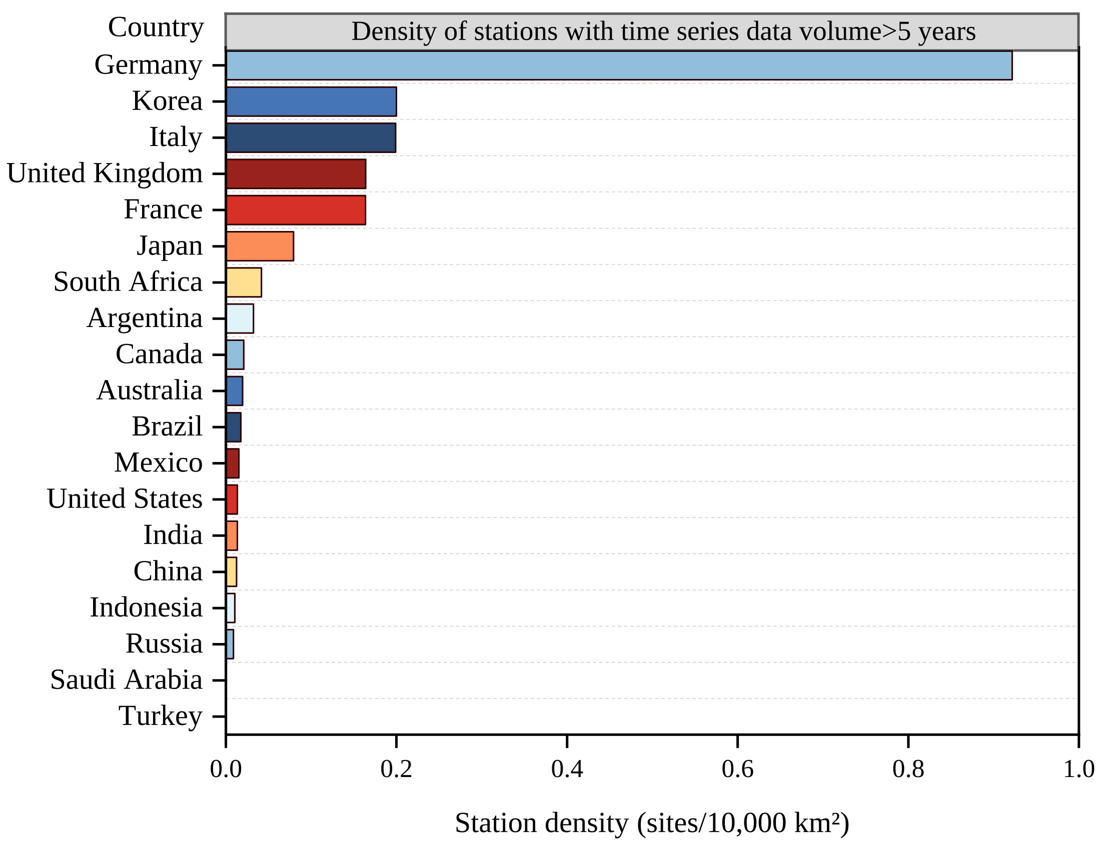


Fig. 2 Isotope data volume statistics for major countries in all regions of the world.

