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Application of Machine-Learning-Based Objective Correction Method in the Intelligent Grid Maximum and Minimum Temperature Predictions

Jing Liu[1,2,3], Chuan Ren[4*], Ningle Yuan[1], Shuai Zhang[1], Yue Wang[1]

[1]Key Opening Laboratory for Northeast China Cold Vortex Research, The Institute of Atmospheric Environment, China Meteorological Administration, Shenyang, China
[2]Shenyang Meteorological Observatory, Shenyang, China
[3]Liaoning Meteorological Warning Center, Shenyang, China
[4]Liaoning Meteorological Information Center, Shenyang, China
Email: liujingsyau@sina.com, yuanlele_66@sina.com, *chuanrendalg@sina.com

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Abstract

Post-processing correction is an effective way to improve the model forecasting result. Especially, the machine learning methods have played increasingly important roles in recent years. Taking the meteorological observational data in a period of two years as the reference, the maximum and minimum temperature predictions of Shenyang station from the European Center for Medium-Range Weather Forecasts (ECMWF) and national intelligent grid forecasts are objectively corrected by using wavelet analysis, sliding training and other technologies. The evaluation results show that the sliding training time window of the maximum temperature is smaller than that of the minimum temperature, and their difference is the largest in August, with a difference of 2.6 days. The objective correction product of maximum temperature shows a good performance in spring, while that of minimum temperature performs well throughout the whole year, with an accuracy improvement of 97% to 186%. The correction effect in the central plains is better than in the regions with complex terrain. As for the national intelligent grid forecasts, the objective correction products have shown positive skills in predicting the maximum temperatures in spring (the skill-score reaches 0.59) and in predicting the minimum temperature at most times of the year (the skill-score reaches 0.68).

Keywords

Machine Learning, Sliding Training, Forecast Correction, Maximum and

Minimum Temperature

1. Introduction

Shenyang is located in the southern part of Northeast China, at the center of the Northeast Asia and Bohai Rim Economic Circle. It is a comprehensive hub city connecting the Yangtze River Delta, Pearl River Delta, and Beijing *et al.* regions to the Northeast region. The Shenyang region is mainly composed of plains, with mountainous and hilly areas concentrated in the southeast, and multiple rivers passing through the territory. The special geographical environment leads to frequent meteorological disasters such as megatherm, cold wave, rainstorm, etc. Therefore, the research on maximum and minimum temperature forecasting is very important, which can provide scientific reference for disaster prevention and decision-making management of government departments.

Over the past few decades, thanks to the development of numerical weather forecasting models, observation systems and assimilation technologies, the accuracy of numerical weather forecasting has been greatly improved [1]. The resolution of numerical weather prediction also has been improved, and the assimilation scheme has been continuously optimized [2] [3] [4].

High precise fine-scale temperature forecast serves as an important tool in quantifying human comfort, health threats with extreme temperature and energy consumption. There is a need to forecast temperature accurately in order to prevent unexpected hazards caused by temperature variation, such as megatherm, frost, cold wave and drought which may cause financial and human losses [5]. To reduce the uncertainty of numerical prediction, the idea of multi-mode ensemble forecasting was first proposed by Krishnamurti *et al.* [6] which is to conduct ensemble forecasting after obtaining the best combination of multiple different numerical model predictions according to certain statistical methods.

Using statistical and physical methods to reduce the deviation of daily maximum and minimum temperature predictions is one of the important research directions in numerical prediction post processing [7]. The improved scheme's predicted temperature, historical bias, initial field bias and Kalman filter inversion bias as the predictor are all optimal. In addition, the scheme's forecast quality for the maximum and minimum temperatures in 2017 is significantly better than that of both ECMWF and CMA (China meteorological administration) [8].

Oshima [9] uses a combination of principal component analysis, classical correlation analysis and singular value decomposition to regress and forecast the monthly average temperature in January and July in Japan. The results show that the prediction effect of the model is not as good as that of the statistical downscale prediction, and this difference is mainly caused by the inaccurate terrain of the model. In the central plains of Kansas, there is a significant correlation between nighttime 2 m temperature and terrain height [10]. The surface temperature at 2 m is interpolated from the lowest layer temperature in the model, which increases the prediction error [11].

Application of the artificial neural network (ANN) [12], long short-term memory [13] and convolution neural network (CNN) [14] in numerical prediction correction have become new topic. ANN was used to forecast daily maximum temperature and minimum temperature in order to provide a best-fit prediction with the observed data using ANN algorithms [15]. Using multiple meteorological elements from a single numerical prediction model to construct a weather forecast model [16], there was a correction method for multi-model ensemble prediction of temperature in North China based on machine learning [17].

Urban Micro-scale Temperature Forecast (UMTF) model was developed using machine learning techniques (k-means clustering and support vectors machine) with reference to global ensembles and geomorphometry datasets (sky view factor, daily sun trajectory and urban terrain model) [18]. The hybrid model named ALS with produced by machine learning is particularly effective in areas where the accuracy of station temperature forecast is low [19]. Using the K-Nearest Neighbor (KNN) regression algorithm for error correction, the improvement effect of weather process prediction such as cold air activity and summer maximum temperature is also relatively stable [20].

This article combines business reality, Based on the ECMWF model and national intelligent grid forecast from the China Meteorological Administration, based on wavelet analysis developing objective correction products for maximum and minimum temperature.

There has significantly improved the forecast accuracy of Shenyang stations, basically possessing the ability to replace subjective forecasts with objective forecasts, providing key technical support for maximum and minimum temperature forecasting technique.

