Frontiers in Earth Science

TYPE Methods
PUBLISHED 24 April 2023
DOI 10.3389/feart.2023.1099344

OPEN ACCESS

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SPECIALTY SECTION
This article was submitted to Interdisciplinary Climate Studies, a section of the journal Frontiers in Earth Science

RECEIVED 15 November 2022
ACCEPTED 31 March 2023
PUBLISHED 24 April 2023

CITATION
Mei H, Qishu W, Huijun L, Siyu Y and Guofei W (2023), Correction method by introducing cloud cover forecast factor in model temperature forecast.
Front. Earth Sci. 11:1099344.
doi: 10.3389/feart.2023.1099344

Correction method by introducing cloud cover forecast factor in model temperature forecast

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Objective temperature forecast products can achieve better forecast quality by using one-dimensional regression correction directly based on the present model temperature forecast product, and the forecast accuracy can be further improved by adding appropriate auxiliary factors. In this paper, ECMWF forecast products and ground observation data from Fujian are used to revise the surface temperature at 2 m by introducing a cloud cover forecast factor based on the model temperature forecast correction method. Analysis shows that the forecast deviation of daily maximum and minimum temperature after the revision of a single-factor forecast is obviously correlated with cloud cover. A variety of prediction schemes are designed, and the final scheme is determined through comparative testing. The following conclusions are drawn: all schemes based on cloud cover grouping can improve forecast performance, and the total cloud cover scheme is generally better than the low cloud cover scheme. There is a good positive correlation between the forecast deviation of maximum temperature and the mean total cloud cover; that is, the more cloud cover, the bigger the deviation. The minimum temperature is negatively correlated with cloud cover when the cloud cover is less than 40% and positively correlated for the rest. The absolute forecast deviations of the maximum and minimum temperatures are larger when the total cloud cover is less. Whether for T_{max} or T_{min} forecast, the binary regression scheme after grouping consistently showed the best performance, with the lowest MAE. The final scheme was used to forecast the maximum and minimum temperature in 2021, and most verification indicators showed improvement in most forecast periods. The forecast accuracy for the 36-h daily maximum and minimum temperature is 81.312% and 91.480%, respectively, which is 2.4%–2.6% higher than the single-factor regression scheme. The forecast skill scores (FSS) reach 0.065 and 0.086, indicating that the method can effectively improve forecast quality in a stable manner and can be used for practical forecasting.

KEYWORDS

the maximum temperature, the minimum temperature, cloud cover, MOS method, forecast accuracy, mean absolute deviation

1 Introduction

In recent years, with the advancement of numerical forecast and the continuous improvement of statistical methods such as model output statistics (MOS), perfect prognosis (PP), artificial neural networks (ANN), Kalman filter (KF), and the support vector machine (SVM) (Huang and Xie, 1993; Zhang and Sha, 2001; Wang et al., 2004; Chen et al., 2005; Wu et al., 2007; Qian et al., 2010; Chen et al., 2011; Li et al., 2011), the accuracy of temperature forecasts has been greatly improved, but it is still unable to meet people's growing demand for accurate and refined temperature forecasts. Therefore, methods of improving the accuracy of forecasts is an urgent issue. Temperature is sensitive to local weather and geographical characteristics. The MOS is the most commonly method used in daily temperature forecasting. It can introduce many forecast factors that are difficult to introduce by other methods, match local weather and climate characteristics, and make appropriate corrections to the systematic deviations of numerical models (Liu et al., 2004).

The MOS forecast method usually requires a certain length of historical data samples to achieve better forecast results. The samples should preferably have the same climate background characteristics, and the consistency factors of the samples should be as large as possible. Che et al. (2011) used the K-mean clustering method to make seasonal divisions in North China for temperature forecasts; the forecast error is generally smaller than the traditional seasonal division. Zhi et al. (2010, 2014) compared the different training periods of super-ensemble temperature forecasts and found that a sliding training period is better than a fixed training period. Wu et al. (2016) further optimized the division method of the training period. They used the quasi-symmetric sliding training period method to revise the model temperature forecast by selecting the sample data 1 month before and after the forecast date and also considered the model consistency and the sample's climate characteristics, which significantly improved the forecast quality. However, methods that highlight the training period do not consider the influencing factor of temperature. Many scholars in China have introduced multiple factors. Liu et al. (2004) selected multiple factors for MOS forecasts, and the forecast verification results showed that the short-term temperature forecast was improved in most cases. Zhang et al. (2011) used the MOS method to select 11 factors on the basis of T213 to forecast the daily maximum and minimum temperatures of 124 stations in Yunnan Province, and the forecast results were improved, especially in summer. Zhu and Mu (2013) established a MOS forecast equation based on the WRF model, using temperature, wind, sea level pressure, relative humidity, and precipitation at Urumqi Airport as forecast factors. The accuracy of the hourly temperature forecast was significantly improved compared with the forecast results directly output by the model. The introduction of multiple factors to establish equations can improve temperature prediction, but the factors should be selected to optimize the role of the main factors.

