

Test and Evaluation of Relative Humidity Forecast in Each Competition Area of the "14th National Winter Games" by Intelligent Forecasting Methods

Sitong LIU, Xuefeng YANG*

Hulunbuir Meteorological Bureau, Hulunbuir 021008, China

Abstract Based on ground observation data of relative humidity, the prediction performance of STNF and MIFS in each competition area during February 13–26, 2024 was tested and evaluated by using two intelligent forecasting methods (STNF and MIFS). The results show that STNF had better performance in forecasting relative humidity in high-altitude areas, and was suitable for fine forecasting under complex terrain. MIFS improved the short-term forecast of some low-altitude stations, but the long-term reliability was insufficient. STNF method performed better than MIFS during 0–24 h. As the prediction time extended to 24–72 h, the errors of both methods showed a systematic increase trend. STNF had higher precision, lower root mean square error and smaller mean error in most regions under the background of most weather systems, showing its superiority as a forecasting method of relative humidity. However, the precision of MIFS was slightly higher than that of STNF in Liangcheng without system background, revealing that MIFS may also be an effective option in some specific conditions.

Key words Intelligent forecast; Relative humidity; Model test

DOI 10.19547/j.issn2152–3940.2025.01.009

The "14th National Winter Games" is the first major national winter sports event held after the Beijing Winter Olympics, as well as the first national comprehensive games hosted by Inner Mongolia, and meteorological elements play an important role in the whole event. Many scholars have made detailed studies on the meteorological support for major events such as the Winter Olympics. For instance, Chen Mingxuan *et al.*^[1] introduced the operation and evaluation results of the "Weather Forecast Demonstration Plan for Smart Winter Olympics in 2022" (FDP), and for the first time carried out real-time demonstration applications of new technologies such as artificial intelligence interpretation and revised forecast and sub-100-meter objective forecast in complex mountain venues of the Winter Olympics, which has strongly supported the high-standard meteorological service support for the Winter Olympics. Xu Jingfeng *et al.*^[2] conducted a comparison experiment on machine learning correction of 10 m wind speed forecast at 100-meter scale in complex mountains for the Winter Olympics, and found that the introduction of complex terrain and forecast errors played an important positive role in the correction of 10 m wind speed deviation. Wang Zaiwen *et al.*^[3] studied the prediction method of ground temperature and wind speed at the Winter Olympic site under complex terrain based on CMA-BJ numerical prediction model, and further improved the precision of 10 m wind speed correction prediction by the prediction method. Chen Zijian *et al.*^[4] analyzed the process of a cold pool in the

Zhangjiakou Competition Area of the Winter Olympics, and constructed a conceptual model of the establishment, development, maintenance and dissipation process of the cold pool. The smooth progress of ice and snow sports events is closely related to meteorological conditions. In this paper, the performance of two intelligent forecasting methods (STNF and MIFS) in forecasting relative humidity in the forecasting stations of different competition areas during February 13–26, 2024 was tested to understand the forecasting capability of different intelligent forecasting methods and summarize experience for meteorological support services for major events in the future.

1 Data and methods

Objective forecast data generated based on the two intelligent forecast methods are from the demonstration plan for the "14th National Winter Games" and stored in CSV data format, including the results of hourly forecast during 0–24 h and three-hour forecast during 24–72 h. The period is from January 16 to February 29, 2024. The information of the selected 11 stations are shown in Table 1. The starting time of prediction is 05:00 and 17:00, and the actual observation data is the relative humidity in the stations.