2. Model Forecasts and Observation Data

As shown in **Figure 1**, the location of the stations is presented and their characteristics are listed in **Table 1**. The study scope is the provincial capital city of the province of Liaoning, with a latitude and longitude of 41˚N - 43˚N and 122˚E - 124˚E. The contemporaneous surface observation data of 5 observation sites

Table 1. Characteristics of the selected synoptic stations.

Stations	Elevation (m)	Longitude (N)	Latitude (E)
Shenyang (SY)	49	123.5100	41.7325
Xinmin (XM)	30.9	122.8531	41.9592
Liaozhong (LZ)	12.2	122.7017	41.5114
Faku (FK)	97.8	123.3983	42.4944
Kangping (KP)	87	123.3453	42.8128

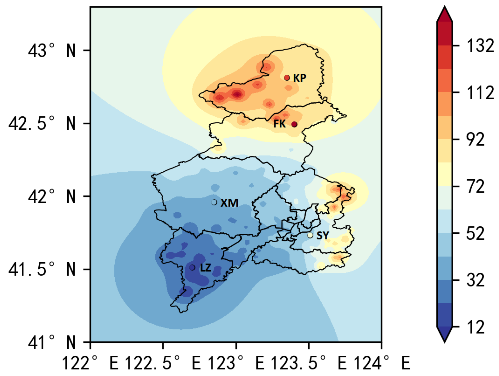

Figure 1. Study ares: Shenyang areas (41˚ - 43˚N, 122˚ - 124˚E).

comes from the data as a serve of China Meteorological Administration. It should be noted that the study areas include five national meteorological observation sites, namely Shenyang (SY), Liaozhong (LZ), Xinmin (XM), Faku (FK) and Kangping (KP).

2.1. Data

The ECMWF model forecasting data from 1 January 2019 to 31 December 2021 were used for correction post-processing, with a time span of 1096 days. The temporal and spatial resolutions of the model are 3 h and 0.1˚ (about 10 km). The other forecast model is national intelligent grid forecast, which was provided by China Meteorological administration. The temporal and spatial resolutions of the model are 1 h and 0.0.3˚ (about 3 km). The two models start twice a day at 00:00 (UTC) and 12:00 (UTC). A total of 37 forecast timeliness of 0 - 36 h was selected. For each forecast timelines, the model produces two forecast results every day, with a sample size of (1096 × 2).

2.2. Methods

2.2.1. Wavelet Analysis

Wavelet analysis is an analytical method that studies the characteristics of signal changes through time and the frequency. According to machine learning algorithms, using wavelet power spectrum to judge the significance of periodic signal fluctuations, the significance test of wavelet power spectrum is implemented using a 95% confidence level red noise test. Due to edge effects appearing in the wavelet power spectrum, wavelet influence cones (COI) are used to represent the wavelet spectral region and corresponding edge effects.

2.2.2. Sliding Training Correction

1) According to the service requirements of China Meteorological Administration, the intelligent grid forecast product and the urban station forecast product need to adopt the neighborhood method to correspond, which means the grid point nearest to the site is selected as the prediction value of the site. If there are multiple grid points with equal distances, the northeast corner grid point is selected. Based on this, this paper calculates the 24 h forecast products

respectively, and calculates the difference between them and the observed data on the corresponding date. The time series of the difference between the maximum temperature and the minimum temperature at five stations is obtained.

2) Using the time series of the difference between the maximum temperature and the minimum temperature of the latest forecast timeliness, the periodic characteristics of the maximum temperature and the minimum temperature of the different forecast timeliness of each urban station were analyzed.

3) Carry out sliding training on the maximum and minimum temperature cycles of 5 urban stations. The maximum temperature of Shenyang (SY) Station (sliding period t) is taken as an example to illustrate. When calculating the 24 h sliding correction, slide the selected date forward t d. The average value of the difference between the previous t days' forecast and observation is called the sliding correction deviation of the 24 h maximum temperature forecast. By adding the correction deviation and the guiding forecast, the correct value of the 24 h maximum temperature at Shenyang Station can be obtained.

2.2.3. Scoring Indicators

The forecast accuracy, mean absolute error and forecast skill were used to evaluate the forecast correction effects.

1) Forecast Accuracy (F)

$$F_2 = \frac{n_2}{n} \times 100\% \tag{1}$$

where n_2 is the number of samples which is less than 2, n is the total number of samples, F_2 represents the percentage of the predicted temperature with the observed temperature error less than 2˚C.

2) Mean absolute error (MAE)

$$T_{\text{MAE}} = \frac{1}{N}\sum_{i=1}^{N}\left|F_i - O_i\right| \tag{2}$$

The T_{MAE} is the mean absolute error of temperature, which can better reflect the actual situation of the predicted value error. F_i is the forecast temperature at station i (time), O_i is the actual temperature at station i (time), and N is the number of participating stations.

3) Forecast skill (FS)

$$\text{FS} = \frac{T_{\text{MAEC}} - T_{\text{MAEN}}}{T_{\text{MAEC}}} \tag{3}$$

T_{MAEC} is the mean absolute error of the objective correction products. T_{MAEN} is the mean absolute error of the national intelligent grid forecast. When $T_{\text{MAEC}} = 0$, FS = 1.01.

