Estimation of probable maximum precipitation of a high-mountain basin in a changing climate

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ABSTRACT

To estimate the probable maximum precipitation (PMP) in a changing climate, this study proposes a new PMP estimation framework based on weather research forecasting (WRF) initialized with temperature (predicted by post-processing) for changing climate conditions. First, in order to determine temperature disturbance influencing PMP under climate change, a random forest (RF) model considering error correction is introduced to predict the temperature in the future. Results show that the revised RF model could improve accuracy in temperature prediction. Furthermore, numerical experiments of disturbance amplification of three factors (humidity, wind speed, and temperature) using the WRF model are conducted. This new scheme could consider the effect of three elements (horizontal range, vertical layer, and ratio) of influencing factors’ maximization on PMP. Results indicate that for the most unfavorable precipitation scenario of each factor magnification, the combination of three elements is different. Then, the joint amplification numerical experiments of three factors proved the existence of their interactions when multi-factors changed simultaneously. Finally, this method was tested in a high-mountain basin, the Upper Nujiang River Basin. Results showed that the increase of wind speed plays a leading role in rainfall enhancement, and the rising of relative humidity and temperature has a certain disturbance effect on rainfall.

Key words: changing climate, humidity, probable maximum precipitation, temperature, wind speed, WRF model

HIGHLIGHTS

• An improved probable maximum precipitation (PMP) estimation method based on weather research forecasting initialized with temperature for changing climate conditions.
• A revised RF model improving temperature prediction accuracy.
• A new scheme considering the effect of three elements (horizontal range, vertical layers, and ratio).
• Physical PMP estimation considering their interactions when multi-factors change simultaneously.
• More accurate extreme hydrological design value.

1. INTRODUCTION

There are a lot of water conservancy and hydropower projects on the Tibetan Plateau in China (Zhao 2007). For large-scale water infrastructures, probable maximum precipitation (PMP) is the key design parameter to prevent overtopping or embankment failure (Rouhani & Leconte 2016). PMP is the theoretical maximum precipitation that is physically possible for a given duration over a given storm or a designed watershed under modern meteorological conditions (WMO 2009). The referred definition has no allowance made for climate change. However, climate change has become the international social consensus. And many studies have shown that the climate change of the Tibetan Plateau is obvious (You et al. 2020). Under climate change, extreme precipitation events are projected to be frequent and intense (Allan & Soden 2008). Climate warming in the future could also affect the PMP (Kunkel et al. 2013). Despite many studies about PMP, there is little research on the PMP estimation for high-mountain areas in a changing climate. Hence, reasonable PMP estimation methods suitable for both climate change and alpine regions are urgently needed, which is the focus of this study. Whether under the modern...
meteorological condition or changing climate, PMP estimation methods are mainly divided into statistical and physical hydro-meteorological approaches. For the former, the representative techniques are the Hershfield method (Hershfield 1961) and its modified method applicable to climate change (Sarkar & Maity 2020a, 2020b, 2021). Although the approach is simple and widely applicable, it cannot reflect the influence mechanism of meteorological factors and topography on the PMP. To reflect the influence of the topographic uplift of the Tibetan Plateau on PMP estimation, this study adopted the latter, i.e., physical hydro-meteorological approach. There are a number of methods based on the relationship between PMP and physical factors (Salas et al. 2020). The key factors influencing precipitation were summarized as the moisture factor and dynamic factor (WMO 2009). Hence, a common approach for estimating the PMP is based on the assumptions which include that two kinds of factors are independent of each other and it is a linear correlation between factors and PMP, e.g., storm maximization model (WMO 2009). However, these assumptions remain arguable, which are inconsistent with the nonlinear nature of the atmosphere processes (e.g., Abbs 1999). In view of these deficiencies, an alternative approach using the atmospheric model was presented and explored deeply (Abbs 1999; Ohara et al. 2011; Ishida et al. 2015a, 2015b). In the approach, following the basic idea of the storm maximization model, maximum precipitation was estimated through maximizing the initial or boundary conditions of the numerical model for rainstorms, such as relative humidity maximization, maintaining equilibrium conditions, and atmospheric boundary condition shifting. However, first, there is little research about the effect of three elements (horizontal range, vertical layer, and ratio) of factors maximization on the PMP estimation. Second, the interaction between moisture factor and dynamic factor has not been considered. Additionally, when considering the climate change, there is little research on the PMP estimation considering three factors (moisture, dynamic, and temperature) simultaneously. Hence, physical PMP estimation based on the atmospheric model is still to be explored. Therefore, the main objective of this paper is to improve the model-based PMP estimation method considering multi-factors.

In the proposed method, accurate future temperature projection is necessary for the PMP estimation. The current global climate model (GCM) projection-based future scenario is the main approach to predict the temperature. Although most of the results of GCM have been accepted by researchers, compared with the observation, model bias is a problem that could not be ignored (Li et al. 2010). If the weather research forecasting (WRF) model is directly driven by GCM projections, model bias could be propagated to the precipitation prediction, so for PMP. Therefore, it is generally believed when GCMs are used, it is necessary to be post-processing first. There are many post-process methods of climate model outputs. They may be based on either perfect prognosis or model output statistics (Cannon 2017). In this paper, the former mainly based on a statistical regression model was adopted. By far, the regression model based on machine learning algorithm (MLA) has been widely accepted (Ghosh & Katkar 2012). MLA has strong data mining and self-learning ability and could better fit the nonlinear relationship between independent variables and dependent variables. However, there is little research on the relationship between fitting error and fitting value when applying the MLA to fit. Therefore, an approach using the MLA with the fitting error correction was proposed to improve the future temperature projection.

