Precipitation forecast on the township scale using the frequency matching method

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Abstract. Based on the daily accumulated precipitation from the European Centre for Medium-Range Weather Forecasts (ECMWF) as the forecast data, and the daily accumulated precipitation from ground meteorological stations as observations, experiments of precipitation forecast on the township scale are carried out by means of the frequency matching method. The results show that, compared with the bilinear interpolation, the frequency matching method is more effective in increasing the anomaly correlation coefficient and the equitable threat score, as well as decreasing the root-mean-square error, the false alarm rate of light rain and the missing rate of heavy rain. The frequency matching method can greatly calibrate and improve the refined precipitation forecast on the township scale.

1. Introduction

With the development of the economy and the improvement of the society, the public requirements for the accuracy of daily weather forecasts are gradually increasing \cite{1-2}. The weather forecast based on the spatial scale of the county is not enough to meet the needs of various industries such as agricultural production, disaster prevention and mitigation, transportation and tourism. Therefore, the refined weather forecast on the township scale is necessary, which is aimed at improving the forecast accuracy based on the spatial refinement \cite{3}. For the grass-roots meteorological service, a simple forecast method is easier to promote. Compared with other meteorological elements such as temperature, precipitation is discontinuous and in non-normal distribution. So it is necessary to establish a refined forecast model suitable for daily precipitation \cite{4-6}.

In this study, the frequency matching method is used to calibrate the precipitation forecast. Ebert \cite{7} proposed the idea of frequency matching to solve the problem of the area expansion of light rain and the area reduction of heavy rain caused by the average smoothing effect of ensemble members. Li et al. \cite{8} corrected precipitation forecast biases using the frequency matching method and concluded the method effectively eliminated biases in precipitation amount and areal coverage. Plenty of studies have demonstrated that the frequency matching method is fairly effective in the calibration of the precipitation forecast \cite{9-11}.

The paper aims to examine the frequency matching method to perform the precipitation forecast on the township scale, with the structure organized as follows. The used data and methods are briefly described in Section 2. In Section 3, we present the assessment of forecasts based on both of the
bilinear interpolation and the frequency matching method. Finally, a conclusion and discussion is provided in Section 4.

2. Data and methods

2.1. Data
The daily accumulated precipitation from the European Centre for Medium-Range Weather Forecasts (ECMWF) at 1200 UTC on a 0.125° × 0.125° horizontal resolution is employed as the forecast data, with the period from 1 May to 31 October 2017. The forecast lead time ranges from 24 h to 96 h with an interval of 24 h. The daily accumulated precipitation from 124 ground meteorological stations in Nantong, Jiangsu Province is used as the observation.

2.2. The frequency matching method (FMM)
The systematic difference can be estimated through comparing forecast and observed precipitation frequency distributions. The principle of the frequency matching method is to keep the cumulative frequency distributions of forecast precipitation consistent with observed values [12-14]. The frequency is actually the number of stations at the spatial distribution. The declining average method is used to calculate the forecast and observed frequency as follows:

\[ f_{k,t} = (1 - w)f_{k,t-1} + wf_{k,t}, \quad w = \frac{1}{n} \]

where \( f_{k,t} \) and \( f_{k,t-1} \) are the average frequency of precipitation reaching a certain threshold \( k \) for day \( t \) and \( t-1 \), \( f_{k,t} \) is the frequency at threshold \( k \) for day \( t \) and \( w \) is the decaying weight. \( n \) is the declining average day and is assigned as the value of 30 in this study. That means the training data is accumulated over the initial 30-day period.

The value of precipitation corresponding to the observed frequency equal to the forecast frequency divided by the value of forecast precipitation is the correction coefficient of the forecast precipitation. Correction coefficients for all forecast precipitation are obtained by the linear interpolation. The calibrated value of forecast precipitation by the frequency matching method is obtained by multiplying the forecast value by the corresponding correction coefficient.

2.3. Verification methods
In this study, the anomaly correlation coefficient (ACC), the root-mean-square error (RMSE), the equitable threat score (ETS), the false alarm rate of light rain (FAR) and the missing rate of heavy rain (MR) are used to evaluate the forecast. The ACC can be used to verify the correlation between the forecast and the observation. The larger the ACC, the better the forecast. The smaller the RMSE, the smaller the difference between the forecast and the observation, that is, the smaller the forecast error. When ETS is greater than 0, the forecast is considered skillful, and when ETS equals 1, it is the best forecast. The smaller the false alarm rate of light rain and the missing rate of the heavy rain, the higher the forecast skill.

\[
\text{ACC} = \frac{1}{n} \sum_{i=1}^{n} (f_i - \bar{f})(o_i - \bar{o}) / \sqrt{\left[ \frac{1}{n} \sum_{i=1}^{n} (f_i - \bar{f})^2 \right] \left[ \frac{1}{n} \sum_{i=1}^{n} (o_i - \bar{o})^2 \right]} \\
\text{RMSE} = \left[ \frac{1}{n} \sum_{i=1}^{n} (f_i - o_i)^2 \right]^{1/2}
\]
ETS = \frac{a - e}{a + b + c - e}, \quad e = \frac{(a + b)(a + c)}{a + b + c + d}

FAR = \frac{c}{a + c}

MR = \frac{b}{a + b}

n is the total number of stations. f_i is the forecast value and o_i is the observation. \bar{f} and \bar{o} are the mean value of forecasts and observations. a is the number of stations where forecasts and observations both reach a certain precipitation threshold. b is the number of stations where observations reach a certain precipitation threshold and forecasts do not. c is the number of stations where forecasts reach a certain precipitation threshold and observations do not. d is number of stations where there is no precipitation in observations and forecasts.