2 Research methods

The test methods used in this paper include prediction precision (P), root mean square error ($RMSE$) and mean error (ME), and the formulas are as follows:

$$P = \frac{N_r}{N} \times 100\% \quad (1)$$

In formula (1), N_r is the number of samples predicted accurately; N is the total number of samples participating in the test; it is correct when the error range of relative humidity is $\pm 10\%$.

$$RMSE = \frac{\sum_{i=1}^n (P_i - A_i)^2}{n} \quad (2)$$

In formula (2), n is the number of samples; P_i is the model prediction value; A_i is the deviation of the actual value. $RMSE$ represents the average deviation between the prediction value and the actual value, reflecting the total error. The smaller the $RMSE$ is, the closer the prediction value is to the actual value, and the

better the forecast effect is. On the contrary, the forecast effect is worse.

$$ME = \frac{1}{N} \sum (P_i - A_i) \quad (3)$$

In formula (3), n is the number of samples; P_i is the model prediction value; A_i is the deviation of the actual value. When ME is calculated, the positive and negative errors are offset, and it reflects some systematic errors in the statistical region. When ME is 0, the prediction effect is the best.

Table 1 Information of the stations

Station	Competition area	Altitude//m	Meteorological element
Obstacle chase mountain top in Liangcheng	Liangcheng	2 079.9	Air temperature, wind, and relative humidity
Obstacle chase starting point in Liangcheng	Liangcheng	1 990.0	
Ice Sports Center in Hailar	Hailar	624.0	
Snow skills starting point in Zalantun	Zalantun	556.0	
U-shaped groove starting point in Zalantun	Zalantun	463.0	
U-shaped groove middle point in Zalantun	Zalantun	434.0	
U-shaped groove end point in Zalantun	Zalantun	430.0	
Departure Hall in Kharchin	Chifeng	1 126.0	
Track end point in Kharchin	Chifeng	1 178.0	
Track starting point in Kharchin	Chifeng	1 312.0	
Hilltop reserve area in Kharachin	Chifeng	1 562.0	

3 Test of relative humidity forecast

3.1 Test and analysis of relative humidity at different altitudes By comparing the precision, root mean square error and mean error of relative humidity forecast at different altitudes by two intelligent prediction methods (0–24 and 24–72 h), it is found that the precision of the station at an altitude of 1 312 m was the lowest, while the root mean square error and mean error were the highest, and MIFS forecast was better than STNF. Except for the station, the precision of the other stations was higher, among which the precision of relative humidity forecast in stations below 1 100 mm was higher than that of 1 100–1 600 m and above 1 600 m. STNF model has the best precision for forecasting relative humidity, and the precision of relative humidity forecast based on STNF model in the station at 624 m was as high as 100%. The situation of root mean square error was basically consistent with that of precision. Seen from mean error, the prediction values of relative humidity in the stations below 1 150 m were higher than the actual values, while those of the other stations were mainly lower than the actual values. With the extension of forecasting time, the precision of the two intelligent forecasting methods decreased, and the forecasting error increased.

Through data analysis, it is found that in terms of the correlation between precision and altitude, the two models had excellent performance in high-altitude stations. The precision of STNF during 0–24 h was generally close to or more than 98%, and that of MIFS was slightly lower but generally stable. During 24–72 h, STNF still had high precision. The performance of the two models in low-altitude stations decreased significantly, and root mean

square error was as high as 24.00%–25.77%, indicating that the forecast uncertainty in low-altitude areas was greater.

In terms of model performance, STNF had the advantages of higher precision, lower root mean square error in most stations (especially at high altitudes), and greater stability over time. The feature of MIFS is that the short-term forecast of some low-altitude stations was slightly improved, but the error during 24–72 h significantly increased.

In conclusion, STNF performed better in high-altitude areas, and is suitable for fine prediction under complex terrain. MIFS could improve the short-term forecast of some low-altitude stations, but the long-term reliability was insufficient.

3.2 Test and analysis of relative humidity under different starting time of prediction and periods The changing characteristics of the objective forecast test indicator in time were studied, and the changing characteristics of two objective forecast errors in hourly forecast during 0–24 h and three-hour forecast during 24–72 h under different starting times of 05:00 and 17:00 were analyzed. The changes of forecast precision and root mean square error of relative humidity with the extension of aging were tested.