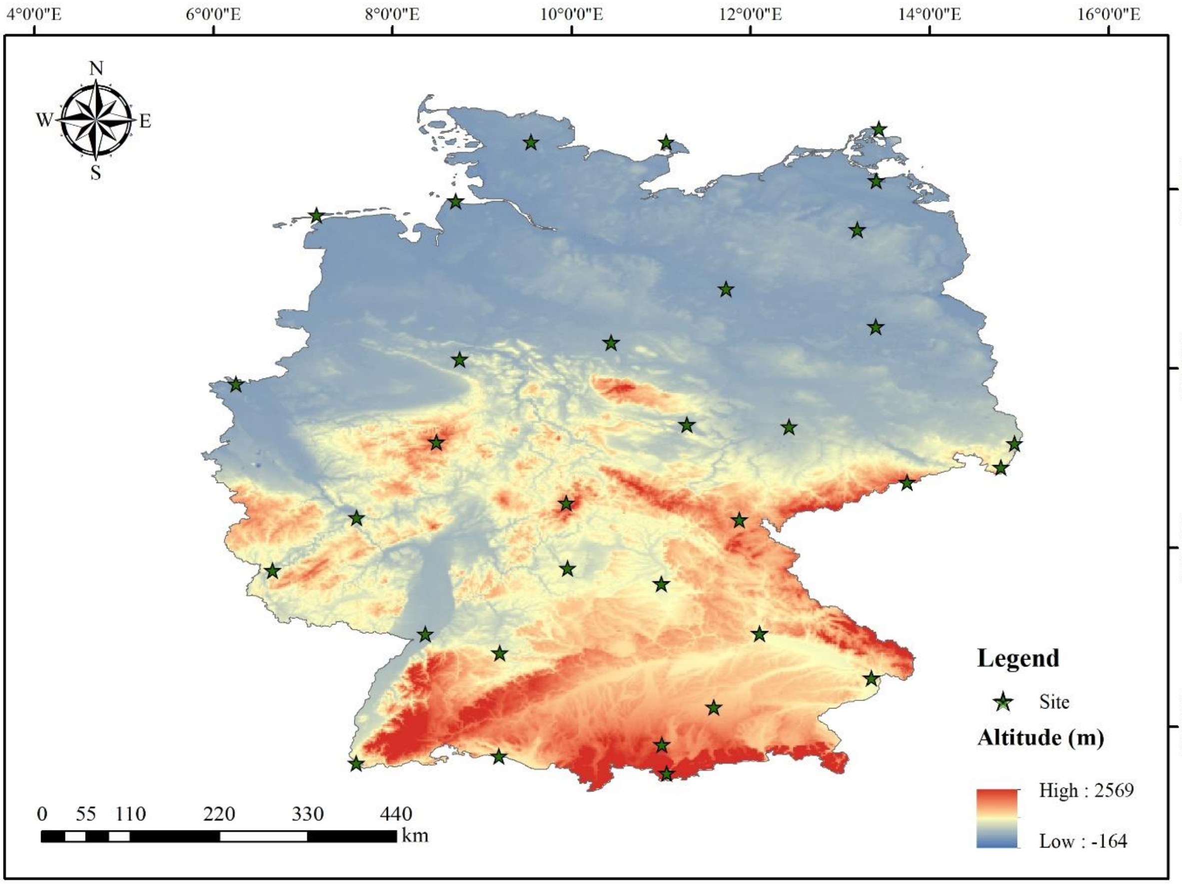
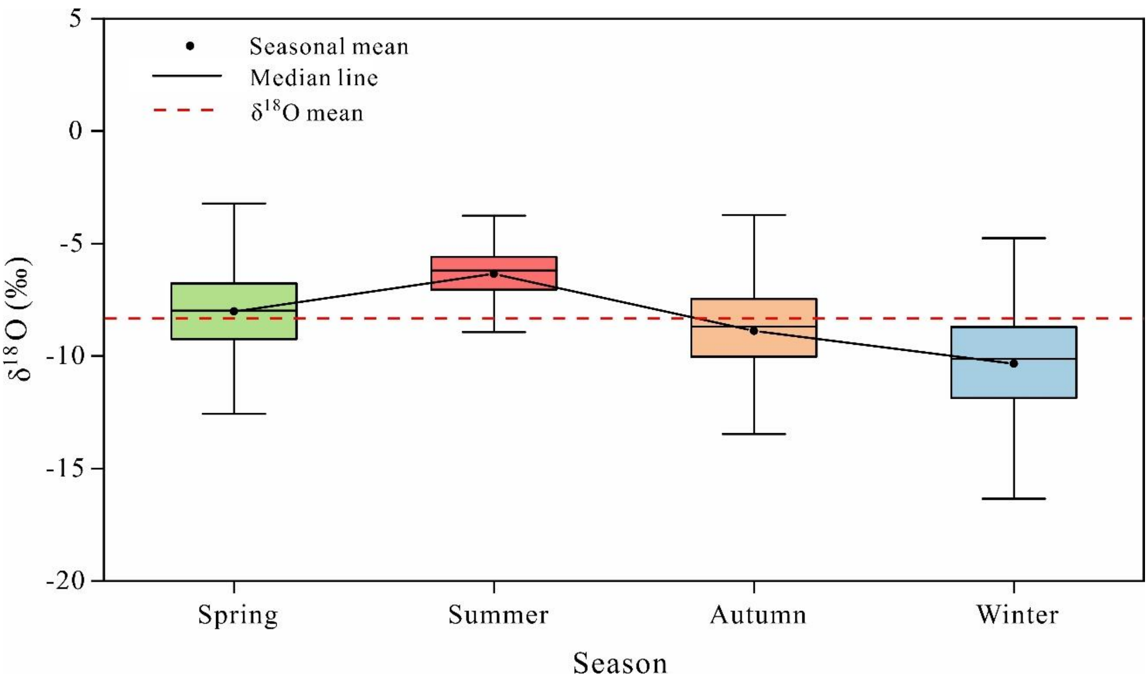


Fig. 3 Location of the study site.



