Post-print: Interpretation and Application of Ningxia Winter Temperature Model Products Based on the Analog Error Correction Method

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Date: 2025-02-27T00:00:00+00:00

Abstract

The frequent alternation of cold and warm events during winter months and within the season increases the difficulty and challenge of short-term climate prediction. Moreover, the overall low prediction skill of climate dynamical models for winter temperatures in Ningxia leads to unstable prediction quality. The development of model interpretation and application methods that combine dynamical and statistical approaches provides effective technical means for improving prediction quality and represents an important direction urgently needed for development in provincial short-term climate prediction operations. Based on the EC model' s nearly 30-year historical hindcast data from the second-generation MODES product of the National Climate Center, winter monthly mean temperature observation data from 19 national meteorological stations in Ningxia, NCEP/NCAR atmospheric reanalysis data, and other sources, this study employs the similar error correction method and utilizes concurrent circulation key region information to conduct model interpretation and application for winter monthly temperatures in Ningxia, aiming to improve the accuracy and objectivity of climate trend prediction in Ningxia. The results indicate that the original EC model prediction results exhibit relatively high prediction skill for winter monthly temperatures in Ningxia overall, particularly demonstrating good capability in capturing trends and anomaly magnitudes. After applying the similar error correction scheme, the prediction skill of the EC model for winter temperatures in Ningxia can still be effectively improved, with particularly noticeable improvement in prediction skill for December and January, where the corrected PS and PC scores exceed 70% and 64%, respectively. The improvement in prediction skill is more pronounced when the January mean temperature shows positive anomalies while December and February show negative anomalies, with greater improvement corresponding to larger negative temperature deviations. The magnitude of model error shows no significant impact on the effectiveness of forecast correction; even when the absolute value of model error is large, this correction scheme can still improve the model temperature prediction skill for each winter month to varying degrees. Therefore, the similar error correction method can further improve the forecast accuracy of temperature trends and anomaly magnitudes for winter in Ningxia under conditions of large model errors, enhance the stability of model prediction skill, and demonstrates good application value in actual operational practice.

Full Text

Preamble

ARID ZONE RESEARCH Vol. 42 No. 2 Feb. 2025

Model Explanation and Application of Winter Temperature in Ningxia Based on the Similarity Error Correction Method

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Abstract: The frequent alternation of cold and warm events in winter months has increased the difficulty and challenge of short-term climate prediction. Additionally, the overall prediction skill of climate dynamic models for winter temperatures in Ningxia is not high, resulting in unstable prediction quality. The development of model interpretation and application methods that combine dynamics and statistics provides effective technical means for improving prediction quality and represents an important direction urgently needed for provincial short-term climate prediction operations. Based on the historical hindcast data of the MODES second-generation products from the National Climate Center, monthly average winter temperature observations from 19 national meteorological stations in Ningxia, and NCEP/NCAR atmospheric reanalysis data, this study employs the similarity error correction method to conduct model interpretation and application of winter monthly temperatures in Ningxia using concurrent circulation key region information, aiming to improve the accuracy and objectivity of climate trend prediction in Ningxia. The results show that the original EC model predictions have relatively high prediction skill for winter temperatures in Ningxia, particularly in capturing trends and anomaly magnitudes. After applying the similarity error correction scheme, the EC model' s prediction skill for winter temperatures in Ningxia can be further effectively improved, with particularly significant improvement in December and January. After correction, the PS and PC scores exceed 70% and 64%, respectively. Moreover, when the January average temperature shows positive anomalies and December and February show negative anomalies, the prediction skill improves more significantly, with larger temperature deficits showing more substantial improvement. The magnitude of model error does not significantly affect the correction effectiveness; even when the absolute value of model error is large, this correction scheme can still improve the winter monthly temperature prediction skills to varying degrees. Therefore, the similarity error correction method can further improve the forecast accuracy of winter temperature trends and anomaly magnitudes in Ningxia even under conditions of large model errors, enhance the stability of model forecast skills, and demonstrates good application value in operational practice.

