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# Analogue Ensemble Averaging Method for Bias Correction of 2-m Temperature of the Medium-Range Forecasts in China

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**Abstract:** The 2-m temperature is one of the important meteorological elements, and improving the accuracy of medium- and long-term forecasts of the 2-m temperature is important. The similarity forecasting method is widely used as a calibration technique in the statistical postprocessing of numerical weather prediction (NWP). In this study, the analogue ensemble averaging method is used to correct the deterministic forecast of the 2-m temperature with a forecast lead time from 180 h to 348 h using the CMA-GEPS model. The bias, mean absolute error (MAE), and root mean square error (RMSE) are used as the evaluation metrics. In comparison with NWP, the systematic error of the model for 2-m temperature is effectively reduced during each forecast period when using the analogue ensemble averaging method. In addition, the differences in forecast errors between regions are reduced, and the accuracy of 2-m temperature forecasts over complex terrain, especially in Southwest China, Northwest China, and North China, is improved using this method. In the future, there is certainly potential to apply the analogue ensemble averaging method to the bias correction of medium- and long-term forecasts of more meteorological elements.

**Keywords:** bias correction; similarity method; medium and long-term forecast

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## 1. Introduction

Medium- and long-range weather predictions represent the transitions between short-term and sub-seasonal forecasts. These predictions are used for drought, flood, and warm and cold trends, and critical, catastrophic, and transitional weather forecasting services [1,2]. Improving the accuracy of medium- and long-range weather forecasting is of great research significance and application value for disaster prevention and mitigation, and other meteorological security. However, due to the chaotic nature of the atmosphere and the deficiencies of the numerical model (i.e., observation errors, imperfect data assimilation techniques, and physical parameterization schemes) [3–11], numerical weather forecasts are subject to inevitable systematic errors. It is necessary to carry out statistical postprocessing methods to remove systematic errors before these forecasts can be used [12,13].

There have been many studies on the bias correction methods of numerical weather prediction. Klein et al. [14] proposed the Perfect Prognostic (PP) method in 1959. In this method, only the predictors of dynamic predictions are used when making forecasts. Then, the Model Output Statistical (MOS) method was proposed and widely used in meteorological centers in many countries [15–17], including the Netherlands [18], the United Kingdom [19], Italy [20], China [17,21], Spain [22], Canada [23], and the United States [15]. This method can include the influences of the specific characteristics of different forecast lead times of the model in the regression equation. The Kalman filter (KF) technique [24–26], Back Propagation (BP) neural network algorithm [27,28], Support Vector Machine (SVM) method [29], and Deep Learning (DL) methods have also been increasingly researched and developed in recent years [30–34].

However, most of the methods require complex techniques to simulate all sources of numerical weather forecast uncertainty, which consumes many computing resources. In 2006, Hamill et al. [35] proposed a theory for the statistical correction of weather forecasts based on observed analogues. The first step of this method is to find similar forecasts in the historical forecast dataset, and then use the corresponding observation results to generate deterministic forecasts or probabilistic forecasts. Mayr and Messner tested three variants of this method in the idealized Lorenz 96 system, and the results showed that these methods excel at longer lead times [36]. Delle Monache et al. [37] evaluated 0–48 h probabilistic predictions of 10-m wind speed and 2-m temperature after correction by the analogue ensemble (AnEn) method. The skill and value of AnEn predictions were compared with forecasts from an NWP ensemble system, and it was found that AnEn exhibits high statistical consistency and reliability and the ability to capture the flow-dependent behavior of errors. On this basis, some researchers have attempted to improve the performance of the AnEn method. Junk et al. [38] explored predictor-weighting techniques to assign unequal weights to the predictors. Yang et al. [39] used two NWP models to postprocess predicted wind speed during storms and found optimal weights for the predictors. A variant method, the Kalman filter predictor-corrector algorithm (ANKF), was applied to the analogues arranged into a series that was rank ordered by descending distance to the current forecast. The improved methods have achieved good results. Alessandrini et al. [40] applied the AnEn method to wind power forecasts and solar power forecasts, effectively improving the accuracy of forecasts and increasing the production of renewable energy. Other studies have used this method to predict atmospheric variables (e.g., wind speed, temperature) [41–43], precipitation [44,45], tropical cyclone (TC) intensity [46–48], and surface particulate matter (PM2.5) [49].

The 2-m temperature is one of the most popular weather elements in daily weather forecasting and has attracted people's attention. Improving the accuracy of 2-m temperature forecasts plays an important role in refining forecasts and improving disaster prevention. In this paper, the AnEn method is applied to the correction of the medium- and long-term deterministic forecasts of 2-m temperature. The forecasts of the CMA-GEPS model during 180–348 h forecast periods are used in the modified approach, and the results before and after the modification are examined and compared to explore the potential application of the analogue ensemble method for medium- and long-term forecasts of meteorological elements.