The local variation of temperature depends on temperature advection, pressure change, atmospheric stability, and diabatic processes (Zhu et al., 2000). Liang and Huang (2006) pointed out that in the absence of large-scale system transit, the diabatic processes are the main factors that affect the temperature change in the near-surface layer, while the diabatic processes are affected by many factors, such as the sky condition, the topography, underlying surface, and vegetation type. Therefore, it is necessary to fully consider the role of cloud cover in temperature forecast. Qin et al. (2007) analyzed the relationship between cloud cover and temperature in Nanning City and found that total cloud cover has a significant negative correlation with mean temperature and maximum temperature, while low cloud cover has a significant negative correlation with maximum temperature and a significant positive correlation with minimum temperature. Zheng et al. (2013) adopted the optimized cloud scheme in GRAPES, and the surface temperature simulated by the model was closer to the observed value. Luo et al. (2014) classified the sky conditions and established the classic MOS forecast model. They selected the numerical forecast product factors corresponding to the general occurrence time of maximum and minimum temperature, which positively and significantly improved the quality of local temperature forecast. Forecasters also make adjustments to temperature forecasts by evaluating the cloud cover in practice, but the specific adjustment extent varies from person to person and cannot be uniformly regulated.

Currently, most MOS temperature forecast methods directly perform one-dimensional regression correction on the model temperature forecast product, which can achieve good correction effects. The forecast quality is not worse than that of multi-factor modeling correction and has been widely used in many meteorological departments. Different amounts of cloud cover will cause differences in the deviation between the model temperature forecast and the actual observation. Therefore, it is meaningful to introduce cloud cover forecast as an auxiliary factor to further optimize the MOS temperature forecast, but few people have studied and applied it in practice. The Fujian Provincial Meteorological Observatory divided temperature samples according to different total cloud cover, established independent models for each subset, and achieved good correction effects. It ranked first in the comprehensive skill of temperature in the 2021 National Meteorological System Intelligent Forecast Technology Method Exchange Competition. In this paper, the optimal scheme of daily maximum and daily minimum temperature forecasts based on cloud cover is selected by further studying the cloud cover groupings and comparing several schemes.

2 Data and pre-processing

2.1 Data

In this paper, the maximum and minimum temperature at 2 m, total cloud cover, and low cloud cover of ECMWF from 2018 to 2021 issued by the China Meteorological Administration were adopted. The ECMWF data are obtained twice a day at 08:00 and 20:00 (Beijing time, same below), and the forecast time period is 0–240 h, the horizontal resolution is $0.125^{\circ} \times 0.125^{\circ}$, and the time resolution is 3 h for 0–72 h and 6 h for 78–240 h. To ensure calculation efficiency and reliability of the observation data, the testing stations are 70 national meteorological stations in Fujian Province.

2.2 Data pre-processing

The inverse distance weighting interpolation method is used to interpolate the ECMWF fine grid point surface elements to the station, and the Cressman objective interpolation method is used as a reference for the weighting coefficients. This is carried out for station-based modeling and forecast. The interpolation method is as follows:

$$P_k = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} W_{kij} P_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{n} W_{kij}} \quad (1)$$

In Formula 1, P_k is the forecast value of the element at the kth station obtained by interpolation, P_{ij} is the forecast value of the element at the grid point (i, j), W_{kij} is the weight factor, and m and n are the numbers of grid points in the latitudinal and longitudinal directions, respectively. The weighting factor used in this paper can be expressed as follows:

$$W_{kij} = \begin{cases} \dfrac{R^2 - d_{kij}^2}{R^2 + d_{kij}^2}, & d_{kij} < R \\ 0, & d_{kij} \geq R \end{cases} \quad (2)$$

In Formula 2, R is the effective influence radius and d_{kij} is the distance from grid point (i, j) to station k. In operational work, for the convenience of calculation, the difference between longitude and latitude is used to represent the distance, and the effective influence radius is taken as 1°.