3. Results

3.1. Temporal Distribution Characteristics of Maximum and Minimum Temperatures

The research areas are located in the south of Northeast China, which mainly composed of plains, with mountains and hills concentrated in the southeast. The Liaohe River, Hunhe River, Xiushui River are all pass through the territory. It belongs to a temperate monsoon climate. Precipitation is concentrated in summer, with a large temperature difference. Cold weather lasts for a long time, nearly six months, the temperature changes rapidly in spring and autumn.

As can be seen in Figure 2, under the unique climate background, the monthly distribution of 2 m temperature also presents obvious characteristics. The temperature in July and August is the highest, and the temperature in January and February is the lowest.

3.1.1. Maximum Temperature

The maximum temperature in the study area presents negative values in January and February, with an annual average of 14.36˚C. The highest values of the maximum temperature from January to March appear in LZ, and from April to August, they appear in SY. Overall, the maximum temperature at SY is the highest

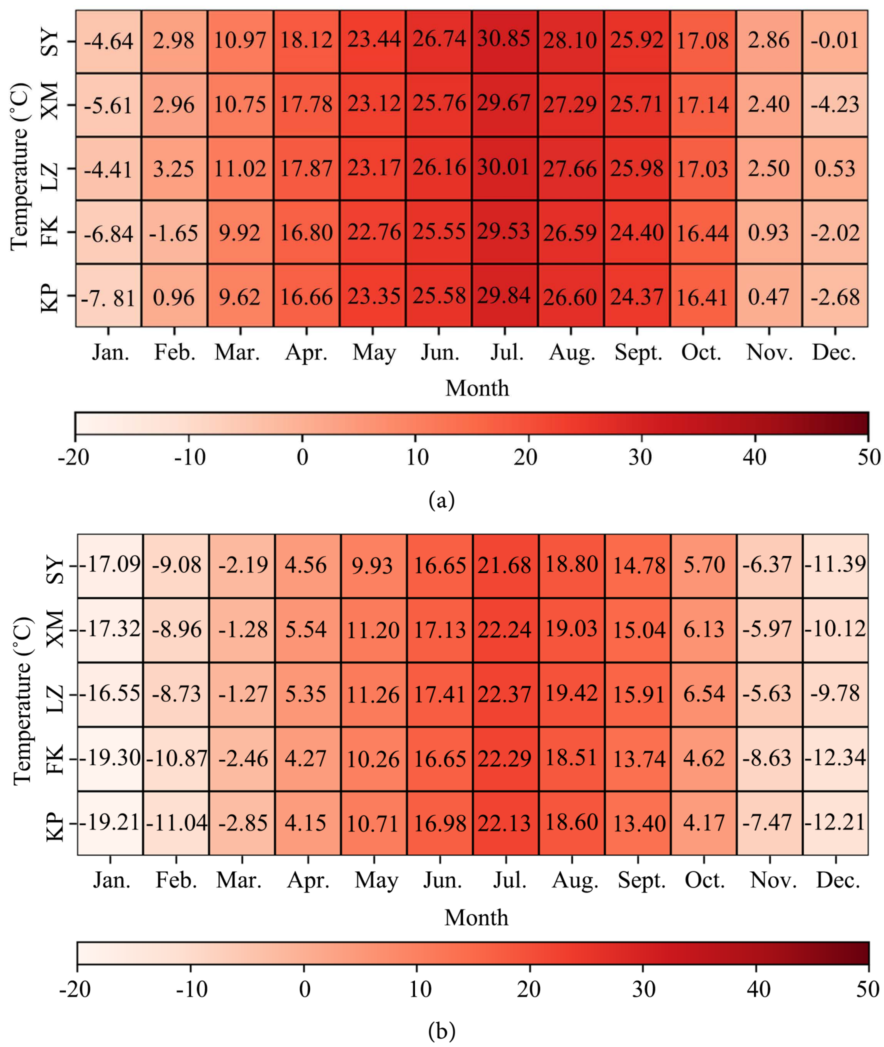

Figure 2. Maximum (a) and minimum (b) temperature at each station in different months. (a) High; (b) Low.

among the five stations for 6 months. It may be that observation site is in a city, and due to a large number of artificial heating, high thermal storage such as buildings and roads, and reduced green space, the city has become "heat island effect", resulting in significantly higher temperatures in the city than in the outer suburbs.

3.1.2. Minimum Temperature

The minimum temperature in the study area is subzero temperature for five months every year. The annual average minimum temperature is 3.82˚C. The highest value of the minimum temperature throughout the year (except for April) occurs in LZ, while the lowest value occurs more frequently in KP.

3.2. Sliding Training Period

The sliding correction cycles of the maximum and minimum temperatures at five observation sites were calculated for 24 hours. For a brief, take SY as an example for Wavelet Analysis. As shown in **Figure 3**, the results show that the optimal training period for the station at the maximum temperature in April is 5 days, and the minimum temperature in January is 3 days.