In our study, combining the improved future temperature prediction and the model-based physical PMP estimation method, a novel model that PMP in a changing climate was estimated by adjusting the temperature of ‘worst storm’, which could produce the PMP, was presented. This model not only introduced the temperature factor of climate warming to model-based physical PMP estimation approach, but also considered the interaction of three factors (moisture maximization, wind speed maximization, and rising temperature) on PMP. Specifically, a reasonable framework that considered the humidity, wind speed, and temperature based on the WRF model to estimate the 3-day PMP for a high-mountain basin, i.e., Upper Nujiang River Basin (UNRB), in a changing climate was constructed. The paper is organized as follows: Section 2 introduces the study area, data, and methodology. In Section 3, future temperature is predicted based on the GCM results post-processing, and PMP under climate change is estimated and discussed. Conclusions follow in Section 4.

2. STUDY AREA, DATA, AND METHODOLOGY

2.1. Study area

In this paper, the UNRB, located between Tangkula and Nyainqentanglha mountains in the southeast of Tibetan Plateau (see Figure 1), was selected as the study region. Precipitation is mainly affected by the westerly troughs and shearing vorticities. Moisture comes from the Bay of Bengal in the Indian Ocean. In rainy seasons, southwest monsoon circulation is the main transportation current (Liu et al. 2018). Rainfall over the UNRB varies with the velocity of moisture-bearing wind blowing against the region.
2.2. Data

In this study, WRF preprocessing system terrestrial dataset is MODIS (30″) supplied by the United States Geological Survey. The initial boundary atmospheric yield data are ERA-Interim datasets by the European Centre for Medium-Range Weather Forecasts (ECMWF), a global atmospheric reanalysis dataset from 1979, continuously updated in real-time. Its spatial resolution is 0.75° × 0.75°, and its temporal resolution is 6 h. The data products include a variety of surface parameters, describing weather as well as ocean-wave and land-surface conditions. Due to the sparsely gauged data in the UNRB (7 stations within 73,484 km²), the China Grid Daily Precipitation Datasets (CGDPD) from the China National Meteorological Center (http://www.nmic.cn) was used as observation in this study (Liu et al. 2018). Based on the CGDPD, observed annual areal maximum 3-day precipitation from 1979 to 2018 is selected as a typical storm to set up the WRF model and estimate the 3-day PMP. All 40 large storms are shown in Table 1. Noted that the 3-day PMP refers to the areal 3-day PMP.

Figure 1 | Map of the study region. Two nested domains of WRF simulations are shown in the insert map.
Table 1 | List of 40 large storms in the UNRB

| Storm ID | Maximum 3-day rainfall | 500 hPa height field |
|----------|-------------------------|----------------------|
|          | Starting date           | Precipitation (mm)   |
|          |                         | Major moisture inflow direction | Major weather system |

| 790713   | Jul. 13, 1979            | 42.5                  | South-west | Monsoon depression |
| 800608   | Jun. 8, 1980             | 36.5                  | South-west | Monsoon depression |
| 810720   | Jul. 20, 1981            | 27.7                  | West-southwest | Trough |
| 820909   | Sep. 9, 1982             | 34.3                  | South-west | Depression shearing |
| 830627   | Jun. 27, 1983            | 49.8                  | South-west | Depression shearing |
| 840712   | Jul. 12, 1984            | 42.5                  | South-west | Low trough |
| 850709   | Jul. 9, 1985             | 39.5                  | South-west | Depression trough |
| 860714   | Jul. 14, 1986            | 33.6                  | South-west | Monsoon depression |
| 870806   | Aug. 6, 1987             | 45.3                  | South-west | Low trough |
| 880616   | Jun. 16, 1988            | 54.4                  | South-west | Low trough |
| 890927   | Sep. 27, 1989            | 32.9                  | South-west | Subtropical high periphery |
| 900729   | Jul. 29, 1990            | 29.3                  | South-west | Monsoon depression |
| 910615   | Jun. 15, 1991            | 34.3                  | South-west | Trough |
| 920623   | Jun. 23, 1992            | 27.8                  | South-west | Low trough |
| 930701   | Jul. 1, 1993             | 26.9                  | South-west | Depression trough |
| 940627   | Jun. 27, 1994            | 28.3                  | South-west | Depression trough |
| 950630   | Jun. 30, 1995            | 32.1                  | South-west | Low trough |
| 960906   | Sep. 6, 1996             | 29.4                  | West-southwest | Monsoon depression |
| 970901   | Sep. 1, 1997             | 29.1                  | South-west | Shearing |
| 980706   | Jul. 6, 1998             | 46.5                  | South-west | Monsoon depression |
| 990626   | Jun. 26, 1999            | 45.6                  | West-southwest | Low trough |
| 000622   | Jun. 22, 2000            | 31.0                  | South-west | high-pressure periphery |
| 010525   | May 25, 2001             | 32.5                  | West-southwest | Low trough |
| 020724   | Jul. 24, 2002            | 32.2                  | South-west | Trough |
| 030824   | Aug. 24, 2003            | 28.0                  | West-southwest | Shearing |
| 040725   | Jul. 25, 2004            | 43.7                  | South-west | Low trough |
| 050622   | Jun. 22, 2005            | 33.4                  | South-west | Shearing |
| 060722   | Jul. 22, 2006            | 24.9                  | South-west | Shearing trough |
| 070831   | Aug. 31, 2, 2007         | 37.4                  | West-southwest | Indian depression |
| 080710   | Jul. 10, 2008            | 34.0                  | South-southwest | Trough |
| 090709   | Jul. 9, 2009             | 38.5                  | South-southwest | Depression shearing |
| 100822   | Aug. 22, 2010            | 36.0                  | South-west | Low trough |
| 110530   | May 30, 2011             | 42.5                  | South-west | Shearing trough |
| 120816   | Aug. 16, 2012            | 31.5                  | South-west | Shearing |
| 130716   | Jul. 16, 2013            | 29.4                  | South-west | Shearing trough |
| 140709   | Jul. 9, 2014             | 28.6                  | South-west | Trough |
| 150701   | Jul. 1, 2015             | 30.1                  | South | Monsoon depression |
| 160711   | Jul. 11, 2016            | 38.0                  | South-west | Depression trough |
| 170630   | Jun. 30, 2017            | 37.6                  | South-west | Low trough |
| 180702   | Jul. 2, 2018             | 41.2                  | South-southwest | Depression shearing |
Moreover, to evaluate the post-processing effect based on different GCMs and reduce the temperature prediction uncertainty, BCC_CSM1.1(m) (Liu et al. 2015) and CCSM4 (Danabasoglu et al. 2012), which are included by the Coupled Model Inter-comparison Project 5 (CMIP5), were selected. These two models can provide global gridded results of meteorological elements (temperature, precipitation, relative humidity, etc.) including historical simulation and future projects.