3. Results

The frequency matching method (FMM) is used to calibrate the precipitation forecast after the grid data from ECMWF is bilinearly interpolated to the stations. In order to compare the forecast ability between the bilinear interpolation and FMM, Figure 1 illustrates the ACC and RMSE of daily accumulative precipitation with lead times from 1 to 4 days. In general, the ACC and the RMSE of the precipitation forecast are decreasing and increasing respectively over the lead time. The ACC by FMM is larger than the one by the bilinear interpolation and the RMSE by FMM is smaller than the one by the bilinear interpolation at different lead times. Therefore, the employment of FMM can improve the correlation between the forecast and the observation and reduce the forecast bias.

![Figure 1](image1.png)

**Figure 1.** The ACC (a) and RMSE (b) of daily accumulative precipitation for 1-4 day forecast lead time of the bilinear interpolation (blue line) and the frequency matching method (red line).

Additionally, forecasts of the lead time of 24 h are taken as an example to study the improvement of FMM on daily accumulative precipitation forecasts over different thresholds. The results are shown in Figure 2. Due to the limitation of the station number, the ETS score is generally small. The largest ETS score occurs at the 10 mm threshold due to its more samples. For thresholds above 0.1 mm and above 50 mm, the forecast is almost incapable due to severe false alarms of light rain and missing of heavy rain. In general, ETS scores of FMM forecasts are larger than those by the bilinear interpolation over all thresholds.
Figure 2. The ETS score over different thresholds of daily accumulative precipitation for 24 h forecast lead time of the bilinear interpolation (blue line) and the frequency matching method (red line).

Figure 3 shows the false alarm rate of light rain and the missing rate of heavy rain over different thresholds of daily accumulative precipitation for 24 h forecast lead time. After FMM, the false alarm rate of light rain and the missing rate of heavy rain over different thresholds are both decreasing compared with the bilinear interpolation. The false alarm of light rain is relatively serious, so the false alarm rate of light rain is decreasing more than the missing rate of heavy rain by means of FMM.

Figure 3. The false alarm rate of light rain and the missing rate of heavy rain over different thresholds of daily accumulative precipitation for 24 h forecast lead time of the bilinear interpolation (blue line) and the frequency matching method (red line).

Figure 4. The false alarm rate at the threshold of 0.1 mm (a) and the missing rate at the threshold of 25 mm (b) of daily accumulative precipitation for 1-4 day forecast lead time derived from the bilinear interpolation (grey column) and the frequency matching method (black column).
As shown in Figure 4, both the false alarm rate at the threshold of 0.1 mm and the missing rate at the threshold of 25 mm of daily accumulative precipitation do not change a lot with increasing forecast lead times. That is, the forecast of light rain and heavy rain for the close forecast lead time is not better than the longer ones. The false alarm rate at the threshold of 0.1 mm and the missing rate at the threshold of 25 mm by FMM calibration are smaller than those by the bilinear interpolation at all lead times. Considering that the decrease of the false alarm rate at the threshold 0.1 mm is even greater than the missing rate at the threshold of 25 mm after the FMM calibration, the frequency matching method can be considered more effective in decreasing the false alarm rate of light rain.

4. Summary
The study of the refined forecast on the township scale by means of the frequency matching method (FMM) compared with the bilinear interpolation has been conducted. The main findings are concluded as follows.

(1) The forecasts calibrated by FMM become more accurate than those derived from the bilinear interpolation, with the larger anomaly correlation coefficient, the smaller root-mean-square error and the larger equitable threat score. In addition, the false alarm rate of light rain and the missing rate of heavy rain are both reduced, which could be attributed to that the observation data is added to correct the forecast of precipitation. Additionally, FMM is more effective in decreasing the false alarm rate of light rain than the missing rate of heavy rain.

(2) The frequency matching method is an intelligent method of the refined precipitation forecast on the township scale, which does not require plenty of computing resources. With the climate background of conspicuous changes [15-20], aiming at more accurate operational forecast of precipitation, it would be effective to promote FMM for the grass-roots meteorological service, particularly for stations on complex terrains [21]. Moreover, further improvement of the method, e.g. the selection of the declining average day, is also of great importance.

(3) Further investigations will also be carried out with respect to forecast experiments on extremes of both precipitation and temperature with statistical and dynamical methods to improve their corresponding prediction skills [22-25] under different climatological backgrounds [26-27], which is in favor of the prevention and mitigation of associated disasters [28-29].

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