Section 2 describes the forecast and observation data. Section 3 briefly summarizes the analogue ensemble average method and verification scores used in this paper. Section 4 contains the results from the postprocessing method compared to CMA-GEPS model forecasts and presents the results from two aspects, forecast lead time and site distribution. Finally, a summary and conclusions are given in Section 5.

## 2. Forecast and Observation Data

In this study, the 2-m temperature element is statistically interpreted, and the CMA-GEPS model is used to make 168–360 h control forecasts from 25 December 2018 to 28 June 2022, with a period of 1282 days. These data are used for the release of the analogue ensemble averaging method. The CMA-GEPS model is a global ensemble forecast system developed by the China Meteorological Administration and is based on the SVs initial perturbation method and integrating the tropical cyclone initial perturbation techniques TCSV, SPPT, and SKEB model perturbation schemes. The control forecast is generated by the CMA-GFS model with a horizontal resolution of 50 km and a vertical resolution of 60 layers. The model starts at 00:00 (UTC, same as below) and 12:00 (only the forecast results from 00 h are used in this article.). The maximum forecast lead time is 15 days. In this paper, 17 forecast lead times of 168–360 h (with an interval of 12 h) are tested.

The contemporaneous surface observation data from 2405 meteorological stations in China were obtained from the data-sharing platform of the China Meteorological Data Service Centre. The outlier values of the observation data were detected with three times the standard deviation and removed. The missing values were filled by linear interpolation to form a more precise and complete observation dataset.

The CMA-GEPS model forecast outputs are grid point data. First, the outlier samples exceeding the climate extreme values of the model data were removed, and then the existing 2-m temperature forecast operational test matching scheme, which does not take into account the vertical height difference between the elevation of the station and the topographic height at which the forecast is located, and a bilinear interpolation method was used to obtain the test station forecast using four grid point forecasts around the observation.

## 3. Methods and Verification Scores

### *3.1. Analogue Ensemble Averaging Method*

In this study, the theory of analogue ensemble forecasts is applied to address the medium-and long-term forecast bias of the 2-m temperature, assuming that long-term, stable numerical models have similar forecast results and error distribution characteristics for similar weather conditions [35]. The analogue ensemble averaging forecasting method is developed based on this idea, and the post-processing process is simplified to find similar forecasts by using historical forecast data and observation data, and the complete revision process is shown in Figure 1.

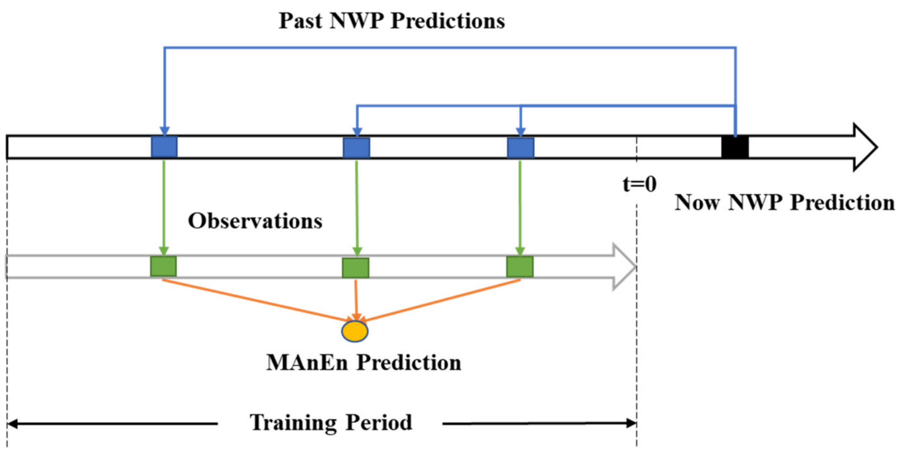



**Figure 1.** Flow chart of the analogue ensemble averaging method (MAnEn).

The realization process of the analogue ensemble averaging method is divided into three steps. First, it is assumed that the similarity measure formula is used to calculate the similarity between the current forecast and the historical forecast datasets with the same forecast time at the same location for the model forecast data starting from the moment $t = 0$ with forecast time $t$ in the future. Then, the top n most similar historical forecasts are selected to find the corresponding actual observations as members of the analogue ensemble forecasts. Finally, a deterministic forecast or probabilistic forecast is generated (in this paper, the arithmetic mean of the members is used as the deterministic forecast result to compare with the model control forecast result.). The similarity measure formula is as follows:

$$\|F_t, A_{t'}\| = \frac{1}{\sigma}\sqrt{\sum_{i=-\tilde{t}}^{\tilde{t}} (F_{t+i} - A_{t'+i})^2} \tag{1}$$

In the above formula, $F_t$ is the deterministic forecast of the future time $t$, $A_{t'}$ is the forecast of the historical time $t'$ at the same spatial position, the same starting time and the forecast lead time, σ is the standard deviation of the time series of the forecast factor, and $\tilde{t}$ is the selected similar forecast time window ($\tilde{t}$ = 1 in this paper). Then, the results of the current forecast time and the one before and after the forecast lead time are used in the calculation of the similarity measure. In contrast to only using the forecast value at a given time, the information over a period of time can be used through the selection of the window to find similar forecast trends when looking for similar historical forecasts. The smaller the result of Equation (1) is, the more similar the prediction of historical time $t'$ is to the prediction of current time $t$.