Keywords: Ningxia; winter temperature; similarity error correction method; model product; interpretation and application

Introduction

Short-term climate prediction involves complex interactions among multiple factors in the climate system across multiple time scales and has long been a global challenge. Against the background of climate warming, winter temperature anomalies in Ningxia exhibit prominent new characteristics. On one hand, winter temperatures show a significant upward trend, with record-breaking extreme maximum temperatures; on the other hand, intra-seasonal temperature variability is large, with frequent periodic low temperatures, and the magnitude of abnormally low temperatures is generally greater than that of abnormally high temperatures. Taking the winter of 2023/2024 as an example, extreme cold and warm events occurred frequently, with four alternating cold and warm periods within the season. In early to mid-December, the average temperature in Ningxia rose to the highest value since meteorological records began for the same period; in mid-January, the temperature dropped to the lowest value since 1961 for the same period; in early to mid-February, the average temperature across the region once again rose to the highest value on record for the same period. The frequent alternation of cold and warm events within months and seasons increases the uncertainty of short-term climate prediction. Moreover, since 2023, climate operations have updated the climate normal values (from 1991-2020 to 1991-2020), and after the baseline temperature state has risen, the difficulty of predicting temperature trend anomalies has also increased, presenting new challenges for winter temperature trend prediction.

The rapid development and application of domestic and international climate dynamic models provide an effective and reliable technical foundation for conducting objective and quantitative climate predictions. Short-term climate prediction typically relies on two methods: dynamic and statistical. Combining the advantages of both to improve prediction levels is currently a widely recognized approach and an important way to enhance climate prediction capabilities. Previously, a similarity error correction method based on dynamic-similarity forecasting strategies was proposed to effectively apply large amounts of historical similarity information to existing complex numerical models to achieve a combination of dynamic and statistical methods. This approach has since been further improved and developed in scientific research and operational applications, demonstrating good forecast correction effects in circulation and precipitation predictions across different time scales. Previous studies have shown that atmospheric circulation has good predictive significance for winter temperatures. By establishing significant statistical relationships between historical circulation fields and element fields and then extracting circulation field information with higher predictive skill from model outputs to forecast element fields, the results often have higher accuracy than direct model outputs. On this basis, using different model results for ensemble prediction can reduce uncertainties associated with the model and interpretation methods themselves.

The overall prediction level of climate dynamic models for winter temperatures in Ningxia is not high, and the prediction quality is unstable. In current provincial-level climate prediction operations in Ningxia, research on effectively utilizing dynamic model products combined with statistical methods to conduct monthly and seasonal temperature model interpretation and application is still limited, which is precisely an important direction urgently needed for the development of provincial short-term climate prediction operations. Winter temperatures in Ningxia are closely related to circulation systems such as monsoon activities and mid-to-high latitude cold air. The key question is how to fully exploit the model' s key circulation information, select appropriate model interpretation and application methods, and improve the quality of temperature prediction in Ningxia. Considering that the similarity error correction method can develop targeted similarity selection indicators and forecast schemes based on circulation impact factors that have significant correlations with winter temperatures in Ningxia, and that it is relatively simple to calculate, computationally efficient, and easy to apply, this study selects this method and combines it with climate model products to conduct model interpretation and application of winter monthly temperatures in Ningxia. The aim is to develop key technologies for short-term climate prediction in Ningxia, improve the objectivity and accuracy of predictions, and better play the role of meteorological disaster prevention and mitigation in local economic and social development.

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1. Data and Methods

1.1 Data Sources

Temperature observation data were obtained from monthly average data of 19 national meteorological stations in Ningxia from 1993/1994 to 2023/2024. Atmospheric circulation data consist of the first version of monthly mean reanalysis data from the National Centers for Environmental Prediction and the National Center for Atmospheric Research (NCEP/NCAR) with a horizontal resolution of 2.5°$×$2.5°. Compared with other variables, this data has higher credibility for temperature fields and provides a good depiction of the 500 hPa geopotential height field. Therefore, this data was selected as the circulation reality field, and the circulation field after the 1990s also has good representativeness.

