Bias reduction technique for local precipitation

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The numerical models have precipitation biases, in particular around the mountain area. Figure 1a,b show the long-term average precipitation of observation (Radar-AMeDAS) and simulation (MSMGPV) in the central part of Japan in winter. The under-estimated and over-estimated precipitations are clearly found in the plain and mountain areas, respectively. This kind of precipitation biases largely influences on the prediction of river discharge, sediment disaster, and flood basin in the local-scale. The reduction of precipitation bias is necessary to reduce the natural disasters.
Topographic resolution is greatly influenced on model precipitation. The precipitation bias could be reduced by the high-resolved model because the topography is getting closer to the real one. On the other hand, the steep mountain causes the calculation error of horizontal pressure gradient. The high resolution is not always the solution of model bias.
Precipitation is caused by the cold and warm front of low-pressure system and the monsoon flows with orographic effect in the relatively wide area except for the heavy rainfall event in local area. In those cases, the weather conditions such as the directions and amount of water vapor transport and the degree of convective instability are not largely different in the areas inside a certain range. Therefore, the precipitation could be occurred in those areas simultaneously. Formation of precipitation is greatly influenced by the orographic features and the wind direction. Therefore, the precipitation distribution patterns are changed corresponding to the change of wind direction. It is assumed that the observed precipitation is corresponded to the distribution patterns of simulated precipitation in the surrounding area. In this study, we have verified the hypothesis using a machine learning approach. If the hypothesis is true, the precipitation could be predicted by the simulated precipitation distribution pattern and the precipitation bias would be largely reduced.
We used the support vector machine (SVM) as the machine learning approach. The classifier was produced by learning the model precipitation patterns (30 x 20) in Region 1 (Fig. 1a) as the feature vectors using the observed precipitation at each grid. Then, the precipitation at each grid was predicted using the classifier. We applied the pairs of dataset of simulated precipitation and the observed precipitation in winter (December to February) from 2014 to 2017 except for January 2015 as the learning data and the pairs in January 2015 as the test data.
Time variations of the precipitations every 3 hours at Point A were shown in Fig. 1c. The variation of predicted precipitation by SVM was well corresponded to the observed precipitation. The monthly average of predicted precipitation by SVM (0.80 mm/hr) is not largely different from the observations (0.77 mm/hr), while the simulated precipitation (0.35 mm/hr) was less than half of the observed precipitation. The precipitation distributions of observation, prediction by SVM, and simulation were shown in Fig. 1d,e,f. The model precipitation bias was largely reduced by the predicted precipitation.
It is expected that there are some patterns of precipitation distributions corresponding to the topography because the precipitation was predicted by the SVM. There should be some relations between the winter monsoon patterns and the orographic precipitation distribution patterns. It is also expected that the simulated precipitation have some relations to the observed precipitation, while the orographic precipitation distribution patterns are largely different each other. The bias reduction technique in this study is developed using those relations. On the other hand, it is necessary to show the relations in more detail to clarify the applicability of the new approach.

Keywords: Machine learning, Bias Reduction, Downscaling