Using Equation (1), n observations corresponding to the most similar historical forecasts ($n$ = 30 in this paper) are selected from the historical forecast dataset as the ensemble members, and the ensemble average is used as the deterministic forecast.

$$F_{AnEnA} = \frac{1}{n}\sum_{i=1}^{n} O_i \tag{2}$$

where $n$ is the number of ensemble members, and $O_i$ is the observation value corresponding to the $i$-th historical forecast.

In this paper, the forecast lead time from 180 h to 348 h of the 2-m temperature (forecast time interval is 12 h) is statistically interpreted by using the analogue ensemble averaging forecast method. The number of similar forecast members is 30. The data duration and parameter settings used in the experiment are shown in Table 1.

**Table 1.** Data duration and parameter setting for each forecast time.

| Forecast Lead Time | Testing Period | Training Period | Selected Lead Time | Analog Ensemble Members |
|---|---|---|---|---|
| 180 h | 20220501–0628 (59 d) | 20181225–20220423 (1216 d) | 168 h, 180 h, 192 h | 30 |
| 192 h | | –20220422 (1215 d) | 180 h, 192 h, 204 h | |
| 204 h | | 1215 d | 192 h, 204 h, 216 h | |
| 216 h | | –20220421 (1214 d) | 204 h, 216 h, 228 h | |
| 228 h | | 1214 d | 216 h, 228 h, 240 h | |
| 240 h | | –20220420 (1213 d) | 228 h, 240 h, 252 h | |
| 252 h | | 1213 d | 240 h, 252 h, 264 h | |
| 264 h | | –20220419 (1212 d) | 252 h, 264 h, 276 h | |
| 276 h | | 1212 d | 264 h, 276 h, 288 h | |
| 288 h | | –20220418 (1211 d) | 276 h, 288 h, 300 h | |
| 300 h | | 1211 d | 288 h, 300 h, 312 h | |
| 312 h | | –20220417 (1210 d) | 300 h, 312 h, 324 h | |
| 324 h | | 1210 d | 312 h, 324 h, 336 h | |
| 336 h | | –20220416 (1209 d) | 324 h, 336 h, 348 h | |
| 348 h | | 1209 d | 336 h, 348 h, 360 h | |

### *3.2. Verification Scores*

For the deterministic forecast, bias reflects the degree of deviation between the predicted results and the real results of the sample. The closer the value is to 0, the smaller the degree of deviation between the predicted relative observations. The MAE and the RMSE measure the deviation between the predicted value and the real value. The RMSE is very sensitive to large or small errors in a set of data, and it will also punish the high difference more. The smaller the value is, the higher the forecast accuracy.

In this paper, the bias, MAE and RMSE are used as verification scores. The formulas are as follow:

$$\text{BIAS} = \frac{1}{n}\sum_{i=1}^{n}(f_i - o_i) \tag{3}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|f_i - o_i| \tag{4}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(f_i - o_i)^2} \tag{5}$$

In the formula, $n$ is the total number of samples, $f_i$ is the predicted value of the $i$-th sample, and $O_i$ is the observed value of the $i$-th sample.

## 4. Results

### *4.1. Comparisons of Different Forecast Lead Time Results between Analogue Ensemble Averaging Forecast and Numerical Weather Prediction Methods*

The bias corrections of 15 forecast periods of 180–348 h at 2405 stations in China were carried out using the analogue ensemble averaging forecast method. The bar chart of the bias of 2-m temperature model forecasts and analogue ensemble averaging forecasts from 1 May 2022, to 28 June 2022, are shown in Figure 2. It can be seen from the figure that the biases of the 2-m temperature model forecasts for the 15 forecast lead times are above 0.5 °C, and the largest bias is 1.29 °C. After correction, the biases are obviously reduced and the values are closer to 0. With the extension of forecast lead times, the biases gradually change from positive to negative and below 0.7 °C. In addition, the bias of the model forecasts for the adjacent forecast lead times is distributed in the high and low phases. This is because the 00 h model forecasts are better than the 12 h forecasts. In other words, the morning forecasts are better than the night forecasts.