Model data were obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) model prediction products (EC model) in the upgraded MODES version (MODESv21_{{{ecmwf}}_{{seas51}}}) dataset from the National Climate Center' s Multi-Model Climate Prediction Product Interpretation and Integration System (MODES), with a spatial resolution of 1.0°$×$1.0°. After verification, evaluation, and operational application in Ningxia, its prediction skill performs well among similar prediction products, and the historical hindcast sequence is complete without missing data. Therefore, this study selected the 500 hPa geopotential height and average temperature data from the EC model with a lead time of 1 month to conduct model interpretation and application. The model temperature data were interpolated to the 19 national meteorological stations in Ningxia using bilinear interpolation.

1.2 Methods

This study uses the similarity error correction method to interpret and apply the EC model forecasts of winter temperatures in Ningxia. The implementation process requires auxiliary methods such as the perturbation correction method, similarity distance method, and sample cross-validation method to execute the similarity error correction scheme. The specific calculation methods are as follows.

1.2.1 Perturbation Correction Method Considering the systematic errors inherent in the model and the lack of 30-year historical hindcast data, the perturbation method was used to preprocess the model prediction results. The perturbation method formula is:

$$TP_i = T_{mod_i} - \bar{T}_{mod_i}$$

where i represents the forecast month; TP_i is the temperature anomaly after perturbation method processing, serving as the model's original prediction result in this study; T_{mod_i} is the model' s original predicted temperature; and $\bar{T}_{mod_i}$ is the observed climatological value.

1.2.2 Similarity Distance Method This study adopts the similarity distance method to select circulation similarity years. This method can compensate for the shortcomings of similarity coefficients and various distance methods by reflecting the "shape" and "value" differences of circulation systems. It is known that in circulation fields, "shape" reflects the position and scope of circulation systems, while "value" reflects their intensity, both jointly affecting the anomaly degree of forecast elements. This method has been widely applied in weather forecasting and climate prediction as a relatively objective similarity identification method.

Let h_i and h_j represent two fields, and h_{ik} and h_{jk} represent the values at the k-th grid point in fields h_i and h_j, respectively. Let $h_{ij}(k) = h_{ik} - h_{jk}$ represent the difference between the two fields at the k-th grid point. Then the similarity distance (C_{ij}) between the two fields is expressed as:

$$C_{ij} = S_{ij} + D_{ij}$$

where:

$$S_{ij} = \frac{1}{M} \sum_{k=1}^{M} |h_{ij}(k) - e_{ij}|$$

$$D_{ij} = \frac{1}{M} \sum_{k=1}^{M} |h_{ik} - h_{jk}|$$

$$e_{ij} = \frac{1}{M} \sum_{k=1}^{M} h_{ij}(k)$$

Here, M represents the number of values in the field; e_{ij} represents the average value of the differences between fields h_i and h_j; D_{ij} represents the value coefficient, which is the average of the absolute differences between the two fields, reflecting the overall numerical difference between them; and S_{ij} represents the shape coefficient, reflecting the dispersion degree of differences between the two fields. The smaller its value, the more similar the shapes of the two fields, characterizing the shape similarity between circulation fields. Generally, the similarity distance between two samples is defaulted to be the average of the value coefficient and shape coefficient.

1.2.3 Validation and Evaluation Methods 1) Sample Testing Method: The sample cross-validation method was used to evaluate the prediction correction results. Assuming there are n years of samples, first select 1 year as an independent prediction sample, use the remaining $n-1$ years of samples for the similarity error correction scheme, obtain the corrected prediction results for the previously selected 1 year, and repeat this process n times until all n years of samples have been selected. Finally, obtain the corresponding prediction correction results for the n years of samples, and then calculate the test scores of the n years of prediction correction results based on observation data. The advantage of this method is that it can make full use of all sample data. In this study, the model hindcast data sample period is not long ($n = 31$), so this method was selected to make the results more statistically meaningful, while also maintaining consistency with the period used for correlation calculations when selecting circulation key regions.

2) Scoring Methods: This study uses the trend anomaly comprehensive (PS), anomaly sign consistency rate (PC), and anomaly correlation coefficient (ACC) commonly used in operations to evaluate the model prediction results. These three scoring methods reflect the prediction performance of forecast products from different aspects: PS reflects the forecast' s ability to grasp the anomaly magnitude of the actual situation, PC reflects the degree of consistency between the forecast and actual anomaly signs, and ACC mainly reflects the degree of consistency between the forecast and actual spatial distribution patterns.