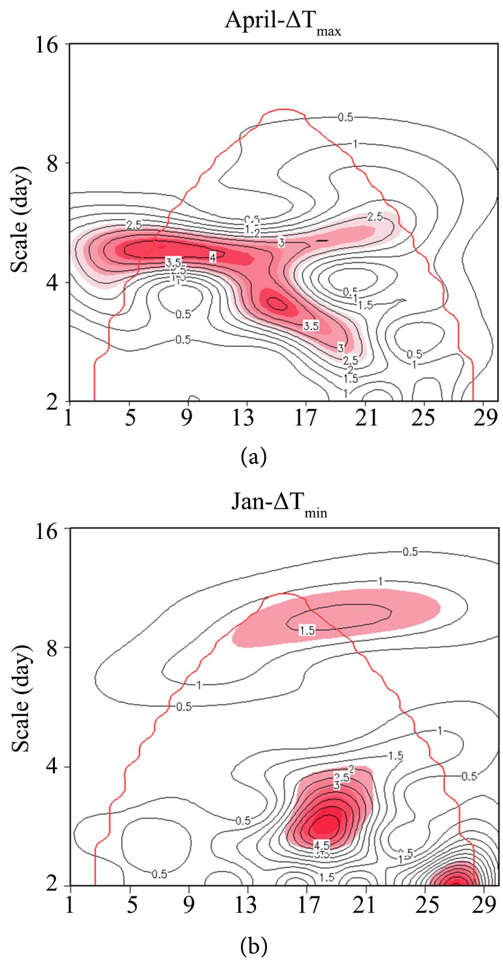

Figure 3. The sliding training period of the maximum (a) and minimum (b) temperature.

The same method can provide the optimal training cycles of the highest (**Table 2**) and lowest (**Table 3**) monthly temperature for each station.

As can be seen from **Table 2**, the sliding training period is between 2 and 7 days, with an average value of 4 days. According to regional analysis, the correction cycle time in LZ region is the longest in a year, which is 5 days, while the other four cities are all around 3 days. Based on monthly analysis, the longest revision cycle is 7 days in October, and the shortest revision cycle is 2 days in August.

Table 2. Monthly maximum temperature forecast sliding training at different sites.

Sta	SY	XM	LZ	FK	KP
Jan.	2	3	3	2	3
Feb.	2	2	7	3	7
Mar.	3	2	3	5	2
Apr.	5	5	5	5	5
May	2	2	7	2	2
Jun.	2	2	2	7	2
Jul.	7	7	7	7	5
Aug.	2	2	2	2	2
Sept.	7	7	7	2	2
Oct.	7	7	7	7	7
Nov.	5	3	5	3	5
Dec.	2	5	5	1	2

Table 3. Monthly minimum temperature forecast sliding training period at different stations.

Sta	SY	XM	LZ	FK	KP
Jan.	3	5	3	3	3
Feb.	2	2	2	5	5
Mar.	2	2	2	2	3
Apr.	7	2	7	7	7
May	7	2	7	7	2
Jun.	7	5	3	5	5
Jul.	7	5	7	7	5
Aug.	2	5	2	7	7
Sept.	5	7	3	7	7
Oct.	3	2	3	3	3
Nov.	5	3	7	5	2
Dec.	7	7	7	7	7

As can be seen from **Table 3**, the sliding training periods for minimum temperature are between 2 and 7 days, with an average value of 4.6 days. According to regional analysis, the longest correction cycle time in a year is 5.4 days in FK, while the other four cities are around 4 days; Based on monthly analysis, the longest revision cycle is 7 days in December, and the shortest revision cycle is 2.2 days in March.

3.3. Analysis on the Effect of Objective Forecast Products in Different Months

According to **Table 2** and **Table 3**, the sliding training periods of five sites in different months are selected to objectively revise the ECMWF forecasts and produce objective correction products for 2 m temperature.

3.3.1. Maximum Temperature

According to Formula (1) and Formula (2), as shown in **Figure 4**, the accuracy of the maximum temperature objective correction products was analyzed. The results show that:

Regardless of the prediction accuracy or mean absolute error analysis, the annual (except November) maximum temperature objective correction products show better results than the ECMWF forecasts.

The accuracy analysis of ECMWF temperature forecasts (T_{EC} for short) and objective correction products (T_{RE} for short) results show that: The average T_{EC} value for the whole year was 41.25%, and the T_{RE} increased to 59.91% after the revision. The accuracy rate after the revision was 45% higher than before. The growing accuracy growth value of objective forecast products from January to December (excluding October and November) is 25% to 233%. According to MAE, the decreasing value of objective correction products from January to December (excluding November) is 24% to 70%. The above results indicate that correction methods improve the quality of maximum temperature prediction in the study area.

After the ECMWF forecast is revised by using the sliding training, the maximum temperature objective correction products have the best forecast ability in LZ, with the accuracy rate increased by 95% and the mean absolute error is decreased by 50%; objective correction products accuracy growth rate in KP is the lowest, only 35%, and the mean absolute error of the objective correction products in FK is decreased by 33%. It shows that the maximum temperature objective correction products perform well in LZ.

3.3.2. Minimum Temperature

As shown in **Figure 5**, the accuracy analysis results of ECMWF and objective correction products at five sites show that: The annual forecast accuracy has increased by 58% and the mean absolute error has decreased by 45%. Objective correction products have improved the quality of minimum temperature prediction in study areas. It is worth noting that the objective prediction method has a