The methodological flowchart of PMP estimation is shown in Figure 2.

### 2.3. Methodology

#### 2.3.1. WRF configuration

The WRF model was used to simulate the selected typical storms in the study basin. The WRF model is a fully compressible, limited-area, non-hydrostatic, mesoscale modeling system (Skamarock et al. 2008). Note that the Advanced Research WRF version 4.0 was used. Figure 1 shows the two-way nested WRF domains. The horizontal grids are 108 × 75 and 122 × 62, with spacing of 30 and 10 km, respectively. The vertical meshes contain 28 sigma levels with the upper boundary at 10 hPa.

#### 2.3.2. Control and sensitivity simulation

In this study, the simulation using the aforementioned WRF configurations with the best parameterization combination is referred to as the control simulation (CTL).

First, we examined the sensitivity of meteorological elements, which can change the moisture or dynamic factor of storm by adjusting the initial and boundary forcing of the WRF simulation.

1. One way to examine the sensitivity of extreme rainfall to humidity through the WRF simulation was presented (Yang & Smith 2018). In their method, atmospheric moisture content was increased by adjusting vertical humidity profiles. However, the responses of precipitation for the increasing humidity at different horizontal or vertical scales are distinct. Our adjustments are as follows:

\[
RH'_{m,n} = (100 - RH_{m,n}) \cdot \alpha + RH_{m,n}
\]  

(1)

where \(RH\) and \(RH'\) represent before and after adjustment of relative humidity, respectively; \(\alpha\) is a multiplication parameter, \(0 \leq \alpha \leq 100\%\); \(m\) is the two nested domains; and \(n\) is the vertical pressure layers.

2. There are few research studies about the sensitivity of extreme rainfall to dynamic factors. To explore it, our study increased moisture motion by adjusting the wind speed at the different horizontal and vertical scales. The adjustments are as follows:

\[
V'_{m,n} = V_{m,n} \cdot \beta = \sqrt{(U_{m,n} \cdot \beta)^2 + (V_{m,n} \cdot \beta)^2}
\]

(2)
where $V$ and $V'$ represent the wind speed before and after the adjustments, respectively; $\beta$ is a multiplication parameter, $\beta > 0$; $UU$ and $VV$ represent the horizontal and vertical components of wind speed, respectively. Although there is no limit on the magnification ratio of wind speed, it should not be unpractically large.

3. (c) In a changing climate, increasing temperature significantly affects the rainstorms including extreme storms. To examine it, the adjustments are made as follows:

$$
T'_{m,n} = T_{m,n} + \gamma
$$

where $T$ and $T'$ represent the temperature before and after the adjustments, °C; $\gamma$ is the increasing temperature under future climate change scenario compared to the annual temperature during the baseline period.

Second, the effects of joint magnification of any two among three factors on precipitation were examined. First, the linear superposition of moisture maximization and wind speed may not lead to the PMP. The reason is for the non-orographic, storms with the highest wind speed do not necessarily produce the most intense precipitation. Second, according to the atmospheric dynamics, the changing of the temperature field will not only affect the moisture field but also change the flow field. Based on the Clausius–Clapeyron relation, increasing temperature can enhance the saturated water vapor pressure and reduce the relative humidity. In the meteorology, temperature change could change the vertical distribution of water vapor (Pall et al. 2006), which can affect the air convection and turbulence. So, there exists an interaction of temperature, humidity, and wind. Therefore, PMP estimation under the climate change is not the linear superposition of maximization of three factors. In this study, the variable-controlling approach was tried to determine the maximization of three elements which produce the most unfavorable storm scenario. Note that the temporal scale of all three factors is the same as that of ERA-Interim datasets, i.e., 6 h.

2.3.3. Post-processing of GCM projects

Through the MLA regression and fitting error correction, this study developed a two-step post-processing method for GCM projects. The details are as follows:

(a) Temperature prediction based on the MLA

The first step is based on the assumption that there exists a statistical correlation relationship between meteorological elements of GCMs’ results and observed temperature. First, supposing the relationship could be expressed as follows:

$$
T = f(t_1, \ldots, t_n; p_1, \ldots p_n; r_1, \ldots, r_n)
$$

where $T$ is the observed areal temperature of the region, °C; $t$, $p$, and $r$ represent the temperature, precipitation, and relative humidity of simultaneous GCMs’ results with the observation, respectively; $n$ is the number of GCMs’ grid over the region; and $f$ represents the relationship. It is no doubt that $T$ should be directly related to $t$. The reason why $p$ and $r$ are added as independent variables is that precipitation and relative humidity can also reflect temperature to a certain extent.

In this paper, for comparison, multiple linear regression (MLR) and two MLAs (random forest (RF), support vector regression (SVR)) were selected to fit the relationship. MLR was used to fit the linear relationship and its principle had been detailed (Wood et al. 2004). RF is an MLA that can train and determine the predictand with a classifier consisting of the classification and regression tree produced with sampling (Breiman 2001). SVR is also an MLA based on the support vector machine (SVM) which uses slack variables and the error penalty parameter to adjust the model complexity and training error (Tripathi et al. 2006). The methodology of RF/SVR has been given in Supplementary Material, Appendix. Both algorithms can solve nonlinear regression optimization problems well.