1.2.4 Similarity Error Correction Scheme The similarity error correction method assumes that similar samples have similar forecast errors, uses the forecast errors corresponding to several similar samples to estimate the current forecast error, and then superimposes the ensemble average of the forecast errors of similar samples onto the current forecast result. For this study, the specific steps of similarity error correction are as follows:

1) Using the 1993/1994-2023/2024 winter monthly model temperature historical hindcast field data (T_{mod}) and station temperature observation field data (T_{obs}), establish the error field (I_T) for the model' s monthly temperature anomaly prediction in Ningxia, and after regional averaging, establish the error sequence (I_T). Regional average the temperature anomaly observation data sequence (IT_{obs}), calculate the correlation between IT_{obs} and the 500 hPa geopotential height field to obtain the high-correlation circulation impact region for winter monthly temperatures, and calculate the monthly key region circulation index (I_{500H}) using the regionally averaged geopotential height. The high correlation between I_T and I_{500H} indicates that the key circulation region can serve as a key factor affecting model temperature errors, meaning this region can be used as a key impact area for selecting historical similar error information.

2) Use the similarity distance method to select the historical actual years most similar to the current forecast month's 500 hPa circulation key region, extract the model temperature prediction error fields (I_T) of these similar years, superimpose them onto the current forecast month' s temperature field (T_{mod}), and obtain the temperature prediction results after similarity error correction. Then calculate the test scores of the prediction results before and after correction.

2. Results and Analysis

2.1 Determination of Circulation Key Regions Affecting Model Errors

Using the cross-validation method to evaluate the corrected prediction results for winter months, calculate the correlation between the regional average error sequence (I_T) and the 500 hPa geopotential height anomaly field for winter months from 1993/1994 to 2023/2024 to identify the mid-to-high latitude key circulation distribution patterns affecting monthly temperature anomalies. As shown in Figure 1, the winter monthly 500 hPa geopotential height field over the Eurasian continent generally exhibits a north-south opposite phase pattern. Although the positive and negative geopotential height anomaly areas vary slightly from month to month, the overall characteristic shows that when the Ural Mountains and their vicinity have negative geopotential height anomalies and northern China has large-scale positive geopotential height anomalies, this circulation configuration is not conducive to cold air moving southward and therefore favors above-normal temperatures in winter months in Ningxia, and vice versa.

Regional average the 500 hPa geopotential height field in the areas passing the 99.9% confidence level test in Figure 1 (i.e., the key region range). Subtract the regionally averaged sequence of areas with negative correlation coefficients from that of areas with positive correlation coefficients to obtain a new sequence, then standardize this new sequence and define it as the 500 hPa key region circulation index (I_{500H}). Additionally, subtract the actual temperature anomaly from the monthly model temperature anomaly prediction results from 1993/1994 to 2023/2024 to obtain the monthly temperature anomaly error field (I_T), and after regional averaging, obtain the error field regional average sequence (I_T). As shown in Table 1, I_T and I_{500H} have good correlations, all passing the 99.9% confidence level test, indicating that using the above circulation key regions as key impact areas for selecting historical similar error information is reasonable.