The daily maximum temperature (T_{max}) and the daily minimum temperature (T_{min}) are calculated as the maximum and minimum temperatures over a 24-h period, respectively. Cloud cover (total cloud cover or low cloud cover) is calculated as the 12-h mean cloud cover, and the mean cloud cover at a given point is the mean of all available cloud cover forecasts at that point within a given forecast time period. Because the latest ECMWF data are usually obtained later than the forecast start time, the forecast in this paper is the correction of the model lag of 12 h; that is, the first day of operational forecast corresponds to the 12–36-h period of the model forecast and so on for the other forecast periods.

3 Methods

3.1 Correction method

The one-dimensional linear regression equations for T_{max} and T_{min} at a certain forecast period for each station are established using the least square method:

$$S_i = a + bF_i. \quad (3)$$

In Formula 3, S_i is regression correction temperature at the *ith* forecast period, F_i is the temperature forecast value of the model at this period, a is a constant, and b is the regression coefficient. Taking cloud cover as the division basis, the forecast value and observation value are used to establish a and b for each subset after division and are updated twice a day, and the obtained regression equation is used to correct T_{max} and T_{min} of the corresponding subset.

During the day, direct solar radiation can reach the earth's surface and warm it. If there is cloud cover, the cloud layer will reflect some of the solar radiation, reducing the energy input to the surface and hindering warming. At night, the heat released from the surface dissipates upwards, causing the surface temperature to decrease. If there is cloud cover, the cloud layer can reflect the heat from the surface, thereby weakening heat dissipation and hindering cooling. Therefore, the effect of cloud cover on surface temperature is opposite during the day and night, and the reverse is true under clear skies. Because cloud cover at night and during the day has opposite effects on temperature, daytime cloud cover is used as the auxiliary factor for the correction of T_{max}, and nighttime cloud cover is used as the auxiliary factor for correction of T_{min}.

3.2 Training period

The quasi-symmetric mixed sliding training period method can significantly improve the quality of a temperature forecast by the MOS method and has great application value in operational work (Wu et al., 2016). This paper continues to use this method, and the total samples during the training period mixed samples from 35 days before the forecast date and samples from 35 days after the forecast day of the previous year and used sliding sampling with the forecast date.

3.3 Inspection method

To evaluate the operational performance of the MOS forecast, the mean absolute error of temperature forecast (*MAE*, Zhou et al., 2006), the temperature forecast accuracy (*FA*), and the temperature forecast skill scores (FSS) were used in this paper:

$$FA = \frac{N_r}{N_f} \times 100\%. \quad (4)$$

In Formula 4, FA is the percentage of the absolute deviation between the temperature forecast whose observed value does not exceed 2°C, N_r is the number of stations (times) where the value of the difference between the forecast temperature and the observed value does not exceed 2°C, and N_f is the total number of stations (times) that have been forecasted.

$$FSS = \frac{MAE_0 - MAE_N}{MAE_0} \quad (5)$$

In Formula 5, MAE_O is the MAE of the temperature forecast of the initial scheme and MAE_N is the MAE of the temperature forecast for the improved scheme. When $MAE_O = 0$, $FSS = 1.01$.

4 Scheme comparison and improvement

4.1 Initial scheme design

Based on the observed temperature data from 2019 to 2020 and temperature, total cloud cover, and low cloud cover forecast data from

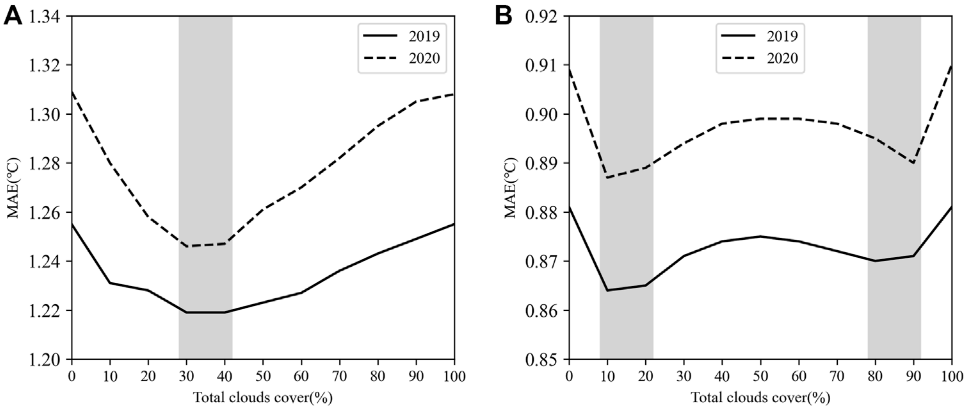

FIGURE 1
Comparison of the *MAE* of different total cloud cover threshold forecasts on the first day. **(A)** T_{max}; **(B)** T_{min}.