(b) Re-correction considering the fitting error

Although the best fitting algorithm is selected from the three algorithms, there is still the error ($\Delta$) between fitting value ($T'$) and observation ($T$). This study tried to analyze the relationship between $\Delta$ and $T'$, then used it to further improve the accuracy. Supposing $f$ represents the relationship, i.e., $\Delta = f(T')$, the fitting results would be re-corrected to be more closed to observation based on the $f$. Finally, after the two-step post-processing, the errors of GCM prediction will be reduced to the most extent.
3. RESULTS AND DISCUSSION

3.1. GCMs’ post-processing

3.1.1. Determination of regression method

The accurate prediction of temperature change is basic to PMP estimation in a changing climate. In this paper, considering the PMP occurrence period, the time of temperature prediction is from June to August. Note that due to the complexity of daily temperature correlation between GCMs’ results and observation, this study focused on the monthly average temperature prediction. Moreover, although BCC_CSM1.1(m) and CCSM are 1850–2012 and 1850–2005, respectively, limited by the observation from ERA-Interim reanalysis datasets, this study sets the baseline period as 1979–2005.

Most studies about climate change show that the temperature will continue to rise in the future (IPCC 2013). Specifically, the range of temperature change is small in the near-future, while large relatively in the far-future, which periods are set as 2021–2060 and 2061–2100 in this paper, respectively. Considering that large temperature changes may affect the PMP strongly, the prediction period in this study is far-future.

Three regression algorithms were used to fitting the relationship between areal monthly mean observed temperatures calculated based on ERA-interim datasets from ECMWF and gridded monthly mean temperature, precipitation, and relative humidity of GCMs’ results. To be specific, the number of selected mesh points over the UNRB for the two GCMs are 12 and 9, respectively. The data during 1979–2000 and 2001–2005 were used for regression calibration and validation, respectively.

Note that RF and SVM are sensitive to control parameters. The grid search method (Huang & Wang 2006) was used to determine them. For RF, three parameters (number of decision trees ($r_1$), minimum sample leaf size ($r_2$), and maximum number of features RF ($r_3$)) are important to the RF. Based on the reference (Probst et al. 2019), the best $r_1$ and $r_2$ were 100 and 5, while $r_3$ is one-third of the number of variables. For the SVM, the error penalty parameter ($C$) and the width factor of the RBF kernel function ($\sigma$) are the key parameters. In this study, the best $C$ and $\sigma$ are 8 and 0.125, respectively.

To evaluate the accuracy of regression, correlation coefficient ($R$), Nash–Sutcliffe efficiency coefficient (NSE), mean absolute error (MAE), and root-mean-square error (RMSE) (Liang et al. 2017; Liu et al. 2019) were used. Among these, the closer the value of $R$ and NSE is to 1, the better regression, while lower MAE and larger RMSE show better accuracy.

Table 2 shows that, among three algorithms, whether for BCC_CSM1.1(m) or CCSM, $R$ and NSE of regression fitting based on RF are the largest, MAE and RMSE are the lowest. Therefore, RF can achieve the best fitting. Figure 3 shows the observation temperature versus fitting values using RF.

Table 2 | Evaluation criteria of regression fitting of BCC_CSM1.1(m) and CCSM in the calibration period

| Evaluation criteria | BCC_CSM1.1(m) | CCSM |
|---------------------|---------------|------|
|                     | MLR | RF  | SVR | MLR | RF  | SVR |
| R                   | 0.75| 0.90| 0.82| 0.76| 0.91| 0.79|
| NSE                 | 0.56| 0.80| 0.58| 0.58| 0.81| 0.59|
| MAE                 | 0.89| 0.54| 0.85| 0.86| 0.55| 0.86|
| RMSE                | 1.07| 0.73| 1.04| 1.04| 0.70| 1.04|
fitting temperature remain the same after re-correction, NSE was improved while MAE and RMSE were decreased to some extent. These indicate the two-step post-processing method presented in this study could achieve more accurate temperature prediction. Then the temperature prediction based on GCMs’ post-processing could be used for PMP estimation under the climate change.

Using the two-step post-processing method, the monthly average temperature from June to August during the far-future (2061–2100) in the UNRB was predicted and then converted to daily temperature by the same ratio enlargement method, and the maximum, average, and minimum daily average temperatures in the far-future were counted. Results show that there is a gradually increasing trend for maximum, average, and minimum daily average temperatures under all four emission scenarios in the far-future (Figure 5).

Moreover, Figure 5 shows that under the same emission scenario, temperatures after post-processing from BCC_CSM1.1(m) and CCSM are different. However, so far there is still no GCM model recognized absolutely around the world. In this study, to reduce the uncertainties, averaging the results would be good practice. Furthermore, compared with observation in the baseline period, the increased range of average annual maximum, average, minimum daily temperatures in the far-future was calculated (Table 4).

It shows that in the UNRB, maximum, average, minimum daily temperatures under all emission scenarios increase by 0.8–1.6 1.2–2.2 and 3.5–4.9 °C, respectively. Meanwhile, the increasing range will increase with the change of emission scenario. The prediction results of far-future temperature in this paper are consistent with other studies (Luosang et al. 2016; Wu et al. 2019). Therefore, the prediction of temperature change will be used to adjust the initial and boundary forcing of the WRF simulations and estimate the PMP in a changing climate.

![Figure 3](http://iwaponline.com/hr/article-pdf/53/1/221/994897/nh0530221.pdf)
3.2. WRF model setup

The WRF parameterization must be determined before using it to simulate the rainstorms. Based on relative references (Rastogi et al. 2017; Yang & Smith 2018), partial parameterization schemes are determined as follows: rapid radiative transfer model for longwave radiation, Dudhia’s scheme for shortwave radiation, and Monin–Obukhov scheme for the surface layer. As for the parameters with great influence on precipitation (microphysics scheme, cumulus parameterization, land surface, and PBL scheme), in this paper, the best one of 16 model physical options combinations (Table 5) was determined by comparing modeled precipitation with observed precipitation of the selected 40 typical storms over the UNRB.