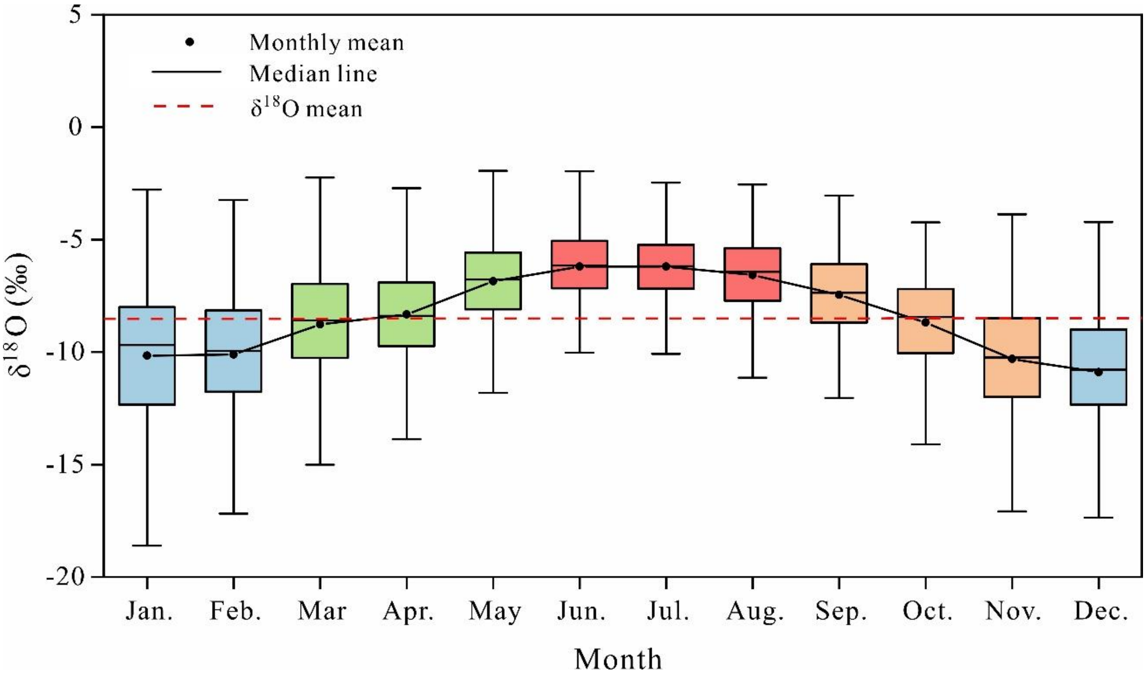


Fig. 4 Temporal distribution characteristics of the precipitation $\delta^{18}O$.

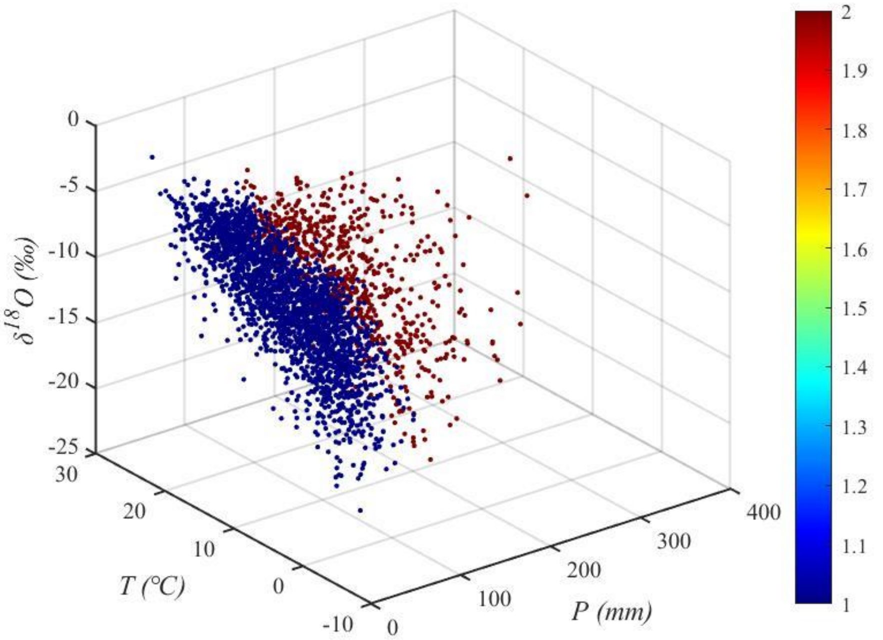


Fig. 5 Spatiotemporal distribution characteristics of the precipitation $\delta^{18}O$ (Blue represents the first cluster, red represents the second cluster).