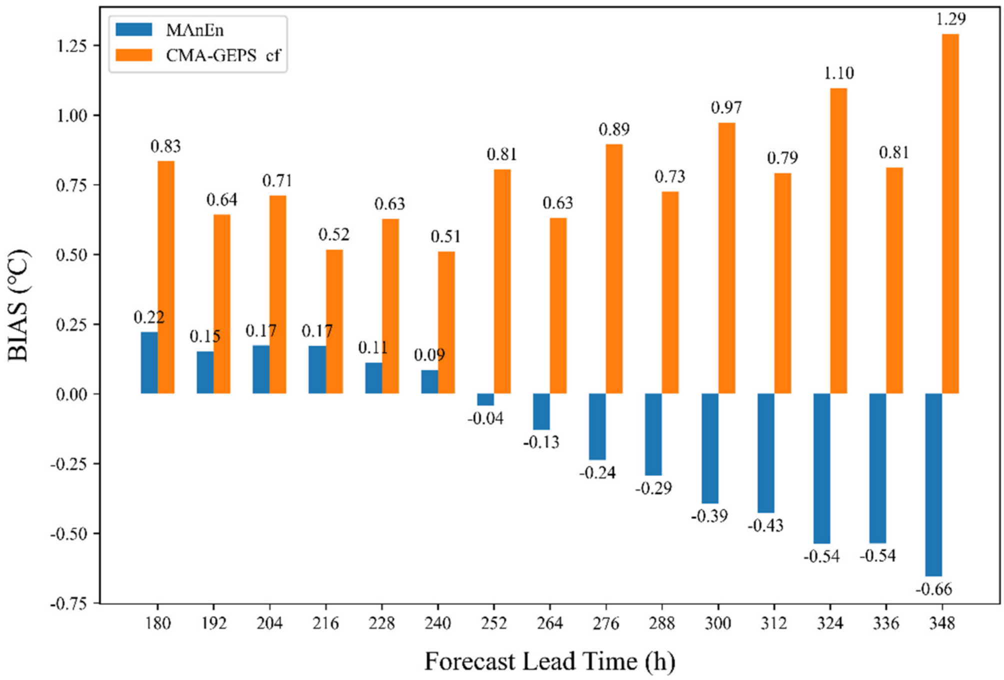
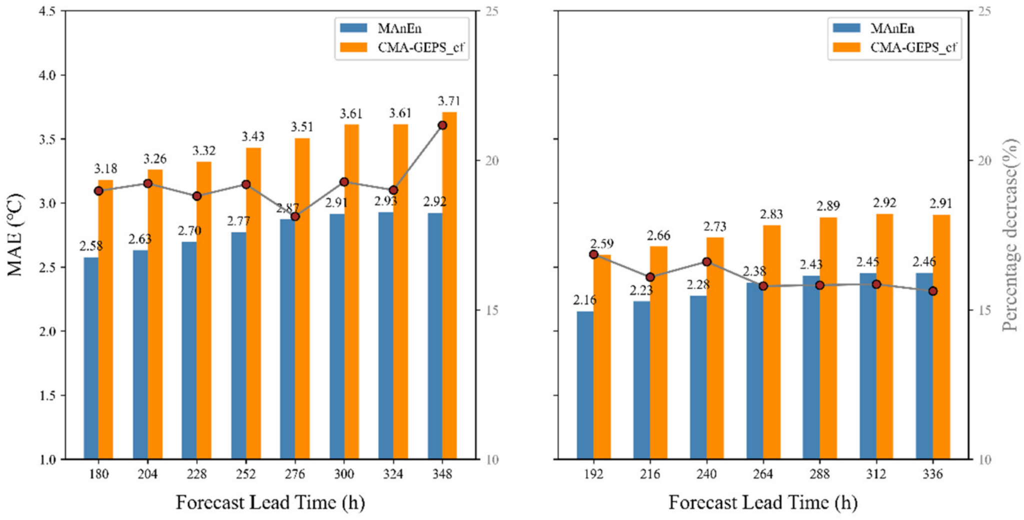



**Figure 2.** The biases of 2-m temperature between analogue ensemble averaging forecasts and model forecasts for the forecast lead times of 180–348 h.

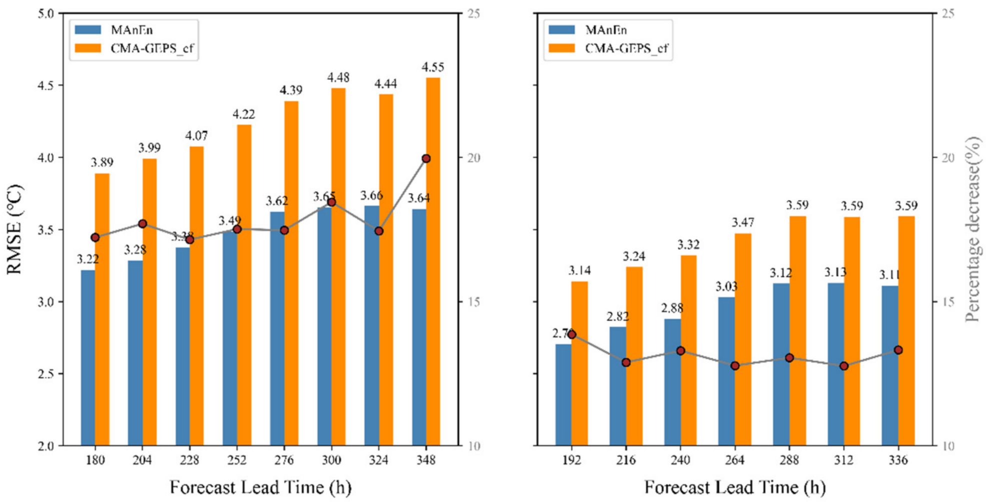
The MAE distributions for the analogue ensemble averaging forecasts and model forecasts under different forecast lead times at 2405 national stations are shown in Figure 3 (the mean of all stations with the same forecast lead time). After bias correction, the MAEs of all forecast lead times are reduced to below 3 °C, with decreases between 15% and 25 %. Figure 3a shows the MAEs of the daily 12 h forecasts for 7–14 days, and Figure 3b shows the MAEs of the daily 00 h forecasts. Comparing Figure 3a with Figure 3b, it can be seen that for the model forecasts, the daily 00 h forecast are always better than the 12 h forecasts. After bias correction is performed, using the analogue ensemble averaging method, the forecast gap between 00 h and 12 h forecasts improves.