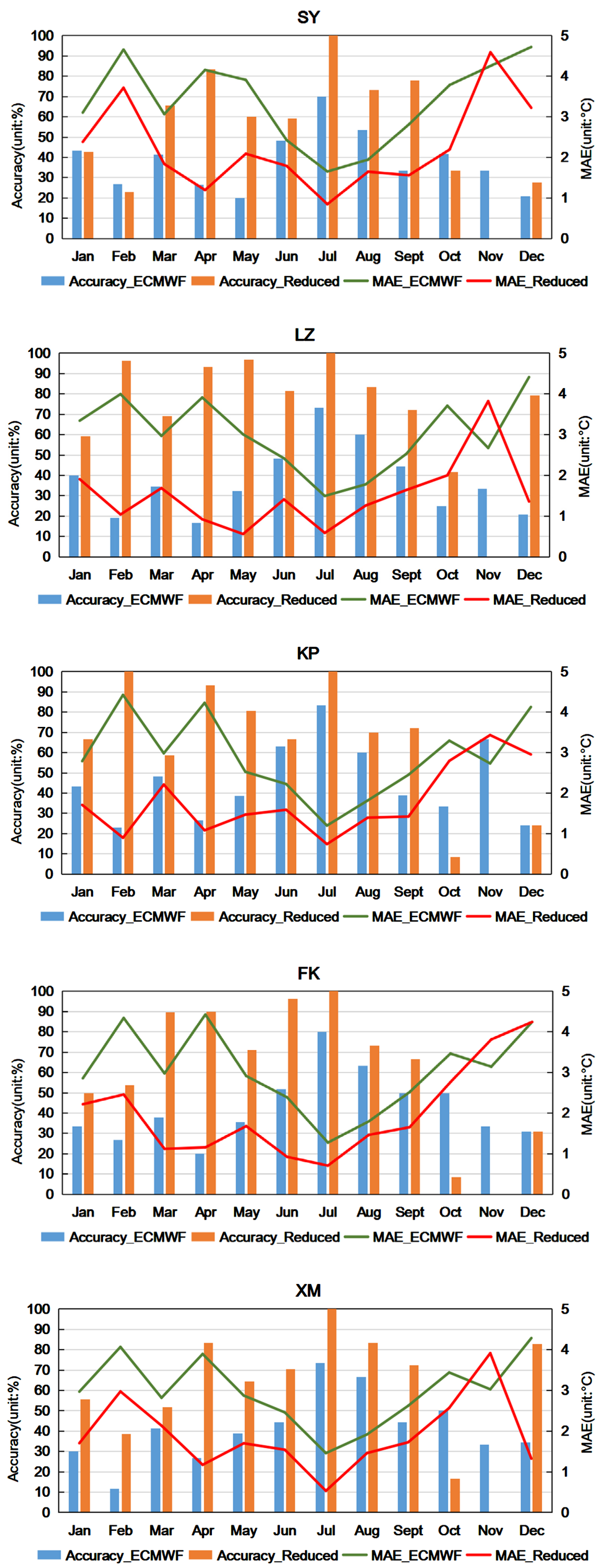

Figure 4. Accuracy of maximum temperature objective correction products in different months. Bar (for accuracy): Blue stands for ECMWF; Orange stands for objective correction products; Line (for MAE): Green stands for ECMWF; Red stands for maximum correction products.

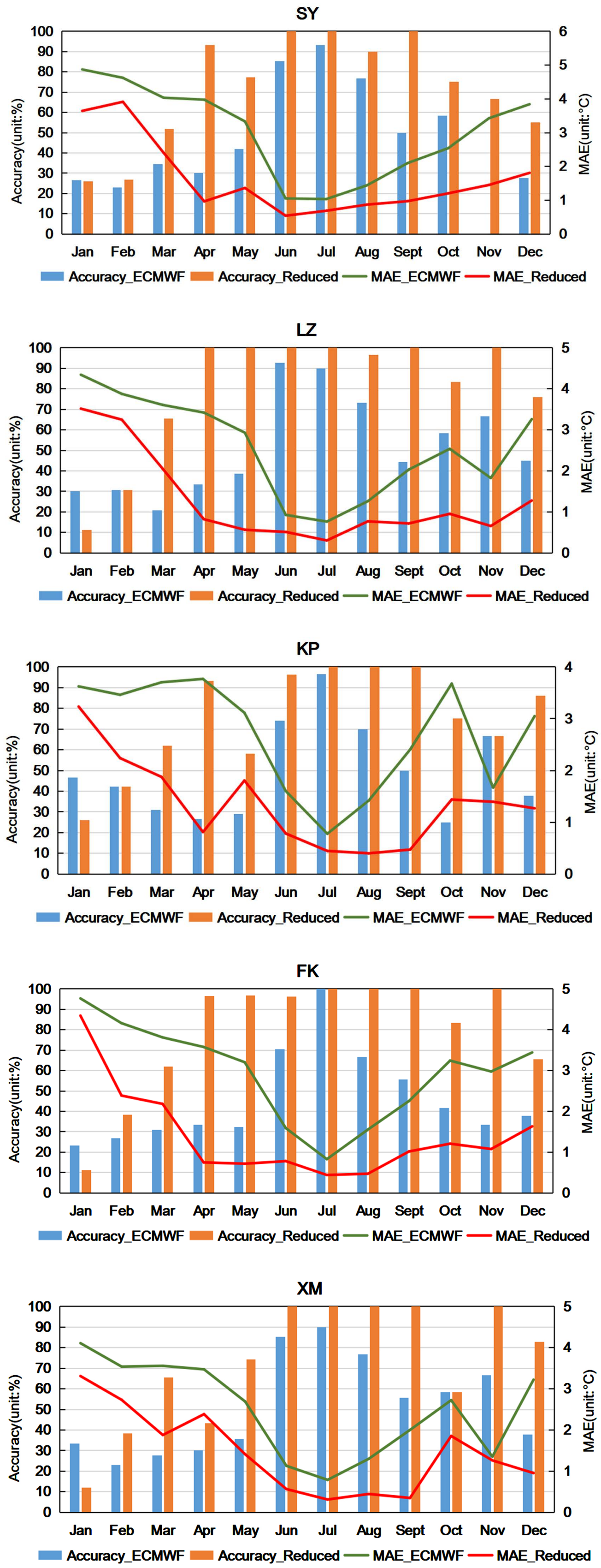

Figure 5. Same as **Figure 4**, but for minimum temperature.

higher ability to predict the minimum temperature than the maximum temperature. The objective forecast products of minimum temperature have the best forecast ability in XM, with the forecast accuracy increased by 118% and the mean absolute error reduced by 70%. Both the forecast accuracy and the mean absolute error analysis show that the forecast effect of the objective correction products of the annual minimum temperature is better than ECMWF.