First, the maximum 3-day storm during August 1988, which is also the maximum 3-day precipitation during 1979–2018, was simulated through the WRF with 16 physical combinations, respectively. The results with different parameterizations are listed in Table 6. It shows that the absolute error in case 11 or 15 is smaller than other cases, i.e., 0.9 and −0.7 mm, respectively. Therefore, cases 11 and 15 could be selected as two alternative combinations.

Table 3 | Evaluation criteria of BCC_CSM1.1(m) and CCSM after two-step post-processing in the calibration period

| GCM model         | $R$   | NSE  | MAE  | RMSE |
|-------------------|-------|------|------|------|
| BCC-CM1.1(m)      | 0.90  | 0.81 | 0.50 | 0.75 |
| CCSM              | 0.91  | 0.83 | 0.50 | 0.70 |

Figure 4 | Comparison of the observation versus fitting values using RF with re-correction: (a) and (c) are for BCC_CSM1.1(m) in the calibration and validation periods, respectively. (b) and (d) are for CCSM in the calibration and validation periods, respectively.
Furthermore, 40 typical storms were simulated using cases 11 and 15, respectively. Results show that comparing the observed 3-day precipitation, the mean absolute values of relative error of case 11 or 15 are 29 and 21%, respectively (Figure 6). It indicates simulation with case 15 is better than that with case 11. Therefore, case 15 was determined as the best parameterization combination.

3.3. Single factor sensitivity analysis

To analyze the influence of three elements (vertical column, horizontal range, and magnification ratio) of factors on precipitation, we did a lot of experiments of perturbing initial and boundary conditions. Meanwhile, these experiments could verify the rationality of linear formula used by the traditional moisture or wind maximization methods (WMO 2009). The typical

Table 4 | Increase range of average annual maximum, average, minimum daily temperatures in the far-future compared with those in the baseline period (°C)

| Scenario temperature | RCP26     | RCP45     | RCP60     | RCP85     |
|----------------------|-----------|-----------|-----------|-----------|
|                      | Max.      | Avg.      | Min.      | Max.      | Avg.      | Min.      | Max.      | Avg.      | Min.      |
| Baseline             | 17.6      | 13.0      | 4.9       | 17.6      | 13.0      | 4.9       | 17.6      | 13.0      | 4.9       |
| 2061–2100            | 18.4      | 14.2      | 8.4       | 18.7      | 14.6      | 8.8       | 18.9      | 14.8      | 9.3       |
| Increase range       | 0.8       | 1.2       | 3.5       | 1.1       | 1.5       | 3.9       | 1.3       | 1.7       | 4.4       |

Figure 5 | Prediction of temperature change in the far-future in the UNRB under four scenarios: (a) RCP26; (b) RCP45; (c) RCP60; and (d) RCP85. Max., Avg., and Min. represent the maximum, average, minimum daily average temperatures from June to August year by year. Note that BCC is the abbreviation of BCC_CSM1.1(m).
storm of perturbing experiments was selected as the maximum areal 3-day precipitation during 1979–2018 in the UNRB, i.e., rainstorm on June 16–18, 1988 (880616).

### Relative humidity

Considering more than 90% of atmospheric moisture content is concentrated in the troposphere, moisture in the troposphere is decisive. And inside the troposphere, the radial and latitudinal distribution of moisture is uneven. To evaluate the impact of vertical column and horizontal range of relative humidity enlargement on the 880616 storm in the UNRB, considering the two nested domains of WRF in the UNRB and 28 vertical layers of ERA-Interim (marked as 0–27), sensitivity experiments were designed as 18 perturbing scenarios of horizontal range (referring to WRF domains) and vertical layers with the same magnification ratio of 90%. Note that here the magnification ratio is 90%, not 100% because that if setting the relative humidity at 100%, the relative distribution of atmospheric moisture could be damaged. The atmospheric pressure corresponding to the vertical layer of ERA-interim is shown in Table 7. Specifically, 18 perturbing scenarios are pairwise combinations between WRF nested domains (①, ②, and ③ and ③) and different pressure layers (0–6, 0–9, 0–13, 0–17, 0–22, and 0–27).

### Table 5 | Combination of parameterization options in the WRF model

| Case number | Microphysics scheme | Cumulus parameterization | Land surface | PBL scheme |
|-------------|---------------------|--------------------------|--------------|------------|
| 1           | WSM3                | Kain-Fritsch             | Noah         | Boulac     |
| 2           | WSM3                | Kain-Fritsch             | Noah         | YSU        |
| 3           | WSM3                | Kain-Fritsch             | Five-layer thermal diffusion | Boulac |
| 4           | WSM3                | Kain-Fritsch             | Five-layer thermal diffusion | YSU    |
| 5           | Purdue Lin          | Grell-Devenyi            | Noah         | Boulac     |
| 6           | Purdue Lin          | Grell-Devenyi            | Noah         | YSU        |
| 7           | Purdue Lin          | Grell-Devenyi            | Five-layer thermal diffusion | Boulac |
| 8           | Purdue Lin          | Grell-Devenyi            | Five-layer thermal diffusion | YSU    |
| 9           | WSM3                | Grell-Devenyi            | Noah         | Boulac     |
| 10          | WSM3                | Grell-Devenyi            | Noah         | YSU        |
| 11          | WSM3                | Grell-Devenyi            | Five-layer thermal diffusion | Boulac |
| 12          | WSM3                | Grell-Devenyi            | Five-layer thermal diffusion | YSU    |
| 13          | Purdue Lin          | Kain-Fritsch             | Noah         | Boulac     |
| 14          | Purdue Lin          | Kain-Fritsch             | Noah         | YSU        |
| 15          | Purdue Lin          | Kain-Fritsch             | Five-layer thermal diffusion | Boulac |
| 16          | Purdue Lin          | Kain-Fritsch             | Five-layer thermal diffusion | YSU    |