(**a**) (**b**)

**Figure 3.** MAE and percentage decrease of analog ensemble averaging forecasts and model forecasts. (**a**) Daily 12 h forecasts for 7–14 d; (**b**) daily 00 h forecasts for 8–14 d.

The conclusions embodied in Figure 4 are similar to those in Figure 3, i.e., the RMSE and percentage decrease of the forecasts of 2-m temperature at 2405 national stations with forecast lead times of 180–348 h using the analogue ensemble averaging method and NWP model.




(**a**) (**b**)

**Figure 4.** RMSE and percentage decrease of the analog ensemble averaging forecasts and model forecasts. (**a**) Daily 12 h forecast for 7–14 d; (**b**) daily 00 h forecast for 8–14 d.

The analogue ensemble averaging method is used to test the 240 h forecasts of 2-m temperature for 2405 national stations from 1 May to 28 June 2022, and to examine the variation of the RMSE (Figure 5). As shown in Figure 5, the RMSE of the daily model forecast with a forecast lead time of 10 d is approximately 3.5 °C. After bias correction using the analogue ensemble averaging method, the RMSE is reduced to approximately 2.5 °C–3 °C, and the RMSE is reduced by 16% during the test dates.

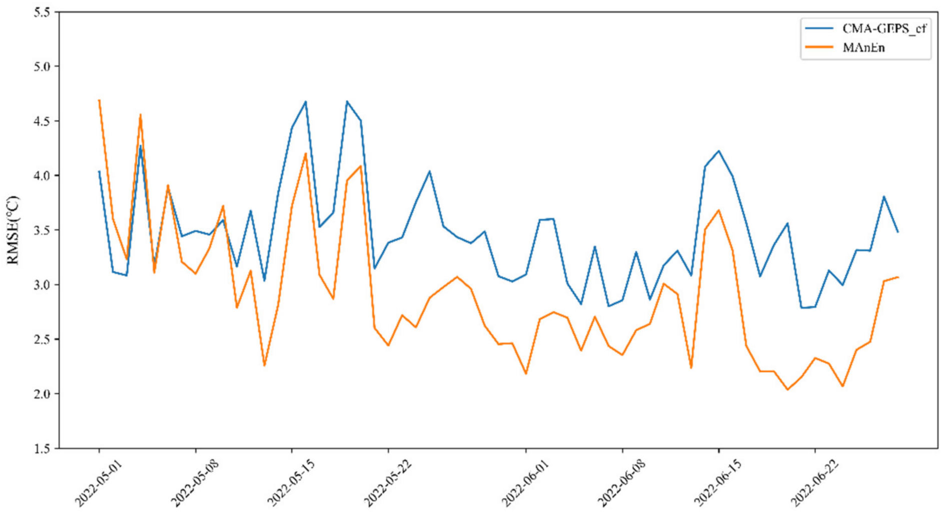



**Figure 5.** RMSE of daily 240 h forecast for 1 May–28 June 2022.

### *4.2. Tests of Forecast Ability at the Stations*

The RMSE distributions of the model forecasts and analogue ensemble averaging forecasts of 2405 stations with forecast times of 192 h, 240 h, 288 h, and 336 h from 1 May to 28 June 2022, are compared and analyzed, as shown in Figure 6.

It can be seen from the diagram that with the extension of the forecast lead times, the RMSE at the 2405 stations increase (comparing Figure 6a,c,e,g, and b,d,f,h, respectively), for both the model forecasts and the analogue ensemble averaging forecasts. The forecast difficulty of 2-m temperature gradually increases with the extension of the forecast lead times. For the same forecast lead time (comparing Figure 6a and b, c and d, e and f, g and h), the RMSE of the model forecasts are reduced for most stations, especially in Northwest, Southwest, and North China, when using the analogue ensemble averaging forecast method. The 8-d, 10-d, 12-d, and 14-d forecasts are greatly improved, and the rest of the region is also improved. For the four forecast lead times, the percentage of stations with reduced RMSE to all stations is shown in the following table (Table 2).