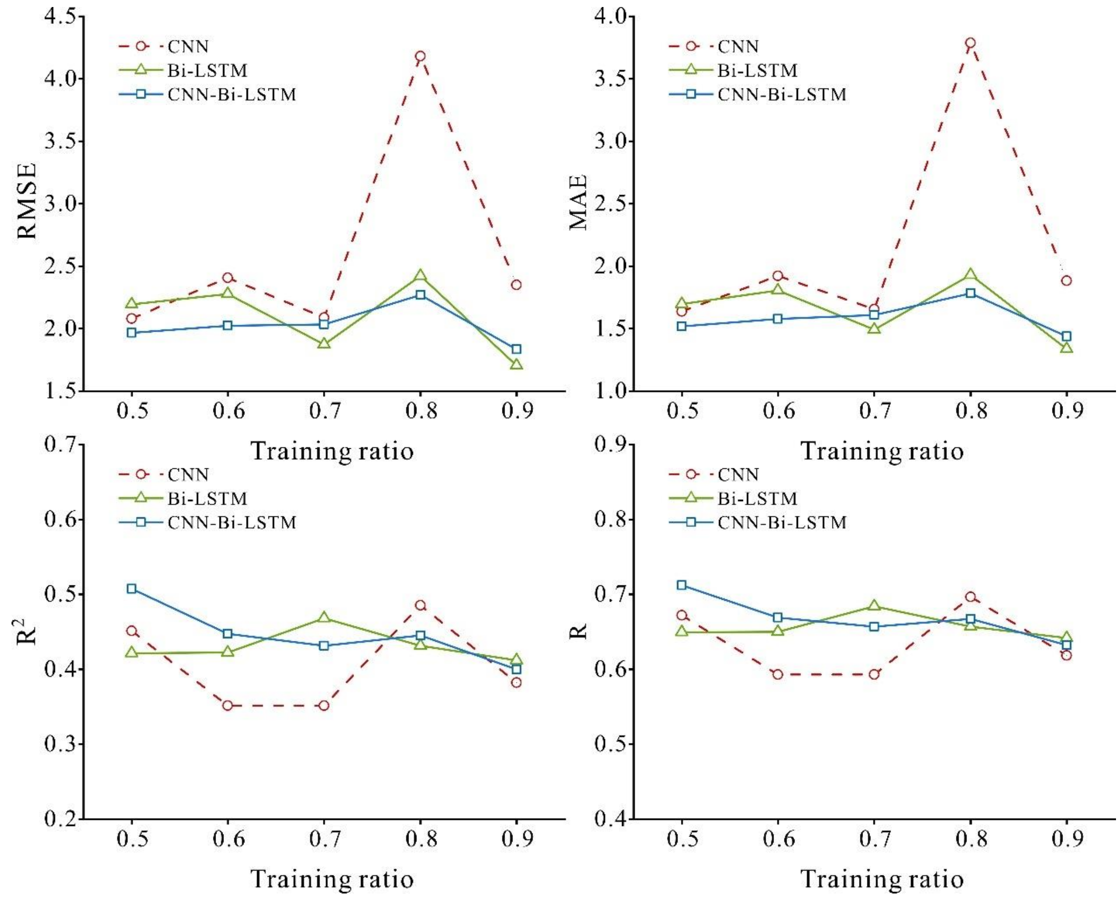
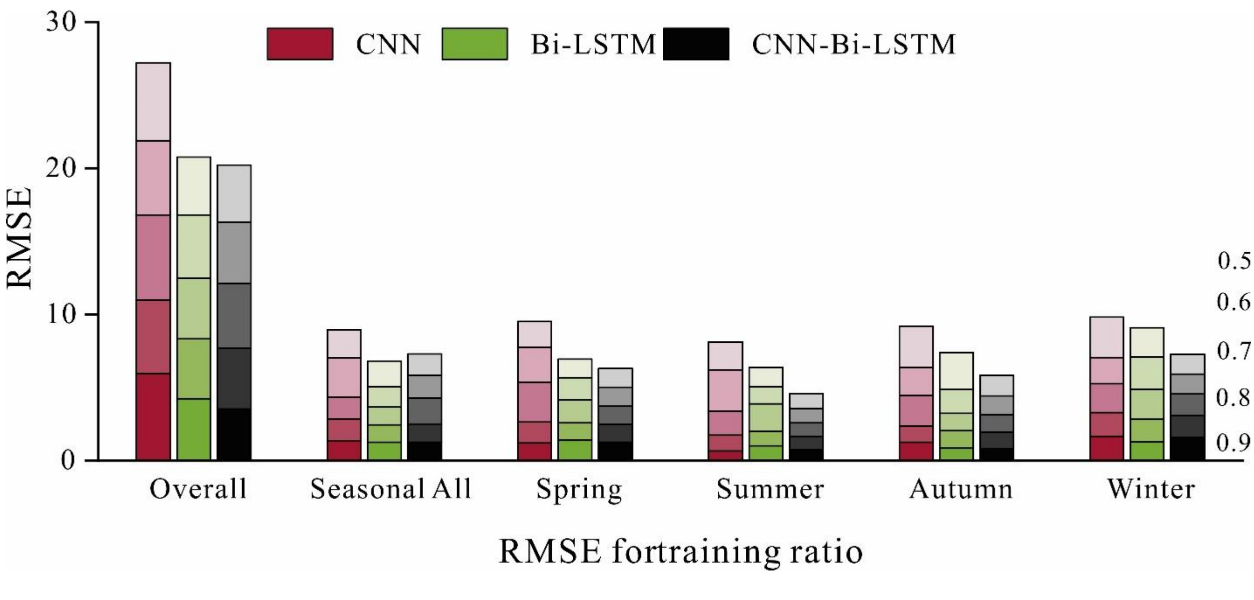