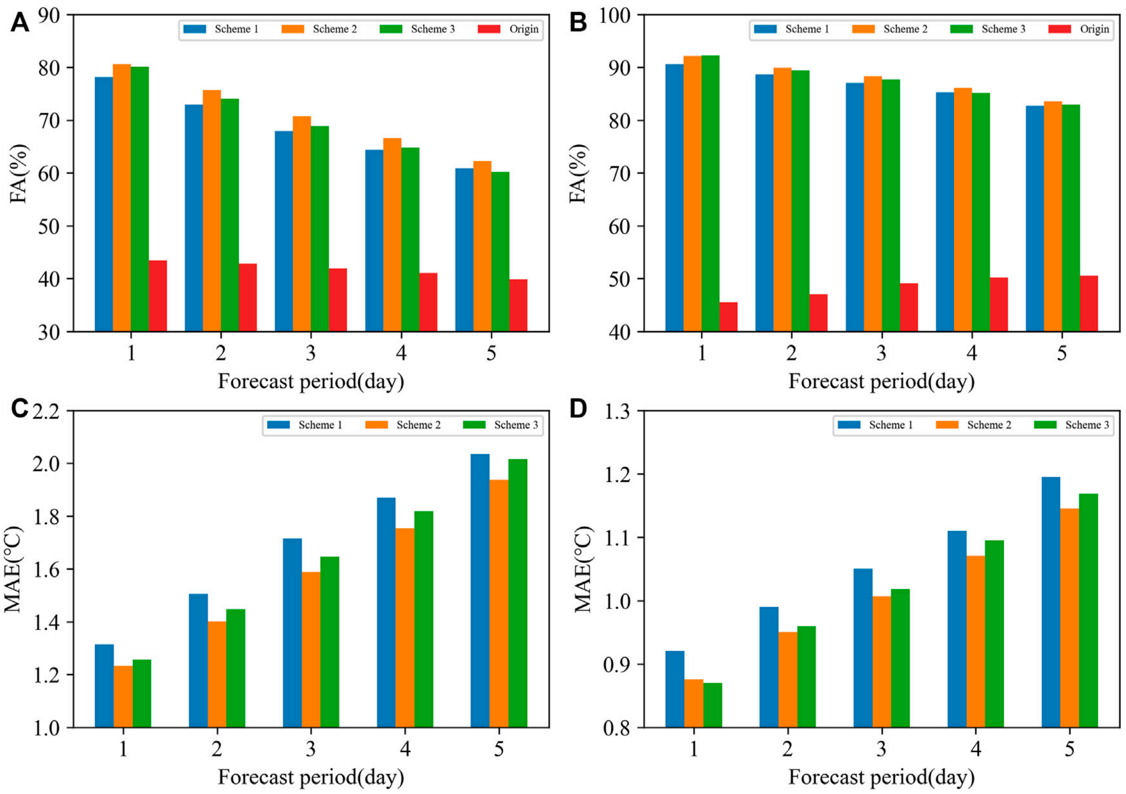

FIGURE 2
Comparison of the forecast results of the three schemes from 2019 to 2020. **(A)** *FA* of T_{max} (unit: %), **(B)** *FA* of T_{min} (unit: %), **(C)** *MAE* of T_{max} (unit: °C), and **(D)** *MAE* of T_{min} (unit: °C).

ECMWF, three schemes are designed and compared to discuss the feasibility and the improvement direction of introducing cloud cover.

Scheme 1: No grouping, using the quasi-symmetric mixed sliding training period method (one-dimensional regression) to model and revise all temperature forecast samples (Wu et al., 2016).