### Table 6 | Simulation results with different parameterization combinations

| Case number | 3-day precipitation (mm) | Error (mm) | Case number | 3-day precipitation (mm) | Error (mm) |
|-------------|--------------------------|------------|-------------|--------------------------|------------|
| 1           | 52.6                     | −1.8       | 9           | 51.8                     | −2.6       |
| 2           | 50.7                     | −3.7       | 10          | 48.2                     | −6.2       |
| 3           | 55.8                     | 1.4        | 11          | 55.3                     | 0.9        |
| 4           | 52.2                     | −2.2       | 12          | 50.5                     | −3.9       |
| 5           | 43.3                     | −11.1      | 13          | 46.7                     | −7.7       |
| 6           | 40.5                     | −13.9      | 14          | 46.5                     | −7.9       |
| 7           | 48.9                     | −5.5       | 15          | 53.7                     | −0.7       |
| 8           | 41.1                     | −13.3      | 16          | 50.2                     | −4.2       |
Experiments results show that on the one hand, the vertical layers being kept constant, the magnification of relative humidity in only ② domain of the WRF has little impact on the precipitation. On the other hand, when the magnification of relative humidity in only ① domain or ① and ② domains, the simulation results of precipitation are similar, and compared with the CTL, the increase of 3-day precipitation keeps the same (Figure 7(a)). When the magnification horizontal is ① or ① and ② domain, with the increase of vertical layers, the precipitation increases but when the pressure layers expand to 17 or more, the 3-day rainfall tends to be stable (100.8 mm).

To evaluate the impact of ratio of relative humidity enlargement on the 880616 storm in the UNRB, sensitivity experiments were designed as follows: magnify the relative humidity in the same vertical layers (0–27) but different domains (①, ②, ①, and ②) by 10–100%. Results show the 3-day precipitation increase with the magnification ratio of relative humidity increase; however, when the ratio reaches 90–100%, the 3-day precipitation tends to be stable (100.8 mm) (Figure 7(b)). Furthermore, if only enlarge the relative humidity in the inner domain ②, no matter what percentage is magnified, the maximum 3-day rainfall has little change.

### 3.3.2. Wind speed

Similarly with relative humidity, to evaluate the impact of vertical column and horizontal range of wind speed enlargement on the 880616 storm in the UNRB, we designed 18 scenario experiments, i.e., magnifying the wind speed by three times in different vertical layers and different domains. Experiments results (Figure 7(c)) show that when keeping the vertical layers constant, only wind speed magnification in domain ② of WRF has little impact on the precipitation; whether the magnification domain is ① or ① + ②, compared with the CTL, the change of 3-day precipitation is similar. Specifically, the precipitation increased at first and then decreased, and the maximum 3-day precipitation (70.8 mm) occurred when wind speed in the 0–13 vertical layers (from the ground to 500 hPa high level) was magnified.

The traditional wind maximization method in orographic regions assumes that the observed storm rainfall over a mountain range varies in proportion to the speed of the moisture-bearing wind blowing against the range. In this paper, to determine the
relationship between storm rainfall and wind speed in the UNRB, sensitivity experiment design was that multiplying the wind speed of initial and boundary conditions by 1.1–20 when the domain and vertical layers of enlargement were 0–12 and 0–13, respectively. Results (Figure 7(d)) show that (a) when the ratio of enlargement is 1.1–12, the 3-day precipitation will increase. However, it is not a linear relationship between the increased range and enlargement ratio. Specifically, the increased range of 3-day precipitation will decrease; (b) when the ratio of wind speed enlargement is 13–18, the 3-day precipitation is reduced slightly; (c) when the ratio exceeds 18, the 3-day precipitation tends to stable. These results are accordant with the phenomenon that storms with the highest wind speed do not necessarily produce the most intense precipitation and indicate the irrationality of linear formula in the traditional method. For the 880616 storm in the UNRB, when the ratio of wind magnification is 12, the 3-day precipitation reaches the maximum (121.9 mm), compared with the original storm (54.4 mm), the increasing range is 124%. Note that in the sensitivity experiments of wind speed enlargement, the maximum magnification ratio was 20 because of the upper limit of wind speed.

3.3.3. Temperature

The relationship between temperature field and precipitation is uncertain, much less the PMP. To evaluate the impact of temperature change on the PMP, similarly with relative humidity and wind speed, this study did a sensitivity experiment of temperature adjustment of initial and boundary conditions. Our experiments were increasing the temperature field by 1, 1.5, and 2 °C of the 8806016 storm, respectively. Note that the adjustment horizontal ranges were all the WRF domains.

**Figure 7** | 3-day precipitation of 880616 storm with the different scenarios: (a) increase RH by 90% in different horizontal domains or different vertical layers; (b) increase RH by different ratios in same vertical layers (0–27) but different domains or different magnification ratios; (c) magnify wind speed by three times in different horizontal ranges and vertical layers; (d) magnify wind speed by different ratios; and (e) increase temperature field of the WRF model.
but the adjustment vertical layers were different because that the responses of temperature increase at different high levels under global warming are distinct (Giorgi et al. 2010).

Results (Figure 7(e)) show that the responses of 3-day precipitation of 8806016 storm after temperature adjustments are different under the scenario of same pressure layers and different increase ranges, or different pressure layers and same increase ranges. When increasing the temperature from the ground layer to 100 hPa (0–22 layers), the precipitation has changed obviously. The reason may that the average elevation of the UNRB is about 4,769 m, i.e., 500 hPa (13th layer), so that only when the pressure layer of temperature adjustment is more than 500 hPa, the rainfall will change obviously. From Figure 8, precipitation decreases when adding the temperature by 1 °C but increases when adding the temperature by 2 °C. The reason may be that the rise of temperature will increase the saturated vapor pressure but reduce the relative humidity, the effect on precipitation being positive or negative.

3.4. Pairwise combination of three factors amplification

3.4.1. Relative humidity and wind speed

To check out the independence of atmospheric moisture and dynamic, we did sensitivity experiments of joint enlargement of relative humidity and wind speed. The experiments were designed as follows: a pairwise combination between increasing the relative humidity by 0–100% and multiplying the wind speed by 1–20. Note that the horizontal and vertical ranges of relative humidity magnification and wind speed magnification are \( \oplus + \odot \) domains and 0–27 layers, \( \odot + \odot \) domains and 0–12 layers, respectively. The results can be seen in Figure 8(a).