Fig. 6 Overall precipitation $\delta^{18}O$ forecasting.



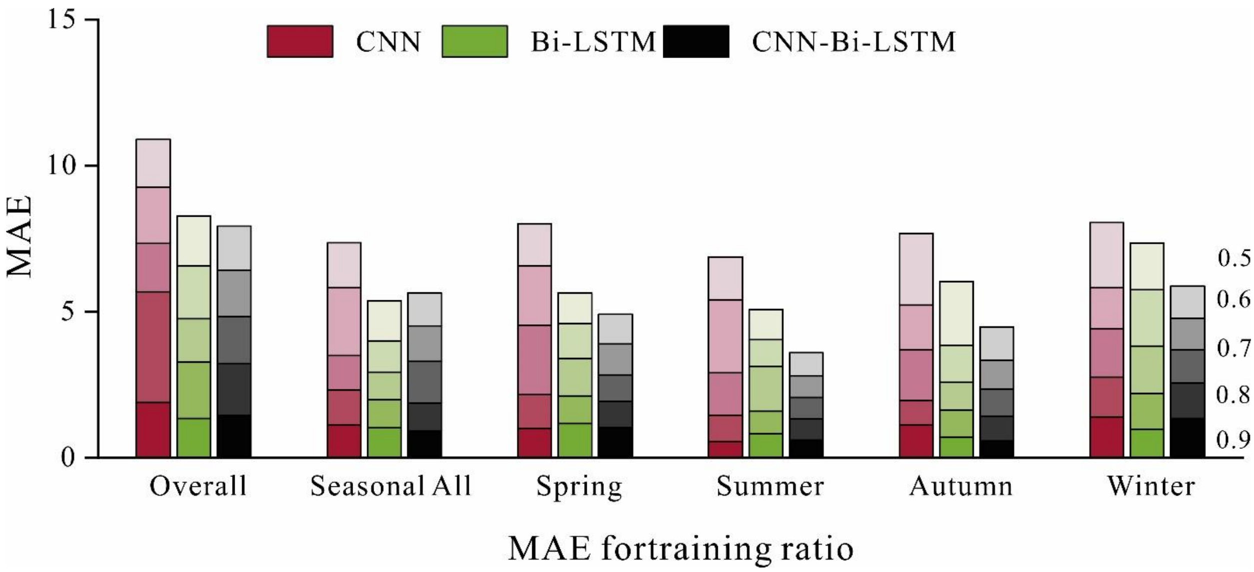


Fig. 7 Seasonal $\delta^{18}O$ forecasting.