Scheme 2: Grouping by total cloud cover, the temperature forecast samples with total cloud cover less than the specified threshold value are grouped for separate modeling correction, and the remaining samples are grouped as another group. The exhaustive method is used for the cloud cover threshold, starting from 0% total cloud cover as the threshold, increasing to 100% at 5% intervals; 21 cloud cover values were selected as grouping thresholds for correction.

Scheme 3: Grouping by low cloud cover, the temperature forecast samples with cloud cover less than the specified

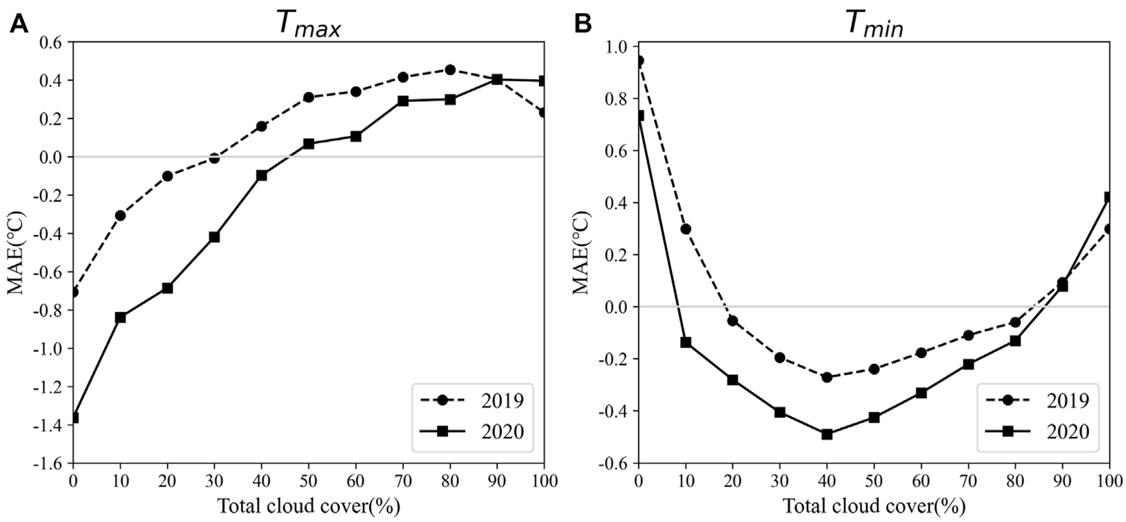

FIGURE 3
Relationship between the mean deviations of 12–36 h forecasts of temperature and the total cloud cover in 2019 and 2020. **(A)**: T_{max} and **(B)**: T_{min}.

threshold are grouped for separate modeling correction, and the remaining samples are grouped as another group. Groupings of the cloud thresholds are the same as in Scheme 2.

According to the forecast results of Scheme 2 (Figure 1A), the absolute forecast deviation of T_{max} for the first day is less than that of no grouping (the threshold of 0% cloud cover can be approximated to no grouping). When about 30%–40% cloud cover is used as the grouping threshold, the forecast result is better, the *MAE* is small, and the *MAE* of the optimal threshold can be reduced by about 0.05°C. For the T_{min} forecast (Figure 1B), the *MAE* of grouping is also less than that of no grouping. The improvement is obvious when grouping by the less and more cloud cover threshold intervals, and grouping by the less cloud cover threshold is slightly better than grouping by the more cloud cover threshold. Because the potential for improvement of the T_{min} forecast is smaller than that of the T_{max} forecast, there is not much difference between the different thresholds. The performance of Scheme 3 is similar to that of Scheme 2 and will not be presented separately.

The optimal threshold scheme of T_{max} and T_{min} among the 21 grouping methods of Scheme 2 and Scheme 3 was selected to compare with Scheme 1 and the original uncorrected results. The results are shown in Figure 2. Seen from *FA*, the forecast results of T_{max} and T_{min} in all three revised schemes were significantly improved compared with the original uncorrected ones, and the improvement rate in the first 5 days was 100% or above. For T_{max}, the scheme grouping by total cloud cover performed better than the other two schemes in all forecast periods in terms of *FA* and *MAE* (Figures 2A, C). The *FA* of the scheme grouping by low cloud cover improved compared with no grouping in the first 4 days, but it was not better on the fifth day, while the *MAE* improved in all time periods. For T_{min}, the performance of Scheme 2 was also the best compared with the other schemes in all forecast periods (Figures 2B, D), followed by Scheme 3, and both schemes were better than Scheme 1 in terms of *FA* and *MAE*. In general, the introduction of cloud cover improved the forecast performance, and the introduction of total cloud cover was better than low cloud cover.

