Statistical Downscaling Precipitation Forecast for Hydropower Industry and Its Calibration Using Frequency Matching Method

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Abstract. This study deals with high-resolution precipitation forecasts for hydropower industry using a statistical downscaling method based on the linear regression of the categorized daily precipitation forecasts taken from the European Centre for Medium-Range Weather Forecasts (ECMWF), Japan Meteorological Agency (JMA), the US National Centers for Environmental Prediction (NCEP), and the United Kingdom Met Office (UKMO), in the TIGGE archive as well as the quality-controlled precipitation data from China Merged Precipitation Analysis (CMPA). To further improve the forecast skill of the daily precipitation, the calibration of the precipitation forecast has been performed by using a statistical postprocessing approach called the frequency matching method (FMM). The results show that the statistical downscaling forecast skill using categorized precipitation scheme is much larger than that of bilinear interpolation and that using uncategorized precipitation scheme in terms of the equitable threat score (ETS), anomaly correlation coefficient (ACC) and root-mean-square error (RMSE), no matter the precipitation is light rain, moderate rain, or heavy rain and the above. The calibration of the precipitation forecasts using FMM can significantly reduce the false alarm of the light rain and the missing rate of the heavy rain and the above. Hence, it can improve the inflow forecast skill in the hydrological models which make use of observed and predicted precipitation as input variables.

Introduction

Recently medium-range QPFs have been addressed to improve inflow forecast skill [1,2,3]. Due to the forecast uncertainty of the numerical models, some authors tried to use ensemble precipitation forecasts in their inflow forecasts [4,5,6]. As the global ensemble prediction models can only provide relatively low-resolution precipitation forecasts which cannot satisfy the demand of the hydropower industry, it is necessary to use downscaling technique to produce high-resolution QPFs for the hydrological models. Statistical downsampling is frequently used as it is not so expensive and relatively easy to operate [7,8] and it can provide medium-and extended-range forecast in a vast area, or even in a global scope. Zhi et al.[7] established regression equations based on different categories of daily rainfall to improve the high-resolution precipitation forecasts in their statistical downscaling algorithm.

It has long been demonstrated that the precipitation forecast error has negative impact on the forecast skill of hydrological models [9,10]. Many studies have performed successful precipitation forecast calibration through statistical postprocessing approach [11,12]. Zhu and Luo [13] developed a method called the frequency matching method (FMM) for precipitation forecast calibration. The FMM algorithm significantly reduces systematic precipitation forecast errors and can produce more realistic precipitation patterns. Nevertheless, this method has some common limitations with extreme events and dry bias elimination like other precipitation calibration approaches.

This study aims to investigate high-resolution precipitation forecasts for hydropower industry using a statistical downscaling method and the FMM calibration approach.
Data and Methods

Data
Multimodel ensemble forecasts of the precipitation were taken from European Centre for Medium-Range Weather Forecasts (ECMWF), Japan Meteorological Agency (JMA), the US National Centers for Environmental Prediction (NCEP), and the United Kingdom Met Office (UKMO), in the TIGGE archive. More details about TIGGE data can be found in Zhi et al. [14]. The forecast data of each model cover the period of 1 June to 31 August 2010, 2011 and 2012, with the forecast area in China, the horizontal resolution of 1°×1°, and the forecast lead time of 24–168h. For verification of the forecast data and the statistical downscaling as well as the precipitation calibration, we took the hourly precipitation data from China Merged Precipitation Analysis (CMPA) which is quality-controlled based on more than 2,400 gauge observations over China and the CPC (NOAA Climate Prediction Center) Morphing (CMORPH) satellite QPE [15]. The CMPA data cover the period of 1 June to 7 September 2010, 2011 and 2012 for the same area, with the horizontal resolution of 0.1°×0.1°.

Statistical Downscaling Method
To gain high resolution forecast data, we shall interpolate the global model forecast into the higher resolution data. Then the high resolution forecast will be calibrated. In this study, statistical downscaling applies linear regression method to establish the statistical relationship between the model forecasts and the observed values after Krishnamurti et al.[16]:

\[ y_i = ax_i + b \]

where \( a, b \) are regression coefficients, \( x_i \) is the model forecast, \( y_i \) is the observed value in the training period, and the calibrated forecast in the forecast period. It should be noted that the model forecast will be interpolated into the high resolution grid point at the same spatial and temporal resolutions as the observational data. After the regression coefficients are calculated in the training period at each grid point, the forecast will be calibrated in the forecast period by using the above mentioned regression equation. Cross-validation is applied to establish regression equation in the training period. In addition, the precipitation forecasts are divided into three categories based on the daily rainfall amount, namely, 0.1-9.9 mm (light rain), 10.0-24.9 mm (moderate rain), and over 25mm (heavy rain and the above). The regression equation is established for light rain, moderate rain, and heavy rain and above, respectively in the training period. In the forecast period, the precipitation will be calibrated by using respective regression equation for different category of the precipitation. Hereafter, the statistical downscaling forecast using categorized (uncategorized) precipitation in the regression equation is called categorized (uncategorized) precipitation scheme.

Frequency Matching Method
As indicated by Zhu and Luo [13], the frequency matching method (FMM) is a statistical adjustment using cumulative frequency distributions of precipitation forecast and observed values. We can use an observational dataset and preceding forecasts in the training period to construct the respective cumulative frequency distributions for forecasts and observations. In addition, a decaying average is introduced for appropriate historical sampling that makes the cumulative frequency distribution of forecasts match that of the observations. Then a frequency match between preceding observations and forecasts is performed using bilinear interpolation. The precipitation forecast calibration is conducted at each grid point.