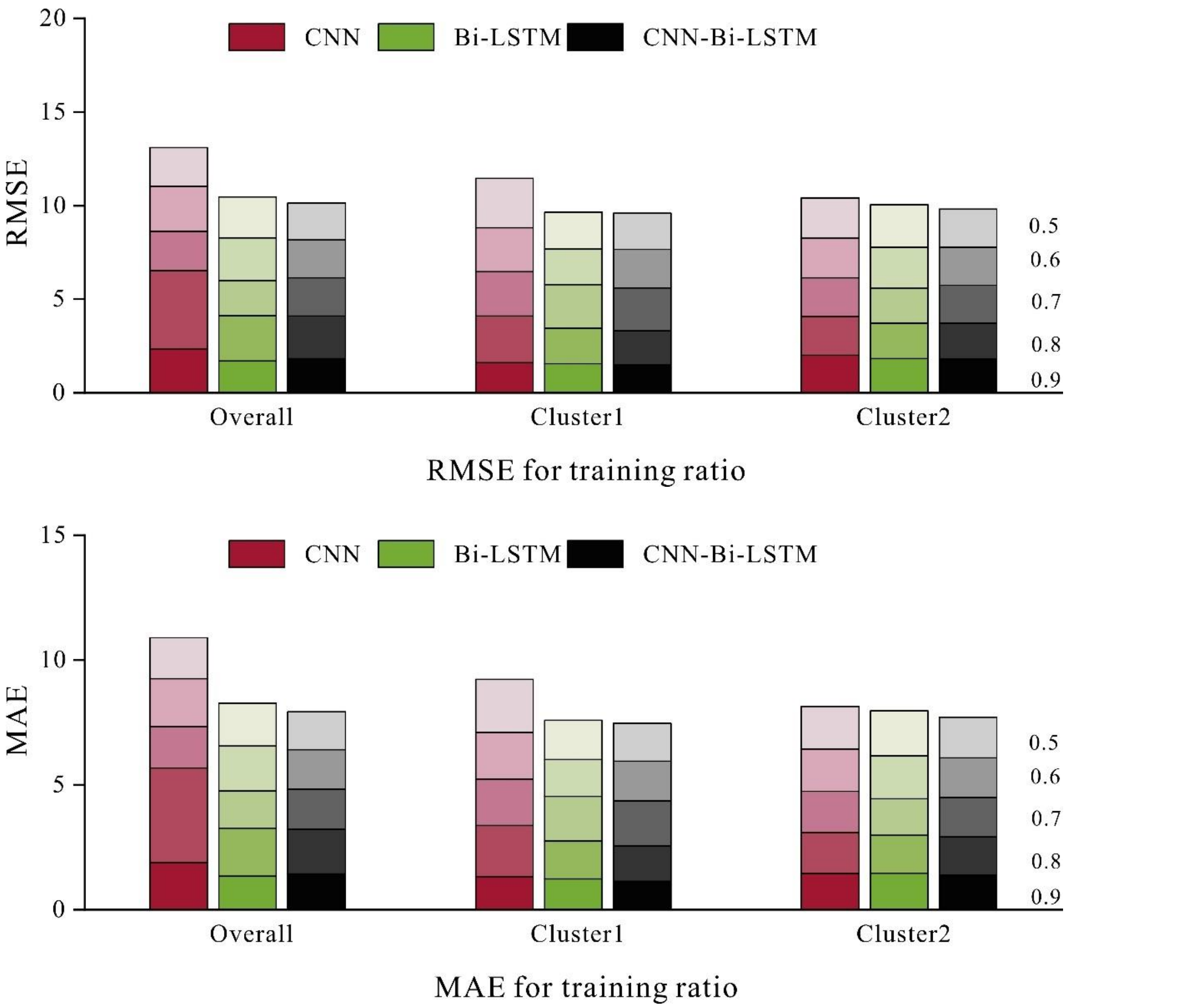


Fig. 8 K-means ++ clustering-based $\delta^{18}O$ forecasting.