**Table 2.** The decreasing percent of RMSE of the stations.

| Forecast Lead Time | Decreasing Percent |
|---|---|
| 192 h | 31.4% |
| 240 h | 29.6% |
| 288 h | 23.5% |
| 336 h | 24.4% |

The RMSE (a, c, e, and g) of 2-m temperature forecasts by the model are obviously smaller in South China, Central China, and East China, than in other regions. This is greatly related to the amount of observation data and the difference in terrain height between the actual measurement and the topographic height at which the forecast is located. In general, the more distributed the stations are, the more abundant the observation data and the more accurate the model forecast. In addition, the temperature forecast error related to the terrain height difference is part of the systematic bias of the model forecast and can be corrected by statistical methods. Figure 7 shows the RMSE distribution for the 2-m temperature forecasts using the 240 h forecast lead time at each station. The terrain height of the observation stations is ordered from smallest to largest after the model forecast and bias correction using the analogue ensemble averaging method.

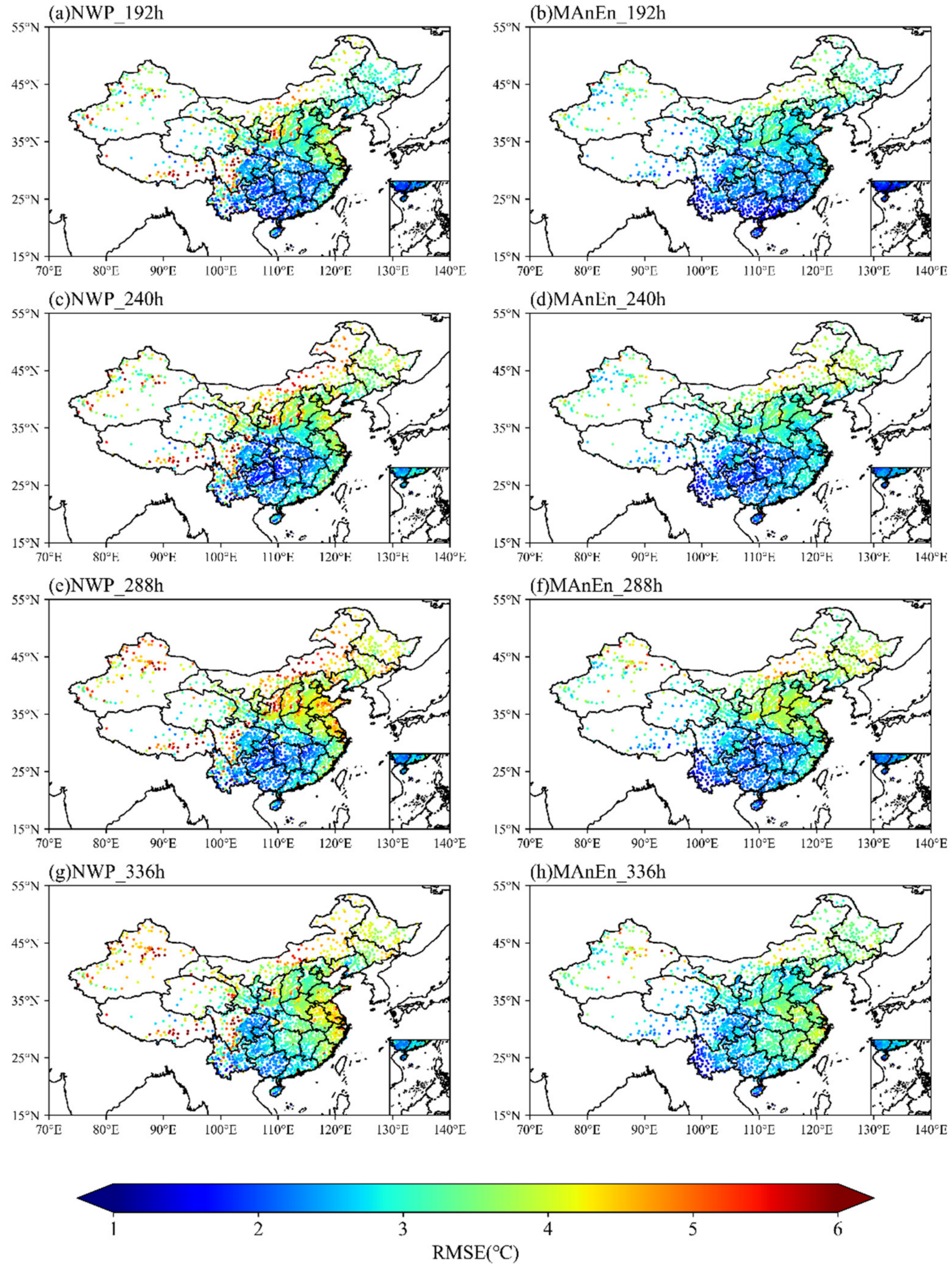



**Figure 6.** RMSE distribution of model forecasts and analog ensemble averaging forecasts for 2405 stations. ((**a**,**c**,**e**,**g**) are model forecasts; (**b**,**d**,**f**,**h**) are analog ensemble averaging forecasts).