![Figure 8](http://iwaponline.com/hr/article-pdf/53/1/221/994897/nh0530221.pdf)
First, it shows that the 3-day precipitation is 100.8 mm in the only relative humidity magnification scenario and 121.9 mm in the only wind speed magnification scenario, while 134.2 mm in the combination of relative humidity and wind speed. This indicates the influences of two factors on storms are not completely superposition, and there may be the interaction of humidity and wind speed. Second, the 3-day precipitation in the only wind speed magnification scenario is 21% more than that when magnifying only relative humidity. It implies that the influence of wind speed on storms outweighs that of atmospheric moisture considering the effects of topography in the UNRB. Third, when the ratio of wind speed enlargement increases, the change of precipitation is different with increasing relative humidity. To be specific, when the ratio of wind speed magnification is less than 7, precipitation first increases then tends to be stable as the relative humidity increases; while the ratio is more than 7, precipitation will first rise and then fall slightly. Overall, when wind speed is large enough, relative humidity has a small influence on the precipitation. Moreover, it shows that whether wind speed or relative humidity is amplified by a single factor or by two factors together, the change of 3-day precipitation for 880616 storm with factors’ magnification will first increase and then tend to be stable gradually, not increase indefinitely. For the 880616 storm in the UNRB, when the ratio of wind speed magnification is 12–20 and the magnification ratio of relative humidity is 40–70%, the maximum of 3-day precipitation is 134.2 mm and the minimum is 126.8 mm. A small gap (7.4 mm) between the maximum and the minimum shows that the 3-day precipitation of 880616 storm will stabilize after the joint maximization of humidity and wind speed. Furthermore, it implies that there is an upper limit for the extreme precipitation in orographic regions in extreme situations.

### 3.4.2. Relative humidity and temperature

The rise of temperature would increase the saturated vapor pressure but reduce the relative humidity, the effect on precipitation being positive or negative. So, the change of precipitation is uncertain when increasing temperature and magnifying relative humidity simultaneously. To determine the impact of joint magnification of temperature and relative humidity on precipitation, sensitivity experiments were that when increasing relative humidity by 10–100%, the temperature field rises by 2 or 4 °C.

Results (Figure 8(b)) show that when increasing relative humidity, the 3-day precipitation will increase but the changing range of precipitation for different rising temperatures is obviously distinct. To be specific, when the increasing range of relative humidity is less than 30%, the 3-day precipitation decreases no matter what the temperature increases. The reason may be that the rising temperature increases the saturated vapor pressure then reduces the relative humidity. Meanwhile, the range of artificial increasing relative humidity (0–30%) is not enough to offset the decreasing relative humidity due to the increasing temperature. Finally, the precipitation decreases. When the range of relative humidity magnification is 50–80%, the 3-day precipitation increases with the increasing temperature. The reason may be that the range of artificial increasing relative humidity is enough to offset the decreasing relative humidity due to the rising temperature; meanwhile, the rising temperature increases the water vapor in saturated air. When magnifying relative humidity by 90–100% and increasing temperature at the same time, the 3-day precipitation decreases obviously. This may be because that when increasing relative humidity by 90–100%, the rainfall has occurred, the water vapor of atmosphere would decrease and the rising temperature only increases water vapor capacity but could not increase atmospheric moisture, then the precipitation decreases.

### 3.4.3. Wind speed and temperature

Similarly, to evaluate the influence of the rising temperature and enlarging wind speed on the precipitation, sensitivity experiments were designed as follows: when rising the temperature by 2 or 4 °C, multiply the wind speed by 1–20.

Results (Figure 8(c)) show that when the ratio of wind speed magnification is less than 7, the influence of rising temperature on precipitation (positive or negative) is uncertain; however, when the ratio is more than 7, precipitation change with the joint enlargement of wind speed and temperature is consistent with the scenario of only wind speed magnification. Moreover, when multiplying the wind speed by 7 or more, no matter the range of rising temperature is 2 or 4 °C, the precipitation is larger than that with only wind magnification.
3.5. PMP estimation

3.5.1. Determination of the worst-case storm

According to the WMO, the main characters of PMP should be theoretical maximum but physical possible under disadvantaged conditions. Therefore, the storm factors (moisture factor, dynamic factor, etc.) should be possible and not magnified infinitely. As a moisture index, the maximum relative humidity could be 100%, which is likely to occur in heavy storms.

It is no doubt that the maximum wind speed record in different regions is different. As a sparsely-populated area, the meteorological stations on the Qinghai Tibet Plateau are sparse, and most of them are located in the mountainous valley area, so the wind data are extremely scarce. In this paper, by referring to the maximum wind speed with the 50-year return period (50-MWS) in coastal areas in China reaches 78.63 m/s (Cao et al. 2019), the maximum wind speed of PMP (PMP-MWS) is set to be 78.63 m/s. It is mainly based on the following considerations: (a) wind speed in inland areas on the edge of typhoon is usually less than that in coastal areas, 50-MWS in inland areas should be less than 78.63 m/s. However, considering that the return period of PMP is close to 10,000 years, the return period of PMP-MWS should be far more than 50 years, i.e., PMP-MWS should be more than 50-MWS. (b) Although the Qinghai Tibet Plateau is located in the inland area, severe wind speed may occur when its unique strong storm weather (squall line) occurs (Li 2002). (c) The average wind speed of 500 hPa height field of 880616 rainstorms is 9 m/s. If 78.63 m/s is taken as the PMP-MWS, i.e., the wind speed is magnified about nine times larger, the 3-day precipitation will be 127.4 mm, which only increases by 26%. Therefore, it is possible for the wind speed to be nine times larger than that of the original storm.