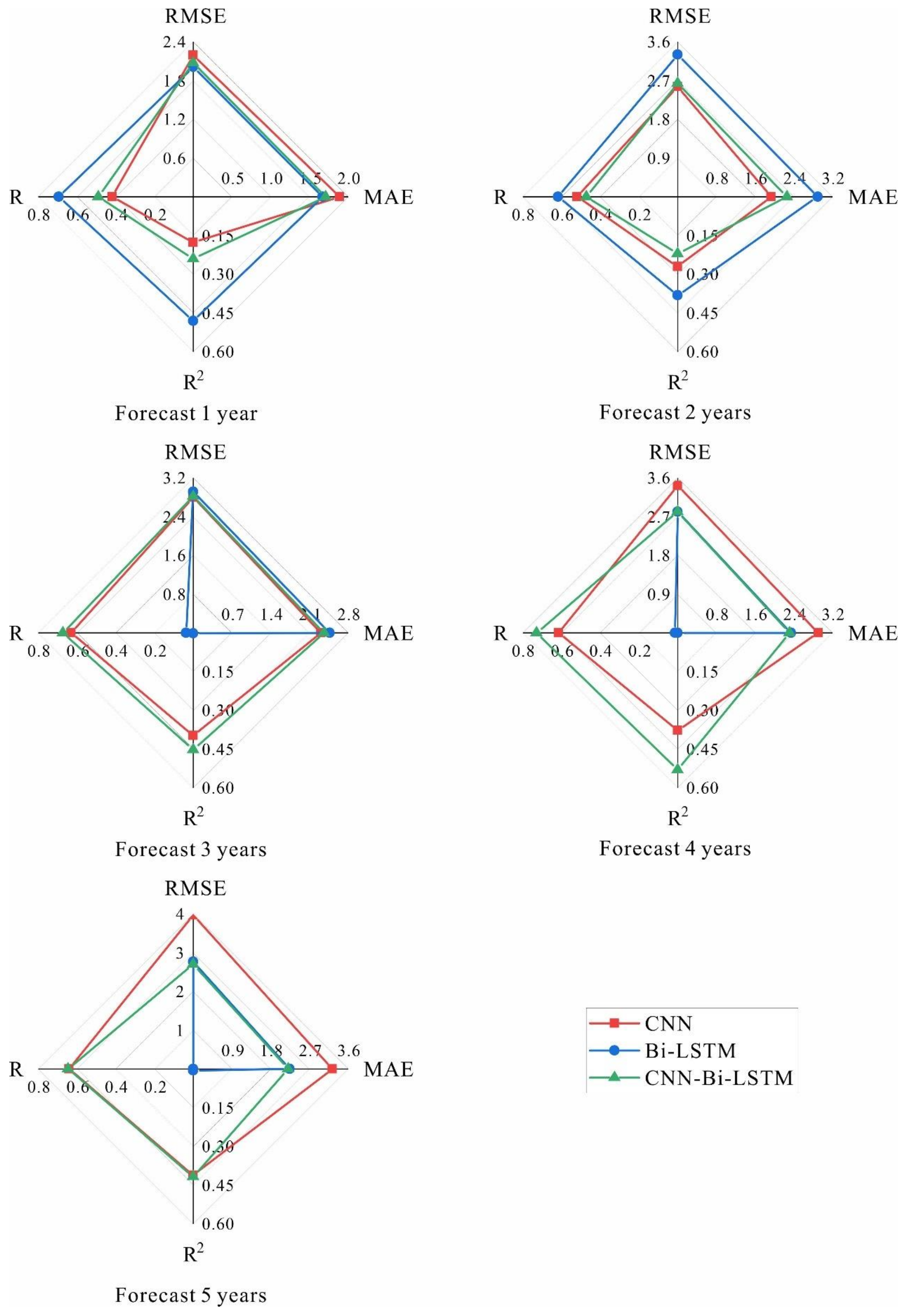
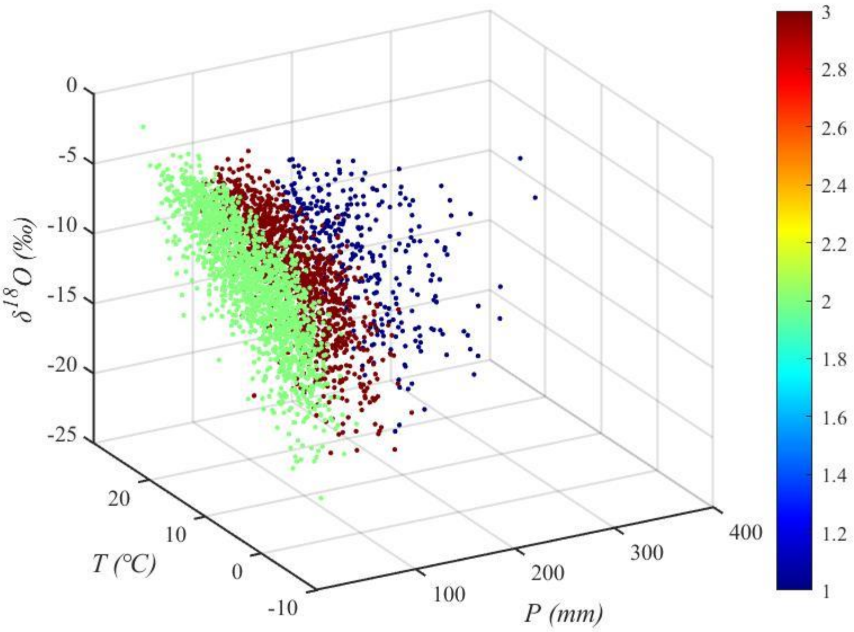
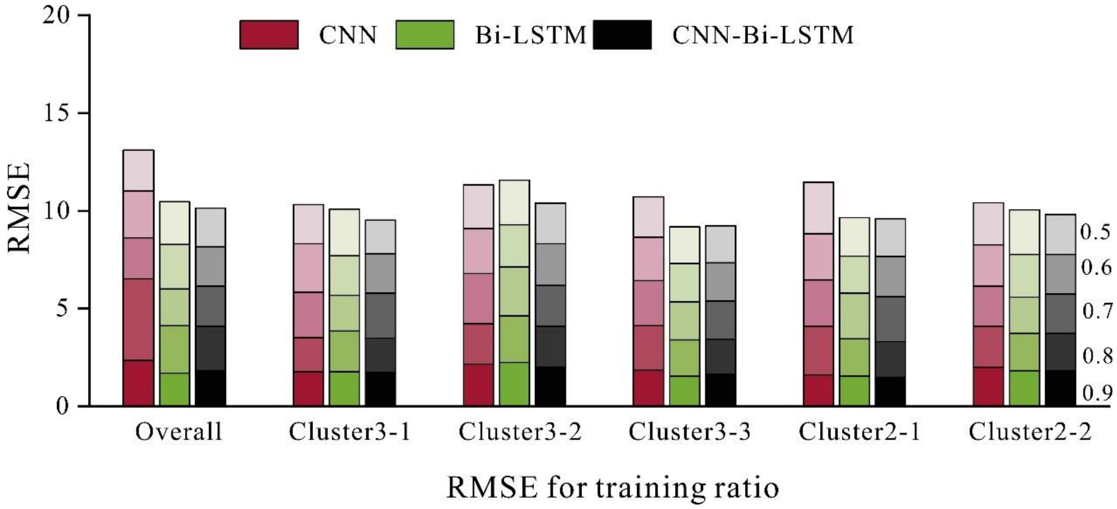
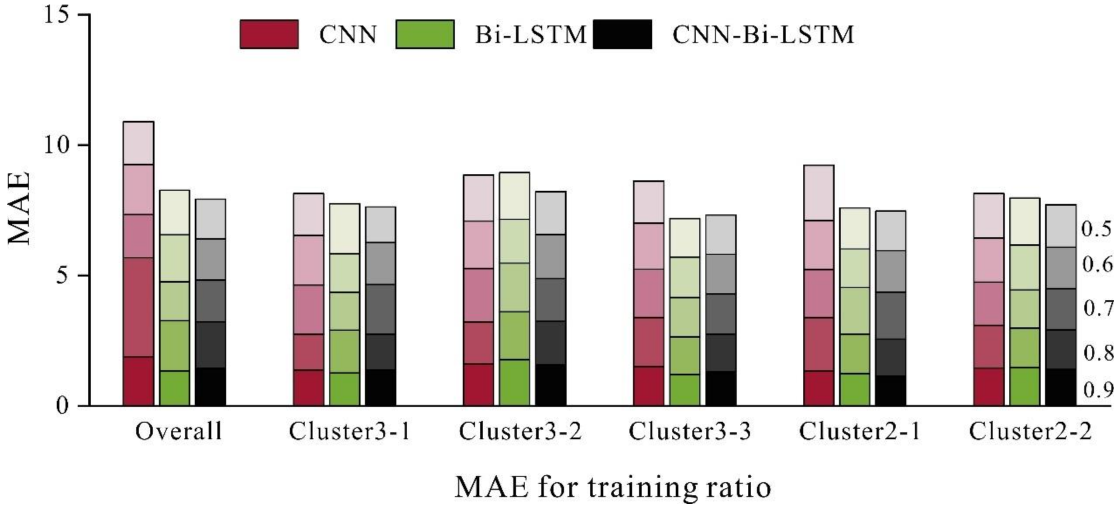


Fig. 9 Comparison of precipitation $\delta^{18}O$ forecasting models for station STUTTGART.



(a) Spatiotemporal distribution characteristics of the precipitation $\delta^{18}O$.





(b) K-means ++ clustering-based $\delta^{18}O$ forecasting.

Fig. 10 Joint forecasting results of K-means ++ clustering and CNN, Bi-LSTM and CNN- Bi-LSTM models.