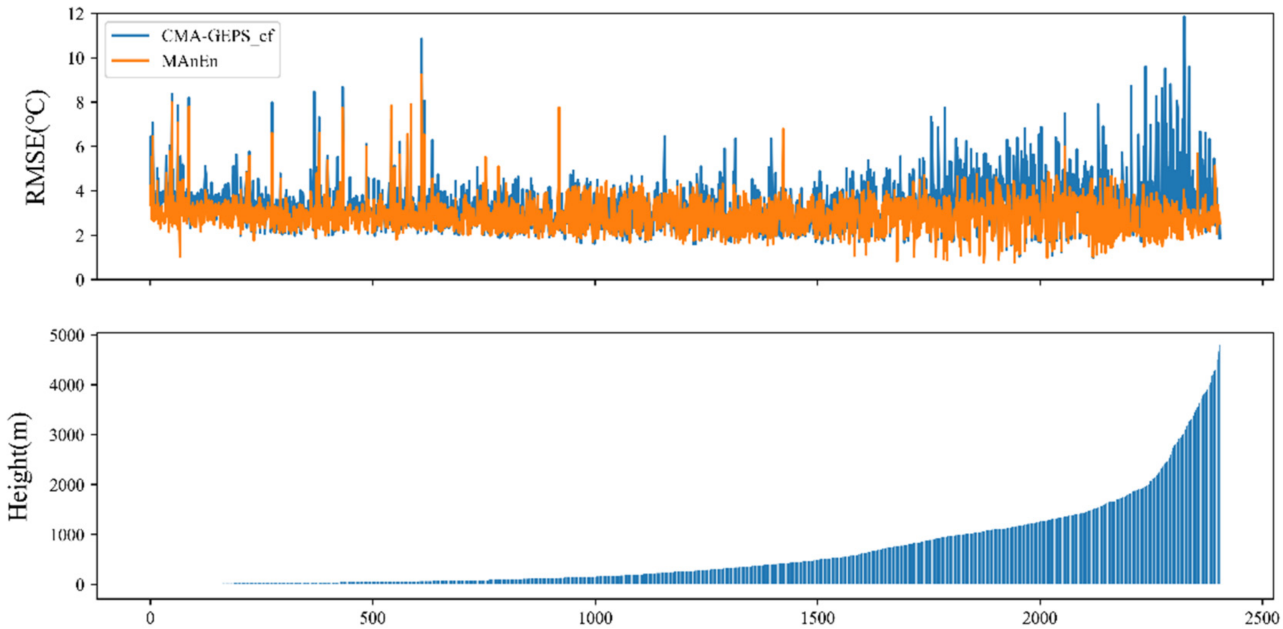



**Figure 7.** RMSE of model forecasts and analog ensemble averaging forecasts and the terrain height of stations.

Figure 7 shows that the RMSEs for the 2-m temperature forecasts at stations with higher terrain height have an increasing trend compared with plain areas, and the errors are larger. This indicates that the temperature prediction error in the complex terrain area has greater uncertainty than that in the plain area. However, after bias correction using the analogue ensemble averaging forecast method, the RMSEs of the 2-m temperature forecasts of each station decrease, obviously, and a relatively consistent size is observed. This indicates that this method corrects the systematic error caused by the terrain height difference between the elevation of the station and the topographic height at which the forecast is located, and the correction effect is more significant for the stations with larger terrain heights.

### *4.3. Forecast Case*

According to the above results, the analogue ensemble averaging method forecasts have better performance than the model forecasts, and the model forecast errors are effectively reduced.

Figure 8 shows the results from the 240-h model forecasts results and analogue ensemble averaging method forecasts starting from 00 h on 5 June 2022, and the 336-h forecast results from 00 h on 22 May 2022. For both the 240-h and the 336-h 2-m temperature forecasts, the results after the correction of the analogue ensemble averaging method are closer to the actual observation than the model forecasts. From the overall regional point of view, after correction, the results from the Southwest, Central and North China are closer to the station observations.