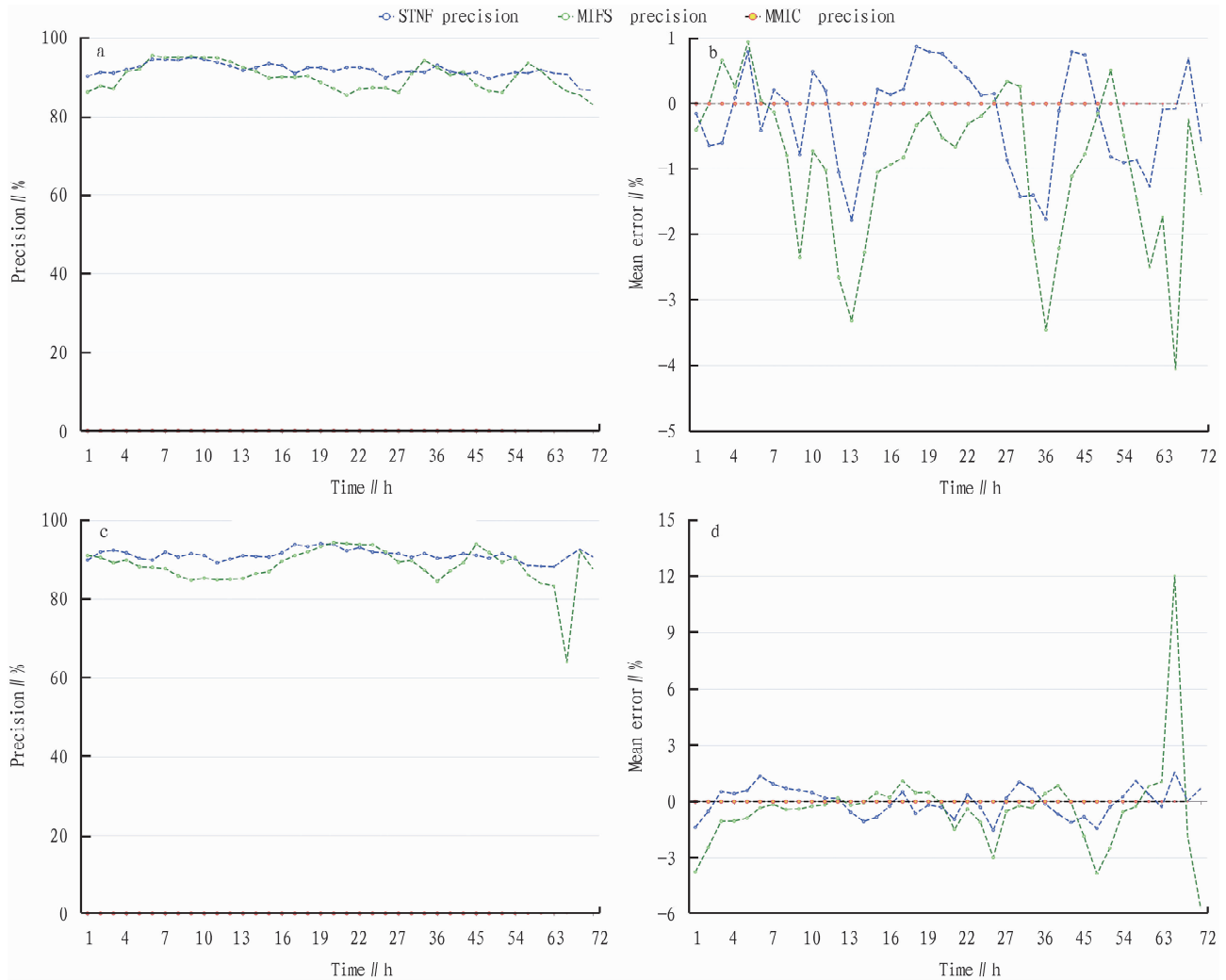
Through data analysis, it is found that when the prediction was started at 05:00, the precision of STNF during 0–24 and 24–72 h was the highest (Fig. 1a), and its root mean square error was the smallest, followed by MIFS. In terms of mean error (Fig. 1b), the prediction values of relative humidity by STNF were mostly higher than the actual values during 0–24 h, while they were lower than the actual values during 8 h, which appeared