The cumulative distribution function (CDF) is calculated as the number of grid points over a given domain where the precipitation forecast or observed values exceed a threshold. The CDFs for both precipitation forecast and the observed values are updated with the Kalman filter method:
\[
\overline{CDF_{i,j}} = (1-W)\overline{CDF_{i,j-1}} + W(CDF_{i,j}),
\]

where variable \( \overline{CDF_{i,j}} \) is the decaying averaged CDF at threshold \( i \) for day \( j \), while \( \overline{CDF_{i,j-1}} \) is the preceding decaying averaged CDF for day \( j-1 \). The newly counted CDF at threshold \( i \) for day \( j \) is \( CDF_{i,j} \), and \( W \) is the decaying weight between 0 and 1, defined by an approximated time sliding window \( nd \):

\[
W = \frac{1}{nd}
\]

More details about FMM can refer to Zhu and Luo [13].

**Equitable Threat Score for Model QPF Verification**

As an objective verification method for model QPFs, the equitable threat score (ETS) is widely used [7,8,17]. The ETS is defined as:

\[
ETS = \frac{a-e}{a+b+c-e},
\]

\[
e = \frac{(a+b)(a+c)}{a+b+c+d},
\]

where \( a \) is the correct forecast of the precipitation, \( b \) is the missing rate, \( c \) is the false alarm, \( d \) denotes the case in which no precipitation is observed and predicted. ETS can be used to verify the precipitation forecast exceeding a threshold. If \( ETS>0 \) (\( ETS\leq0 \)), the forecast has (no) skill.

**Statistical Downscaling of the Precipitation Forecasts**

The statistical downscaling approach mentioned above was applied to the downscaling forecast of the precipitation with higher resolution (0.1°×0.1°) from the global ensemble forecast output data (1°×1°) provided by ECMWF, JMA, NCEP, and UKMO. As shown in Figure 1, the ETS of the downscaling forecast using categorized precipitation scheme is much larger than that of the downscaling forecast using bilinear interpolation and uncategorized precipitation scheme.

![Figure 1](image)

Figure 1. The equitable threat score (ETS) of the 24h-168h forecasts of precipitation over 25mm daily from ECMWF (a), JMA(b), NCEP(c) and UKMO(d) using different downscaling approaches. The bilinear interpolation is denoted by the black line, while the statistical downscaling forecast using categorized (uncategorized) precipitation scheme is denoted by red (blue) line.

In addition, the forecast skill of bilinear interpolation and uncategorized precipitation scheme of the ECMWF ensemble forecast system for heavy rain and above is approximately the same, while the
forecast skill of bilinear interpolation is even larger than that of downscaling using uncategorized precipitation scheme for the other three ensemble forecast systems. In fact, the downscaling forecast skill using categorized precipitation scheme is much larger than that of bilinear interpolation and that using uncategorized precipitation scheme in terms of ETS, anomaly correlation coefficient (ACC) and root-mean-square error (RMSE), no matter the precipitation is light rain, moderate rain, or heavy rain and above[7,8].

**Calibration of the Downscaling Precipitation Forecasts**

The precipitation calibration is performed for the statistical downscaling forecast by using frequency match method described previously. It can significantly improve the forecast skill, especially for heavy rain and above. As shown in Figure 2, the ETS of 24h precipitation forecasts show that the FMM calibration considerably improve the forecast skill of the precipitation over 4mm daily for all four ensemble forecast systems. It can also reduce the missing rate of the precipitation forecast of the heavy rain and above significantly (see Figure 3). In this case, the precipitation calibration is very valuable for hydropower industry.

![Figure 2](image.png)

Figure 2. The equitable threat score (ETS) of the 24h forecasts of daily precipitation exceeding different threshold from ECMWF (a), JMA(b), NCEP(c) and UKMO(d) before (after) the FMM calibration denoted by grey (black) column.

As indicated by Wang[18], the FMM can also reduce the false alarm of the precipitation forecast, especially for light rain, although it cannot eliminate the false alarm completely. In fact, the FMM can significantly improve the 24h-168h forecast skill of the precipitation of light rain, moderate rain and heavy rain and above in terms of ETS, the false alarm, and missing rate.

In general, the calibration of the precipitation forecasts using FMM can considerably reduce the false alarm of the light rain and the missing rate of the heavy rain and above. It can therefore improve inflow forecast skill in the hydrological models which make use of observed and predicted precipitation as input variables.
Figure 3. The missing rate of the 24h forecasts of the precipitation exceeding 25mm daily from ECMWF (a), JMA(b), NCEP(c) and UKMO(d) before (after) the FMM calibration denoted by grey (black) column.

Summary
Statistical downscaling forecasts of the precipitation have been performed by using the categorized precipitation in a linear regression model based on the multimodel ensemble forecasts of the precipitation from ECMWF, JMA, NCEP, and UKMO in the TIGGE archive in an attempt to serve the hydropower industry. Following conclusions are reached:

1) Statistic downscaling forecast skill using categorized precipitation scheme is much larger than that of bilinear interpolation and that using uncategorized precipitation scheme in terms of ETS, ACC, and RMSE, no matter the precipitation is light rain, moderate rain, or heavy rain and the above.

2) The calibration of the precipitation forecasts using FMM can considerably reduce the false alarm of light rain and the missing rate of heavy rain and the above. It can therefore improve the inflow forecast skill in the hydrological models which make use of observed and predicted precipitation as input variables.

It should be noted that the FMM calibration may further improve the precipitation forecast skill if the cumulative distribution function (CDF) is calculated over a smaller domain instead of a large area like China.

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