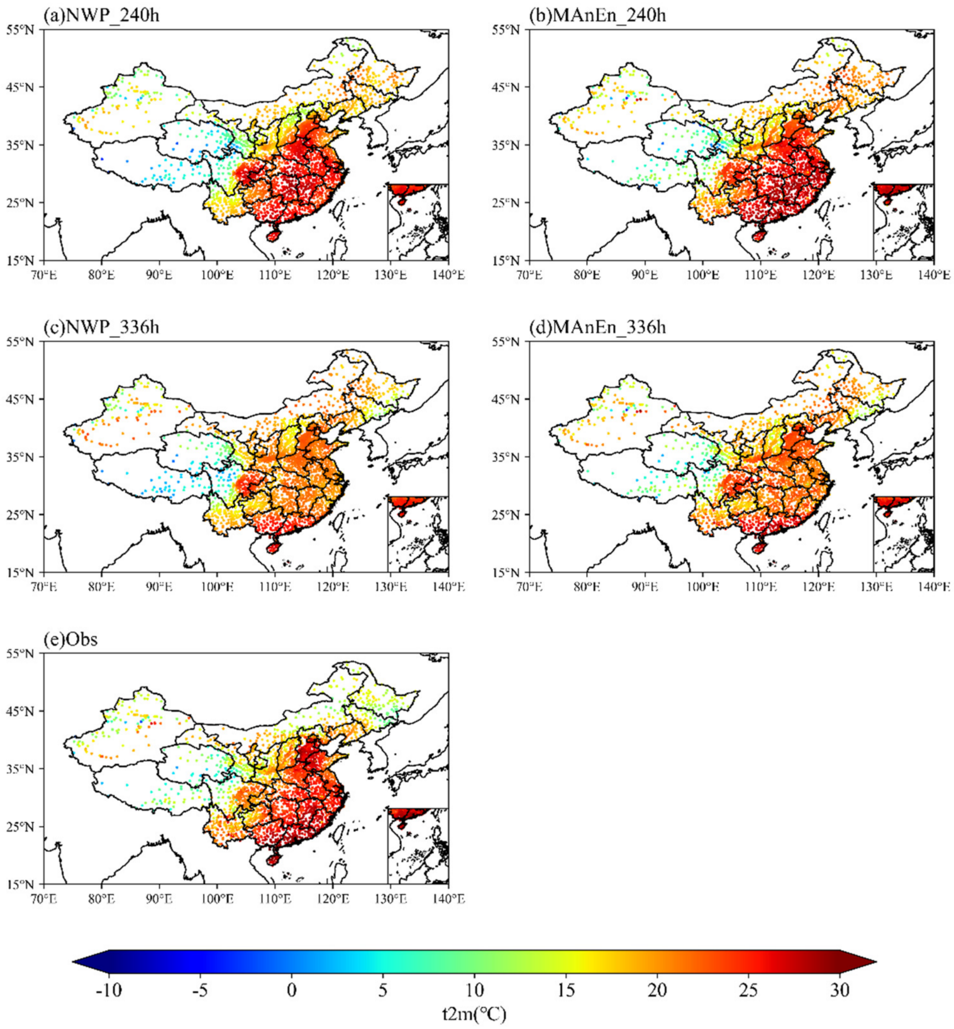



**Figure 8.** Observations, 240-h, and-336 h model forecasts, the analogue ensemble averaging forecasts of 2-m temperature ((**a**,**c**): model forecasts; (**b**,**d**): analogue ensemble mean forecasts; (**e**): observations) at 00:00 UTC on 5 June 2022.

## 5. Conclusions and Discussion

In this paper, the 'analogue' concept is applied to the statistical interpretation of the medium- and long-term forecasts of the model, and the analogue ensemble averaging correction method is developed. Based on the CMA-GEPS model, the 180–348 h forecasts of 2-m temperature and the observation data of 2405 stations in China are tested and analyzed, and compared with the model forecasts. The performance of the analogue ensemble averaging method is analyzed by several key test indexes, such as bias, MAE, and RMSE. The following conclusions are obtained:

(1) The analogue ensemble averaging method has a good correction effect on the long forecast time of 180–348 h and effectively reduces the systematic error of the model forecasts of the 2-m temperature, which is higher at night and lower during the day. The forecast deviation is reduced by approximately 0.5 °C, and the MAE and RMSE are reduced by approximately 10–20%. During the test period from 1 May to 28 June 2022, the RMSE reduction rate of 240 h forecast reached 91% (the proportion of samples with reduced RMSE to all samples). Comparing the correction effect of different forecast lead times, the analogue ensemble averaging forecast method still has a better correction effect in longer forecast lead times.

(2) After comparisons based on the spatial prediction results from 2405 stations, it is shown that the application of the analogue ensemble averaging forecast method

effectively reduces the RMSEs of forecasts in Southwest China, Northwest China, and North China. The improvement rate of different forecast times reaches 31.4%. This method has a more obvious effect on the correction of complex terrain areas.

In this paper, only a factor of 2-m temperature is comprehensively tested and evaluated. In the future, multifactor application tests and evaluations need to be carried out. In addition, for the analogue ensemble averaging correction method, the length of the historical forecast dataset, the design of the similarity measure, the meteorological elements used in the selection of similar historical forecasts, and the forecast lead times are the key factors affecting the correction effect. Therefore, in the future, we will focus on the different forecast elements: (1) establish a longer historical forecast dataset so that there are more opportunities to find results similar to the current forecast; (2) for different forecast elements, more model predictors are used as similar reference factors, and the optimal weight combination is found to improve the correction effect; and (3) the actual data corresponding to the historical forecast selected by the analogue ensemble method can not only generate deterministic forecasts by averaging, but also generate probability forecasts, and can be used for objective correction of precipitation forecasts.

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