4.2 Relationship between cloud cover and temperature correction forecast deviation

In general, the least squares method is used to directly model and correct based on the modeled temperature forecast products. The ideal result of the mean deviation of the objective temperature forecast is unbiased; however, there is a significant correlation between forecast deviation of temperature and cloud cover. Figure 3 shows the relationship between the mean forecast deviation of T_{max} and T_{min} based on Scheme 1 and the total cloud cover with a 12–36 h forecast period in 2019 and 2020 for 70 national meteorological stations. The relationship between low cloud cover and temperature forecast is similar to the total cloud cover, which is not given in the paper. It can be seen that for T_{max} (Figure 3A), the 2-year mean forecast deviation of temperature has a good positive linear correlation with cloud cover; the correlation coefficient is 0.85 in 2019 and 0.95 in 2020. The forecast value is often less than the actual when the cloud cover is below 30%–40% and has a large linear slope. The forecast tends to be greater than the actual when the cloud cover is above 40% and has a smaller slope. For T_{min} (Figure 3B), a negative correlation exists below the threshold of 40% cloud cover, with a steep linear slope; the correlation coefficients were −0.96 in 2019 and −0.89 in 2020. Conversely, a positive correlation with a smaller linear slope was found above the threshold of 40% cloud cover; the correlation coefficients were 0.95 in 2019 and 0.96 in 2020. The common point of T_{max} and T_{min} is that the absolute deviation will be larger when the cloud cover is low. Although the influence of cloud cover has been considered in the ECMWF temperature forecast, there is still a strong mean correlation between the mean forecast deviation and cloud cover. Meanwhile, schemes of grouping by cloud cover demonstrate an improvement in forecast accuracy. Therefore, the multiple regression scheme introduces a cloud cover factor based on cloud cover grouping that can be used in professional work. In the following, schemes will be designed and compared to select the best.