3.4. Analysis on the Effect of Objective Correction Products in Different Seasons

Through the accuracy analysis of objective correction products in different months, it is found that the correction effect of objective correction products on the maximum temperature in November is not ideal, even less than the ECMWF. In order to comprehensively analyze the correction effect of objective correction products under local climatic scenario, this paper evaluates the prediction performance of objective correction products for maximum and minimum temperatures from different seasons. Spring is in March, April, and May. Summer is in June, July, and August. Autumn is in September, October and November. Winter is in December, January, and February.

3.4.1. Maximum Temperature

As shown in **Figure 6**, it analyzes the maximum temperature forecast accuracy and MAE of each sites in different seasons. The result shows that: objective methods in spring, summer, and winter all have ability to correct the maximum temperature forecast. The accuracy improvement values of the five sites in spring are 87% to 211%, 15% to 46% in summer, and 2% to 194% in winter, respectively, the forecast accuracy of objective correction products is higher than ECMWF. Overall, the objective method has the best correction effect for spring and the worst correction effect for autumn. In autumn, only SY and LZ have achieved good correction results, improved the accuracy of the forecast products. From the analysis of different sites, the correction effect of LZ Station is the best throughout the year, the accuracy improvement of 115%. The correction effect of KP Station is the worst; the accuracy improvement was only 47% throughout the year.

MAE also shows that the objective correction product has excellent correction ability for the ECMWF, and MAE of all sites throughout the year is reduced by 50%.

3.4.2. Minimum Temperature

As shown in **Figure 7**, it shows that the objective correction product has the correction ability for all sites. The accuracy analysis results show that: the objective methods for the four seasons of the year have the correction ability for the minimum temperature forecast, with the most obvious correction effect for spring, and the worst correction effect for summer and winter.

The accuracy improvement values for the five sites were 97% - 186% in spring, 14% - 23% in summer, 43% - 123% in autumn, and 12% - 41% in winter. From the analysis of different stations, the spring correct effect for LZ Station is the best, with an accuracy improvement of 186%, but throughout the year, the correct effect for FK is the best, with an accuracy improvement of 84%, on the contrary, KP is the worst, accuracy improvement was only 50%. MAE also shows that the objective correction products have the good ability to correct the ECMWF temperature forecast, and MAE of all sites throughout the year has decreased by 37%. It is worth noting that the ability of objective correction methods to predict the minimum temperature is better than the maximum temperature.