Magnification experiments of 880616 storm indicated that the wind speed maximization plays a decisive role in the PMP estimation for the UNRB. To improve the reliability of PMP estimation, it is necessary to investigate the maximum precipitation of other heavy rainstorms under the PMP-MWS. Considering that the period of ERA-Interim initial data is 1979–2018, the sensitivity test of wind speed maximization is carried out for all 40 annual maximum 3-day rainstorms. By comparing the 3-day rainfall variation of 40 rainstorms under the PMP-MWS, the typical rainstorm that could produce the PMP is determined.

Results (Figure 9(a)) show that under the wind speed maximization scenario, the 3-day precipitation produced by different rainstorms is distinct. Compared with the observation, for most rainfalls, the precipitation will increase, while for a few typical rainfalls, the precipitation changes slightly or decreases. The possible reason is that the original wind speed of typical rainstorm is enough big or the rain-making weather system is less affected by wind speed. Actually, storms more affected by the wind speed maximization could produce more rain than others. So, PMP estimation should focus on these storms. Among the 40 typical storms after the wind speed maximization, the 3-day precipitation of 880616 storm is the largest (113.2 mm), while that of 910615, 850709, and 800608 storms is 81.5, 79.2, and 72.6 mm, respectively, which ranked second to fourth. There is a big gap for 3-day precipitation through the wind speed maximization between these four typical storms and the other typical storms. So in this paper, four typical storms are the basic for PMP estimation for the UNRB.

Despite the leading role of wind speed, the maximization of relative humidity has a certain amplification on the precipitation. Therefore, on the basis of the wind speed maximization, the relative humidity magnification of these four rainstorms was done in different percentages from 10 to 100%. Simultaneously, this paper also simulated the rainstorm change with the different relative humidity amplification under the original wind field.

Results (Figure 9(b) and 9(c)) show that compared with the other three storms, the 3-day precipitation of 880616 is the largest (127.4 mm) under the joint maximization of relative humidity and wind speed, i.e., the worst-case storm that magnifying the wind speed nine times and increasing the relative humidity by 40%. Finally, based on the sensitivity experiments of moisture factor (relative humidity) and dynamic factor (wind speed) of 40 typical storms, the 3-day PMP for the UNRB was estimated as 127.4 mm. Meanwhile, we estimated the PMP (274.7 mm) using the traditional joint maximization of moisture and wind speed based on linear superposition (WMO 2009). Comparing the two, PMP estimation using the joint amplification of moisture and wind speed based on WRF was far less than the traditional method. Due to the stronger physical mechanism of the WRF model, its PMP estimation could be more reasonable and indirectly implicate the irrationality of linear superposition assumption adopted by the traditional methods.

3.5.2. PMP in a changing climate

For the PMP estimation under the climate change, the influence of three factors (relative humidity, wind speed, and temperature) should be considered. Based on the sensitivity experiments of single factor magnification, the enlargement of wind speed plays a leading role in strengthening the 880616 rainstorm in the UNRB. Therefore, to evaluate the interaction of relative
humidity and temperature under the wind speed maximization, sensitivity experiments were designed as follows: under the premise that wind speed was multiplied by 9, relative humidity enlargement (the ratio is 0–100%) and temperature increase (the ratio is 1–5 °C) were jointed.

Experimental results (Figure 10) show that when rising the temperature under the wind speed maximization, the 3-day precipitation varies with the different relative humidity magnification, i.e., under this circumstance, precipitation would first increase and then decrease, and when the rainfall reaches the maximum, the ratio of relative humidity magnification is distinct. It indicates that the ratio of relative humidity magnification needs to be determined under the different rising temperature scenario when estimating the PMP in a changing climate.

In this paper, the change of average minimum daily temperature in the annual flood season was used as the perturbation of temperature field of the WRF to estimate the PMP in a changing climate. The reasons are as follows: first, affected by rainfall, the temperature during storms with long duration (here 3-day) may be low relatively. Second, from the temperature prediction results in the far-future, compared with the annual mean value in the baseline period, no matter which emission scenario, the increased range of minimum daily temperature is the largest. Last but not least, one study showed that the greater the temperature rise, the greater the change of extreme rainfall (Witze 2018). Therefore, as the extreme maximum rainfall under the most unfavorable scenario, PMP estimation should take the greater temperature change into consideration.

Therefore, to estimate the PMP in a changing climate, we did the scenario simulation of joint change in relative humidity amplification (the ratio is from 0 to 100%) and rising temperature (corresponding to four climate scenarios) under the wind speed maximization. Finally, we take the rainfall envelopment as the 3-day PMP on the UNRB under each climate change scenario (Table 8).
4. CONCLUSIONS

In this study, the 3-day PMP for a high-mountainous basin (UNRB) in a changing climate was estimated based on the GCMs’ post-processing and WRF sensitivity experiments. Results and findings could be concluded as follows.

For the origin temperature projection from GCMs, a two-step post-processing method, including RF model and error re-correction, was proposed to predict the far-future temperature. This method could generate a more accurate temperature prediction than the RF model. Thus, it is suggested as an important step providing temperature information for the PMP estimation under climate change.

Given the effect of three elements (horizontal range, vertical layer, and ratio) of influencing factors’ maximization, the most unfavorable elements of factors’ amplification were determined based on the WRF simulation for the first time. It could improve the physical-based PMP estimation method.

The simulation experiments of pairwise combination magnification showed that there existed mutual interaction among humidity, wind speed, and temperature. It breaks through the linear superposition hypothesis of factors’ maximization in the traditional PMP estimation. This kind of joint amplification analysis could make the PMP estimation based on the WRF model more reasonable. For the UNRB, PMP estimation should give the priority to the wind speed maximization, simultaneously complemented by relative humidity enlargement and rising temperature.

Finally, considering the effect of humidity, wind, and temperature on PMP, this study presented a procedure of estimating the 3-day PMP in a changing climate for the UNRB. Moreover, whether high-mountain areas, plain or hilly areas, the new physical evaluation framework on factors of PMP proposed in this paper could be a good reference for similar studies.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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