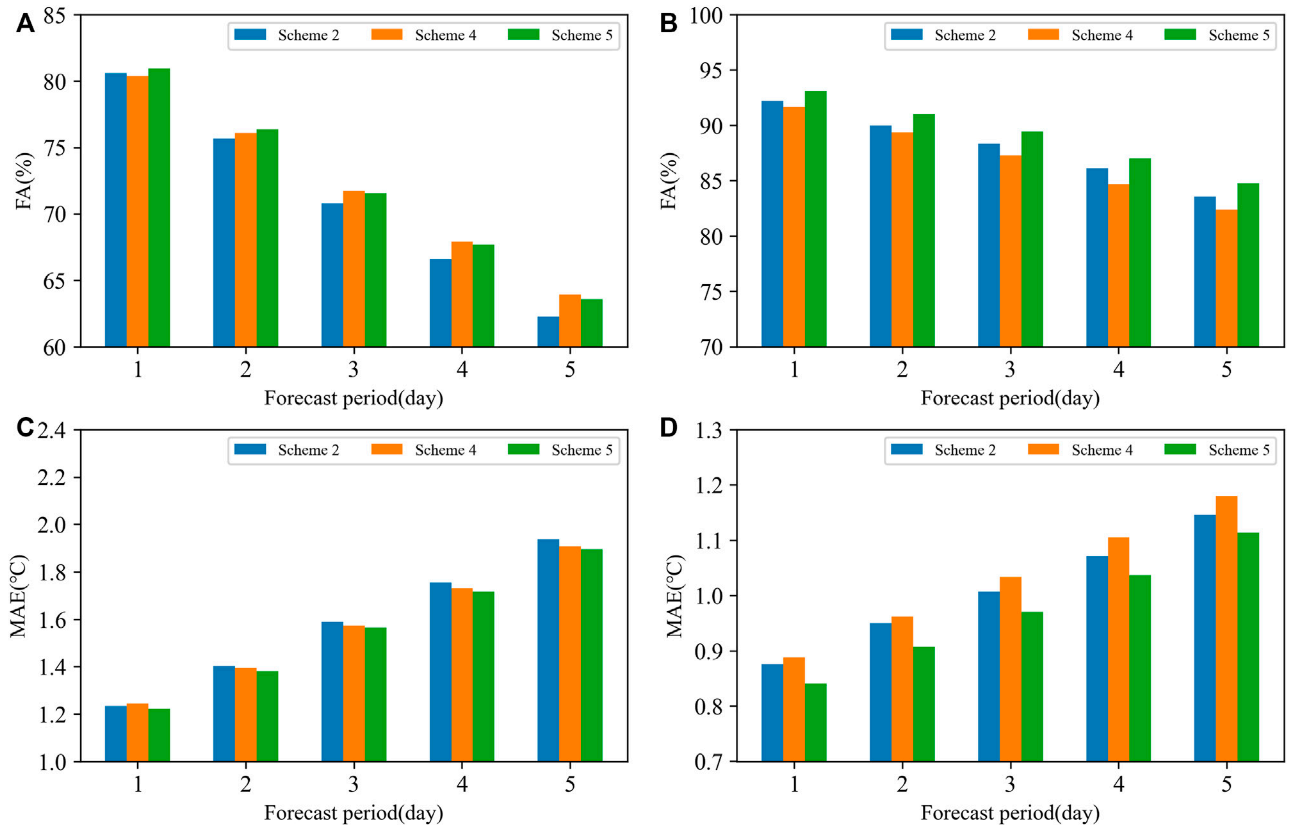

FIGURE 4
Comparison of the forecast results of the three schemes from 2019 to 2020. **(A)** *FA* of T_{max} (unit: %), **(B)** *FA* of T_{min} (unit: %), **(C)** *MAE* of T_{max} (unit: °C), and **(D)** *MAE* of T_{min} (unit: °C).

4.3 Improving scheme design

Based on the aforementioned discussion, improvement plans were designed to maximize forecast performance by considering the roles of total cloud cover, grouping methods, and binary regression methods in the forecast.

Scheme 4: Binary regression, using the quasi-symmetric mixed sliding training period method (Wu et al., 2016), taking temperature and total cloud cover forecast as two forecast factors to establish the forecast equation.

Scheme 5: After grouping by total cloud cover, correction is performed using Scheme 4. From Figure 1A, it can be seen that the optimal threshold for the high-temperature grouping is at 30%–40% cloud cover, and Figure 3 shows that the 40% cloud cover is a special turning point in both T_{max} and T_{min} forecasts. In practical applications, less cloud cover is conducive to the increase of daytime T_{max} and the decrease of nighttime T_{min}. Therefore, the 40% cloud cover is used as the grouping threshold. After grouping, the cloud cover is introduced for binary regression to establish the forecast equation.

Using the aforementioned two plans, a verification experiment was conducted for T_{max} and T_{min} from 2019 to 2020, and the results were compared with Scheme 2 whose grouping threshold is set at 40% cloud cover (Figure 4). In terms of forecast verification results, for T_{max} (Figures 4A, C), the *FA* in Scheme 5 is generally larger than that in Scheme 2. With increased forecast time, the improvement is more obvious, but it is slightly less than that of Scheme 4 on the third to fifth days, while Scheme 4 is slightly worse than Scheme 2 on the 1st day. In terms of *MAE*, Scheme 5 has a slight decrease, which is better than the other two schemes. For T_{min} (Figures 4B, D), the overall improvement of Scheme 5 is more significant than that of T_{max}, and all forecast indicators at all forecast periods are improved compared with other schemes. Scheme 3 is better than Scheme 4. In general, Scheme 5 is superior to other schemes. For T_{max}, there is a linear relationship between the mean forecast deviation and cloud cover, with different slopes between low cloud cover and high cloud cover. Each of the three schemes has advantages, but the performance of the binary regression scheme after grouping performs more stably in terms of *MAE*. For T_{min}, the mean forecast deviation has an opposite relationship between less and more cloud cover. Therefore, the binary regression scheme after grouping can better improve the forecast quality.

4.4 Availability and stability of improvement schemes

Scheme 5 was used for temperature forecast in 2021 to test the usability and stability of the method, and the verification results are shown in Table 1. According to the results of the T_{max} forecast, all

TABLE 1 Test results of T_{max} and T_{min} forecasts at 1–7 d by Scheme 1 and Scheme 5 in 2021.