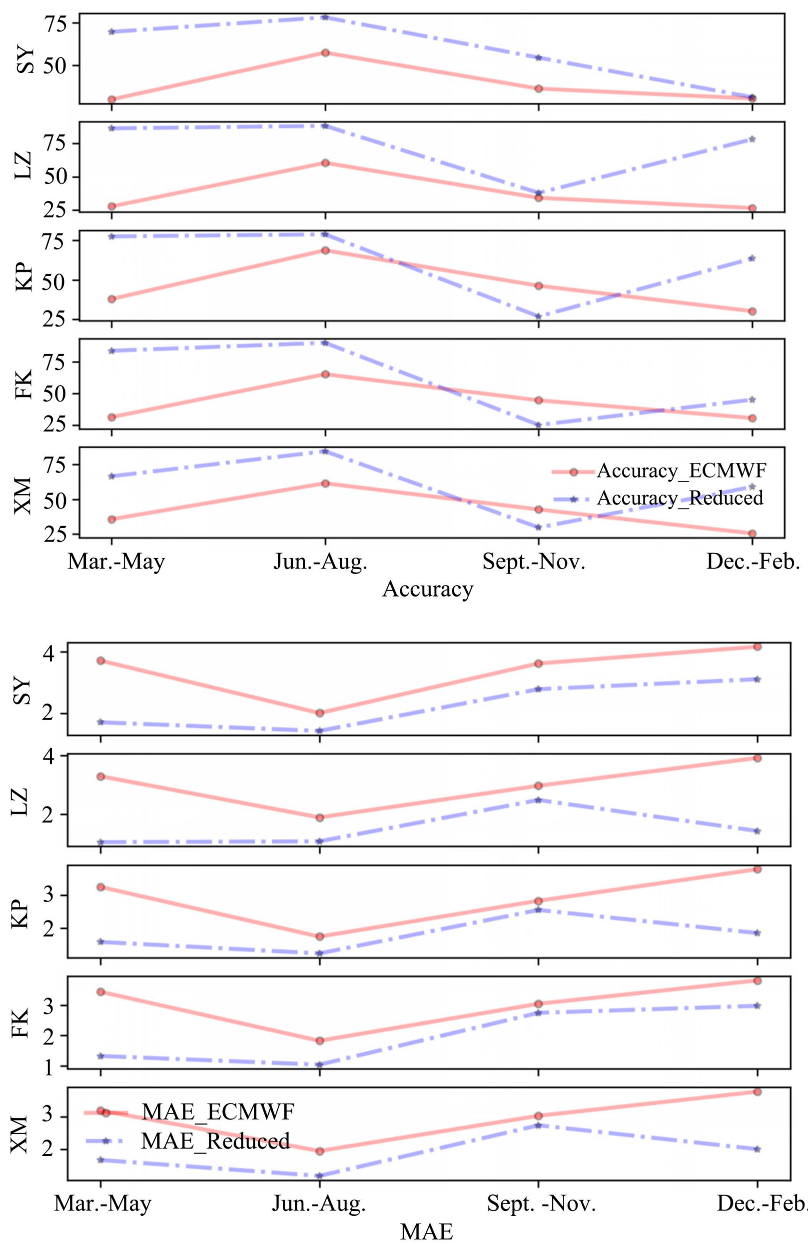

Figure 6. Accuracy of objective correction products for maximum temperature in different seasons. Top: Accuracy; Bottom: MAE; Red discount chart: the ECMWF forecast; Blue Line Chart: Objective Correction Products.

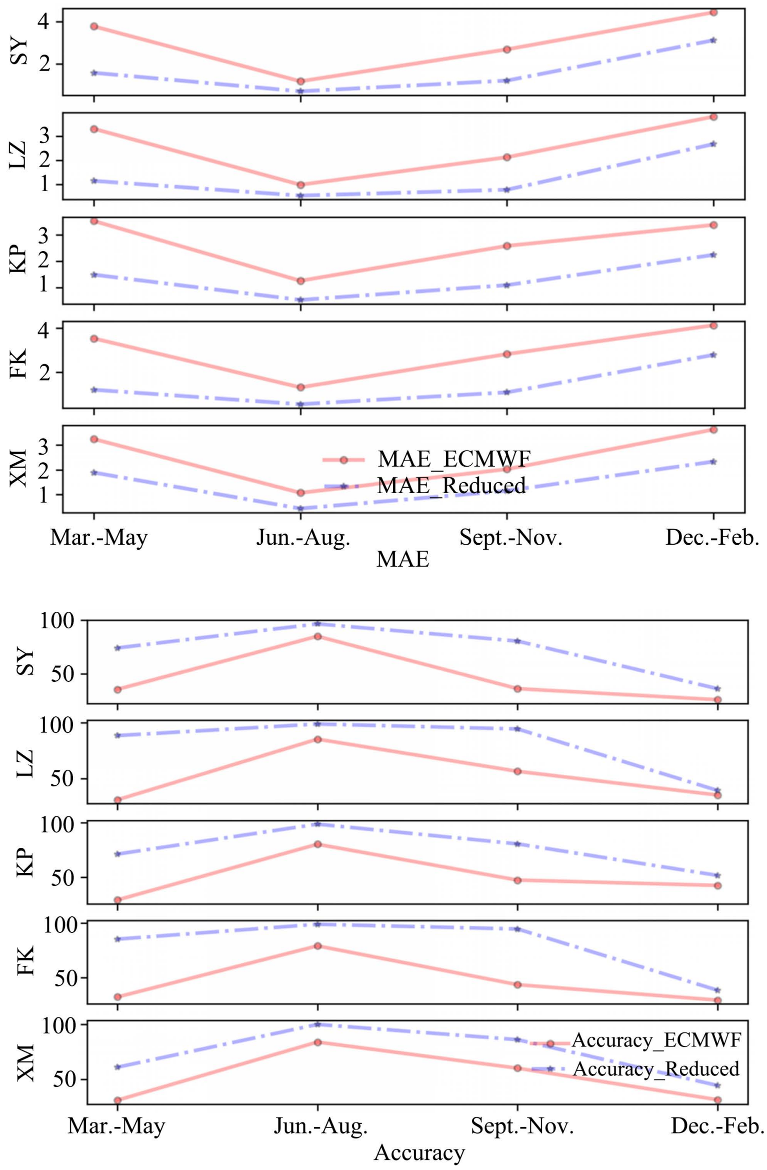

Figure 7. Same as **Figure 6**, but for minimum temperature.

3.5. Forecast Skill Test (FS)

Intelligent grid forecast was produced by China Meteorological Administration. Using forecast skill test to analyze the advantages of objective correction product and intelligent grid forecast, the result is shown in **Figure 8**.

In spring, the maximum temperature objective correction products show positive skills relative to the intelligent grid forecast, but in autumn, it is a negative skill. From the sites analysis, SY only showed positive skills in spring, while LZ and XM showed positive skills in spring, summer and winter. KP performed better in spring and winter, while FK had a significant correction effect in spring and summer. In spring, autumn and winter, relative to the intelligent grid forecast, the minimum temperature objective correction products showed positive skills.