mainly in the daytime. Prediction values were mostly lower than the actual values during 24–72 h, but higher than the actual values during 42, 49 and 65 h, that is, it was easily higher in the early morning. During 0–24 and 24–72 h, the prediction values of relative humidity by MIFS were mostly lower than the actual values during 0–24 and 24–72 h, and higher only in the morning, while error peak appeared in the evening. When the prediction was started at 17:00, the precision of STNF during 0–24 and 24–72 h was the highest on the whole (Fig. 1c), and root mean square error was the smallest, followed by MIFS. In terms of mean error (Fig. 1d), the precision of STNF in 0–24 and 24–72 h was mainly high at night and low during the day, and the error peak occurred in the evening and midnight. During 0–24 and 24–72 h, the prediction values of relative humidity by MIFS were mostly lower than the actual values, only higher in the morning, and the error peak mainly appeared in the noon and evening.

As the prediction was started at 05:00, STNF showed stable

performance during 0–12 h (precision 90%–95%), and root mean square error increased slowly (9.64%–14.46%). Although MIFS had slightly higher short-term precision (*e.g.* 95.54% during 6 h), the error increased faster (root mean square error increased from 11.13% to 16.15%). When the prediction was started at 17:00, the precision of STNF increased from night to next morning (17–24 h), and the error fluctuation was small. MIFS performed well during 19–23 h, but for long-term prediction (*e.g.* 66 h), root mean square error was unusually high (20.97%), and the systematic bias was significant (mean error was –5.77%).

In summary, STNF was suitable for 24- and 72-hour forecast with high stability requirements, and it had better performance especially in the night when the prediction was started at 17:00. During 0–12 h, MIFS can be used in the morning forecast as the prediction was started at 17:00, but its long-term performance needs to be combined with the error threshold for risk control.



Note: a. Precision (starting from 05:00); b. Mean error (starting from 05:00); c. Precision (starting from 17:00); d. Mean error (starting from 17:00).

Fig. 1 Precision and mean error of relative humidity forecast by two intelligent forecasting methods from February 17 to 27, 2024

3.3 Test and analysis of relative humidity in different competition areas The spatial variation characteristics of relative hu-

midity were studied, and the error characteristics of the two intelligent forecasting methods in the four competition areas (Hailaer,

Zhalantun, Liangcheng and Chifeng) in 0–72 h were analyzed. The performance differences of the two intelligent forecasting methods in different geographical locations and different climate backgrounds were explored.

Error analysis of intelligent forecasting methods based on different geographical locations and forecasting periods shows that there were significant spatial and temporal differences in the forecasting performance of relative humidity. During 0–24 h, STNF method performed better than MIFS, and precision was higher by 2.82% and 0.89% especially in Chifeng and Liangcheng. With the extension of the forecasting time to 24–72 h, the errors of the two methods showed a systematic increase trend. The precision of Chifeng decreased by 1.27%–2.69%, and the root mean square error increased by 0.79%–1.85%, reflecting the general law that the forecasting stability decreased with the extension of the forecasting time.

The spatial distribution characteristics show that Hailaer region had the best performance, and the precision of STNF method was 100%–99.95% during 0–72 h, while the root mean square error was less than 5%, which may be related to its unique characteristics of mid-temperate continental climate and stable humidity environment. In Chifeng where error was the biggest, the root mean square error of MIFS method was as high as 16.83%–17.36%, which is inferred to be related to the severe humidity fluctuation in the temperate semi-arid climate. The mean error in the northern areas (Hailaer and Zhalantun) showed a positive deviation (1.41%–4.91%), while the mean error in the southern areas (Liangcheng and Chifeng) showed a significant negative deviation (from –2.67% to –5.34%), reflecting the influence of the difference of humidity change mechanism on the model adaptability under different climate backgrounds.