Statistics		Scheme	1 d	2 d	3 d	4 d	5 d	6 d	7 d
T_{max}	FA (%)	1	78.706	74.178	69.951	67.544	64.179	60.138	55.477
		5	81.312	76.127	72.159	69.034	66.317	62.065	56.718
		Improvement	2.606	1.949	2.208	1.490	2.138	1.927	1.241
	MAE (°C)	1	1.300	1.460	1.610	1.710	1.830	2.000	2.210
		5	1.215	1.380	1.532	1.657	1.775	1.958	2.204
		FSS	0.065	0.055	0.048	0.031	0.030	0.021	0.003
T_{min}	FA (%)	1	89.124	87.771	86.064	83.868	81.034	77.621	74.858
		5	91.480	89.657	87.676	85.228	82.697	78.661	76.374
		Improvement	2.356	1.886	1.612	1.360	1.663	1.040	1.516
	MAE (°C)	1	0.970	1.030	1.090	1.150	1.240	1.350	1.440
		5	0.887	0.950	1.023	1.099	1.171	1.296	1.378
		FSS	0.086	0.078	0.061	0.044	0.056	0.040	0.043

verification indicators in Scheme 5 show significant improvements compared to Scheme 1, with an overall increase in *FA* of 1.2–2.6%. The highest increase is 2.6% on the 1st day; after the improvement, the mean accuracy rate reached 81%. The accuracy continued to increase by about 2% in the fifth to sixth days. *MAE* decreased by 0.04–0.08°C on all forecast periods, except for slightly less on the 7th day. The first 3 days decreased by about 0.08°C, and the FSS can reach 0.05–0.06. In terms of the T_{min} forecast, all indicators of all forecast periods also showed improvement, with an increase of 1.0%–2.4% in FA, and the highest increase was 2.36% on the first day. *MAE* decreased by approximately 0.05°C–0.08°C. The FSS in the first 3 days reached 0.06 to 0.08, and the *FA* on the first day reached 91.48%.

In recent years, the application of the quasi-symmetric sliding training period MOS forecast method has greatly improved T_{max} and T_{min} forecast results in Fujian Province. The method ranks among the top in national forecast quality inspections; especially, the *FA* of T_{min} is basically more than 90%. Under the condition that the forecast accuracy of the original model has not been improved, there is some room for improvement of the forecast results, but the forecast accuracy of Scheme 5 increased by about 2% compared with Scheme 2 in T_{max} and T_{min} forecast in 2021. These findings show that this method can further improve the forecast quality, and it has a certain stability. At present, it has achieved good results in the operational application of actual temperature forecasts in Fujian. Although Scheme 5 showed some improvement in T_{max} forecasts compared to Scheme 4, the difference was not significant, and the best plan should be selected based on local conditions and corresponding evaluations in practical applications.

5 Conclusion

This paper designs a MOS forecast method that uses total cloud cover as a predictor for the 2 m temperature forecast. Different schemes are designed and optimized using multiple verification indicators. The results show that:

1. All grouping schemes based on cloud cover show improvement in forecast performance, and the introduction of total cloud cover shows advantages over low cloud cover.
2. There is a good positive correlation between the annual mean forecast deviation of the T_{max} and the mean total cloud cover. For T_{min}, there is a negative correlation below 40% cloud cover and a positive correlation above it. Both T_{max} and T_{min} forecasts have larger absolute deviations when total cloud cover is less than 40%.
3. Whether for T_{max} or T_{min} forecast, the binary regression scheme after grouping consistently showed the best performance, with the lowest MAE.
4. Based on the optimization of the scheme in the last 2 years, the improved scheme is used to forecast the T_{max} and T_{min} in 2021. The verification indicators show certain improvements in most forecast periods, with *FA* for T_{max} and T_{min} being 81.312% and 91.480%, respectively, which is an improvement of 2.4%–2.6% relative to single-factor regression plans. The FSS of 0.065 for T_{max} and 0.086 for T_{min} indicate that this method effectively improves forecast quality and stability, making it suitable for practical forecasting. The introduction of total cloud cover to the MOS forecast can significantly improve the forecast quality, but the correction effect may be poor when the model's cloud cover forecast has large biases from observations. Further research is needed to determine the reliability of cloud cover forecasts from multiple models and ensemble prediction products.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

HM: methodology and writing. WQ: data curation and software. LH: visualization. YS: editing and translation. WG: validation.

Funding

This work was supported by the Natural Science and Technology Program of Fujian Province (2021J01457), the National Key R&D Program (2018YFC1506905), and the Innovation Project of the China Meteorological Administration (CXFZ2021Z009). The Chinese Meteorological Administration's retrospective summary project (FPZJ2023-061).

Conflict of interest

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