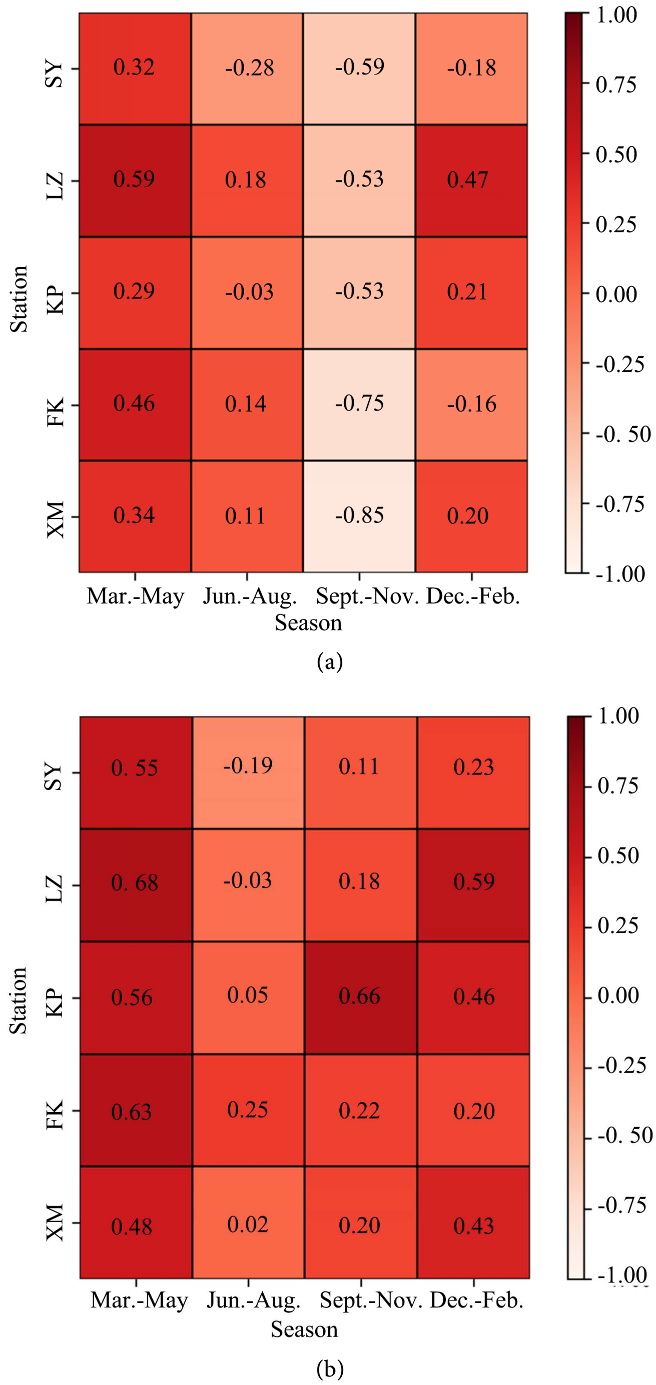

Figure 8. Forecast skill for objective correction products in different seasons. Left: maximum temperature; Right: minimum temperature. (a) High, (b) Low.

From the sites analysis, only SY and LZ showed negative skills in summer, while other sites showed positive skills. The above conclusions objectively indicate that compared to intelligent grid forecast, objective correction products have better prediction effects on minimum temperatures than maximum temperatures. This is consistent with the research conclusion of Liu Xinwei (2020), The accuracy of the highest temperature reported by the intelligent grid forecast is still higher than objective correction forecast. However, the correction effect of objective correction forecast on minimum temperature is higher than intelligent grid forecast.

4. Conclusions

Based on the 5 national meteorological observing stations in Northeast China, observational data, Wavelet analysis and sliding training technologies were used to revise and compare the maximum and minimum temperature forecast of the ECMWF model and national intelligent grid forecast. Accuracy, MAE, FS were used as the evaluation metrics. The main conclusions are as follows:

1) The monthly distribution of 2 m temperature also presents obvious characteristics. The temperature in July and August is the highest, and in January and February is the lowest. The difference between the maximum and minimum temperatures is 50.35 degrees Celsius.

2) According to the wavelet analysis results, the sliding training period of the maximum temperature is smaller than the period of the minimum temperature (the average period of the highest temperature and lowest temperature within 24 hours is 4.05 and 4.63, respectively), and this difference is most significant in August, with a period difference of 2.6 days.

3) In spring, the accuracy improvement values of the five sites are 87% to 211% for maximum temperature and 97% - 186% for minimum temperature. Throughout the year in all sites, the ability of objective correction methods to predict the minimum temperature is better than the maximum temperature.

4) Maximum temperature and minimum temperature objective correction forecasts have good correction effect on the southern, LZ belongs to a plain area with simple terrain, in spring, the accuracy of maximum temperature objective correction products has been improved by up to 211%.

5) According to the seasonal evaluation, compared with national intelligent grid forecast, objective correction products have shown positive skills in predicting maximum temperatures in spring (up to 0.59). In summer, Except for SY and LZ, the minimum temperature prediction shows positive skill (up to 0.68). We can say that the objective prediction product of minimum temperature initially possessed the ability to replace subjective prediction.

5. Discussion

The revision method is good for correcting result and making distribution of the temperature forecast. It can be concluded that the wavelet analysis methods employed in this study are found quite reliable in the temperature estimation study. The applicability of the employed training methods also in the long range temperature forecasting could be analyzed in a future study. It is hoped that the presented study can shed light on future machine learning studies modeling temperature time series. The prediction ability of the maximum and minimum temperature objective correction products generated by the wavelet analysis method is higher than ECMWF and national intelligent grid forecast, which initially has the ability to replace subjective prediction. There are many factors that affect temperature prediction. More scientific and rigorous methods can correct numerical predictions, thereby improving the accuracy of maximum and minimum temperature predictions. In the application, it is suggested to comprehensively apply the method according to the needs of users, which may be able to better solve practical problems.

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Author Contributions

Conceptualization, J. L. and C. R.; methodology, N. Y.; software, C. R.; formal analysis, C. R.; writing-original draft preparation, J. L.; writing-review and editing, L. P.; C. R.; L. Y. revised the paper. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The datasets supporting the conclusions of this paper are private. And it came from the Liaoning Meteorological Observatory, Shenyang, Liaoning, China.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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