2.2 Evaluation of Correction Effects

2.2.1 Evaluation of Prediction Effects Before and After Correction To quantify the skill improvement of the correction scheme, Figure 2 shows box plots of the PS, PC, and ACC prediction skill scores for the original model predictions and similarity error corrected results for winter monthly forecasts with a 1-month lead time from 1993/1994 to 2023/2024. In terms of PS scores (Figure 2a), the mean values for December, January, and February original predictions are 67.9%, 71.7%, and 68.9%, respectively. After correction, the mean values increase to 73.5%, 75.8%, and 70.6%, respectively, with improvements of 5.6%, 4.1%, and 1.7%. The 25th and 75th percentile values also increase to varying degrees, with the 75th percentile exceeding 80% after correction. This indicates that after correction, the anomaly magnitude of monthly temperatures in winter is closer to the actual situation. For PC scores (Figure 2b), the mean values for December, January, and February original predictions are 60.2%, 64.3%, and 60.2%, respectively. After correction, the mean values increase to 64.3%, 68.8%, and 61.3%, respectively, with improvements of 4.1%, 4.5%, and 1.1%. The 25th and 75th percentile values also increase to varying degrees, with the 75th percentile exceeding 70% after correction. This shows that after correction, the temperature trends in winter months are more consistent with actual conditions. For ACC scores (Figure 2c), the mean values for December, January, and February original predictions are 0.05-0.1, 0.1-0.2, and 0.05-0.1, respectively. After correction, the mean values increase to 0.1-0.2, 0.2-0.3, and 0.1-0.2, respectively, with improvements of 0.05, 0.1, and 0.05. Although the ACC scores improve, the overall correction effect is not significant, indicating that after correction, the model' s ability to depict the spatial distribution of winter monthly temperatures is still limited.

Overall, the EC model shows good original prediction effects for winter months, and implementing the similarity error correction scheme results in overall higher prediction skill scores than before correction, with better correction effects for December and January, while improvement for February is not obvious. The main reason is related to the relatively low original prediction skill of the circulation key region for February, where the circulation key region is mainly negatively correlated with temperature. In terms of the three types of skill scores, the improvement measured by PS scores is the most obvious across months, followed by PC scores, with ACC scores being the worst. This indicates that similarity error correction is more effective for improving temperature trends and anomaly levels but relatively weaker in depicting the spatial distribution of temperature. Regardless of correction, the model' s ACC scores remain low, which is similar to previous research results for monthly temperature predictions in Northwest China (such as Xinjiang) with a 1-month lead time, where winter monthly ACC is low. Additionally, this may be related to the model' s relatively low original spatial resolution, making it difficult for the model to reflect spatial differences in predicted elements for a small region like Ningxia.

To further illustrate the improvement effect of this scheme on model prediction skills under different winter monthly average temperature anomalies and model bias backgrounds, taking PS scores as an example (PC and ACC scores are similar, figures omitted), subtract the original model scores from the corrected PS scores to obtain the PS score improvement values (ΔPS) of the correction scheme, and analyze their relationships with IT_{obs} and I_T. Additionally, it should be noted that from Figure 2 analysis, the correction scheme improves the prediction skills for the total sample size.

The relationship between ΔPS and IT_{obs} shows that when IT_{obs} is negative, the prediction skill improvement is more obvious, with more significant improvement as the temperature deficit increases. For December, when IT_{obs} is negative, the prediction skill improves more obviously, and most ΔPS values are positive (Figure 3a). For January, the correction scheme improves the prediction skill for the total sample size, and the improvement shows temperature asymmetry, with more obvious improvement when IT_{obs} is negative (Figure 3b). For February, the correction scheme improves the prediction skill for the total sample size, and the improvement shows temperature symmetry, with more obvious improvement when IT_{obs} deviates further from 0, whether positive or negative (Figure 3c). In summary, when IT_{obs} is negative, the prediction skill improves more obviously, and most ΔPS values are positive.

The relationship between ΔPS and I_T indicates that the magnitude of model error has no significant impact on the forecast correction effect. For December, when the absolute value of I_T is large, the prediction skill still improves, with ΔPS mostly positive and the maximum improvement not exceeding 0.2 (Figure 4a). For January, the correction scheme improves the prediction skill for the total sample size, and the improvement shows symmetry regarding the sign of I_T, with more obvious improvement when I_T deviates further from 0, whether positive or negative (Figure 4b). For February, the correction scheme improves the prediction skill for the total sample size, and the improvement shows symmetry regarding the sign of I_T, with more obvious improvement when I_T deviates further from 0, and the maximum improvement not exceeding 0.1 (Figure 4c). Overall, the sign and magnitude of I_T have little impact on the improvement of prediction skills. Even when the absolute value of monthly model errors is large, this scheme can still effectively correct the model prediction results.