3.4 Test and analysis of relative humidity under the influence of different weather systems The weather systems affecting each competition area on a daily basis during the test period were counted, and the forecast performance of relative humidity by the two intelligent forecasting methods under different weather systems was calculated. The optimal intelligent forecasting method under different weather systems was analyzed.

The precision of STNF was generally higher than that of MIFS, and especially under the background of upper trough and lower vortex, STNF had more obvious advantages. In Liangcheng, the precision of STNF and MIFS had different advantages and disadvantages under different weather systems, but the precision of MIFS was slightly higher than that of STNF under no system background. Under the background of all weather systems, the root mean square error of STNF was generally lower than that of MIFS, indicating that the prediction results of STNF were more stable and accurate. The mean error of STNF and MIFS varied in different weather systems, but in general, the mean error of STNF was closer to zero in most cases, indicating that its forecast deviation was smaller especially under the background of upper trough and low vortex.

In general, STNF showed higher precision, lower root mean

square error and smaller mean error under the background of most weather systems, which shows its superiority as a forecasting method of relative humidity. However, the precision of MIFS was slightly higher than that of STNF in Liangcheng without system background, suggesting that MIFS may also be an effective option in some specific conditions. Therefore, in practical application, an appropriate intelligent forecasting method can be selected according to the specific weather system background to optimize the forecasting performance.

4 Conclusions

Based on data of objective forecast and real stations, the relative humidity in Hailaer, Zhalantun, Liangcheng and Kharachin (Chifeng) predicted by two objective forecasting methods (STNF and MIFS) from January 16 to February 29, 2024 was tested and evaluated. The main conclusions are as follows.

(1) STNF had better performance in forecasting relative humidity in high-altitude areas, and was suitable for fine forecasting under complex terrain. MIFS improved the short-term forecast of some low-altitude stations, but the long-term reliability was insufficient. STNF was suitable for 24–72 h with high stability requirements, and performed better especially in the night when the prediction was started at 17:00. MIFS can be preferred for short-term (0–12 h) morning forecasts starting at 05:00, but its long-term performance needs to be combined with error thresholds for risk control.

(2) STNF method performed better than MIFS during 0–24 h. As the prediction time extended to 24–72 h, the errors of both methods showed a systematic increase trend.

(3) STNF had higher precision, lower root mean square error and smaller mean error in most regions under the background of most weather systems, showing its superiority as a forecasting method of relative humidity, so it is worthy of trust and popularization. However, the precision of MIFS was slightly higher than that of STNF in Liangcheng without system background, revealing that MIFS may also be an effective option in some specific conditions.

References

- [1] CHEN MX, YANG L, QIN R, *et al.* Operation and evaluation of SMART2022-FDP[J]. *Transactions of Atmospheric Sciences*, 2024(3): 361–375.
- [2] XU JF, SONG LY, CHEN MX, *et al.* Comparative machine learning-based correction experiment for a 10 m Wind Speed Forecast at a 100 m resolution in complex mountainous areas of the Winter Olympic Games[J]. *Chinese Journal of Atmospheric Sciences*, 2019, 47(3): 805–824.
- [3] WANG ZW, QUAN JP, ZHANG XY. Forecasting surface temperature and wind speed at Winter Olympics stations over complex terrain based on the CMA-BJ model products[J]. *Acta Meteorologica Sinica*, 2019, 81(6): 926–942.
- [4] CHEN ZJ, LI JB, LI XL, *et al.* Observation and analysis of a cold-air-pool process in Zhangjiakou area for Winter Olympic Games[J]. *Meteorological Monthly*, 2023, 49(6): 708–720.