2.2.2 Selection of Typical Similar Year Cases Using the cross-validation method to evaluate and compare the prediction effects before and after correction for winter months, selecting an appropriate number of similar years plays a crucial role in improving correction skills. If too few years are selected, the correction information contributed by model errors cannot be fully covered; if too many years are selected, the similarity distance becomes larger and similarity decreases, negatively contributing to the correction. Empirical verification shows that selecting the top 3-5 most similar years based on similarity distance yields the best correction effect (the overall improvement in PS scores is the largest, figure omitted). Below, December 2019 is used as an example to illustrate the steps and rationality of the correction scheme.

In December 2019, the average temperature across Ningxia was abnormally high, with most areas 2-3°C above normal. The model' s predicted temperature anomaly for December 2019 showed a "north high, south low" distribution pattern (Figure 6a). After implementing the correction scheme, the predicted average temperature anomaly showed a consistent high pattern across the region (Figure 6b), which was closer to the actual situation in both trend and anomaly magnitude (Figure 6c). The PS, PC, and ACC scores for the model' s original prediction were 75.8%, 64.3%, and 0.21, respectively, while after correction they were 83.3%, 71.4%, and 0.12, respectively. Although the ACC score decreased after correction (Table 3), the overall correction effect based on the similarity error method was good. Through operational trials in the winter of 2023/2024, this correction scheme improved the temperature prediction accuracy for winter months to varying degrees and can significantly enhance the objective prediction skills for winter temperature trends in Ningxia.

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3. Conclusions and Discussion

With the continuous optimization and updating of the monthly dynamic models at the National Climate Center, the verification and interpretation application work for the upgraded MODES products urgently needs to be carried out. This study addresses the biases in the EC model' s winter monthly average temperature predictions by using nearly 30 years of model historical hindcast data and historical observation data for similarity error correction and evaluates the correction effects. The main conclusions are as follows:

1) The EC model' s original predictions for winter months in Ningxia have relatively high PS scores, with mean values of 67.9%, 71.7%, and 68.9% for December, January, and February, respectively, demonstrating good overall prediction skill, particularly in capturing temperature trends and anomaly magnitudes. After implementing the similarity error correction scheme using circulation similarity information, the EC model' s temperature prediction skill can still be effectively improved. The improvement in prediction skill is particularly significant for December and January, with PS scores increasing by 5.6% and 4.1% to 73.5% and 75.8%, respectively, and PC scores increasing by 4.1% and 4.5% to 64.3% and 68.8%, respectively, better predicting the temperature trends and anomaly magnitudes in Ningxia. However, the improvement for February is not obvious, mainly due to the relatively low original prediction skill of the circulation key region for February. Regardless of correction, the model' s ACC scores remain low, as the EC model has difficulty reflecting the spatial differences in winter temperatures in Ningxia.

2) The correction effect shows an asymmetric relationship with temperature anomalies. When the monthly average temperature anomaly is negative, the prediction skill improves more obviously, with more significant improvement as the temperature deficit increases. When the anomaly is positive, the improvement is more obvious for January. Additionally, the magnitude of model error does not significantly affect the correction effectiveness. Even when the absolute value of model error is large, this correction scheme can still improve the winter monthly temperature prediction skills to varying degrees.

Under the development needs of provincial climate operations, this study conducted model interpretation and application of winter temperature trend predictions in Ningxia based on the similarity error correction method. This method corrects prediction results through the difference between model and reality, which can largely reduce the limitations caused by model errors themselves and has certain universal reference value. The advantage of this method is that it includes the contribution of climate models compared with statistical forecasting, and includes the contribution of historical similarity information compared with systematic error correction methods. In addition to being applicable to Ningxia and having the potential to improve temperature forecasting skills in Northwest China, this method can also significantly improve precipitation and circulation forecasting skills across Asia and China, showing significant improvement over systematic error correction forecasting. However, the limitation of this method is that it is affected by model performance and the length of historical hindcast data, and there are certain restrictions in model product selection and key circulation region determination. Future work will update high-resolution model products, consider introducing multi-model members to improve prediction effects, and develop multi-model integrated dynamic-statistical scale prediction correction techniques to further enhance the quality of winter temperature predictions in Ningxia.

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