The dependence of precipitation types on surface elevation and meteorological conditions and its parameterization

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\textbf{S U M M A R Y}

Precipitation types (rain, snow, and sleet) have great impacts on the surface runoff and energy balance. However, many weather stations only record precipitation amount without discriminating its type. Based on CMA (China Meteorological Administration) station data over 30 years, this study investigates the relationship of precipitation types with surface elevation and meteorological variables. Major findings are (1) wet-bulb temperature is a better indicator than air temperature for discriminating precipitation types; (2) precipitation types are highly dependent on surface elevation, and a higher threshold temperature is needed for differentiating snow and rain over a higher-elevation region; and (3) precipitation types are also dependent on relative humidity, and the probability of sleet event rises greatly with the increase of relative humidity. Based on these findings, a new parameterization scheme is developed to determine the precipitation type, with input of daily mean wet-bulb temperature, relative humidity, and surface elevation. Evaluations for China territory show that the new scheme gives better accuracy than 11 other schemes that are used in hydrological and land surface models.

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\textbf{1. Introduction}

Precipitation is one of the most important components in water and energy cycle, and the precipitation types (rain, snow, and sleet) have great impacts on the land surface mass and energy balance (Loth et al., 1993). Snowfall can accumulate at the land surface while rainfall usually infiltrates into soils and converges into rivers or groundwater (Clark et al., 2006). The surface albedo increases greatly when snowfall occurs, which can substantially alter the surface energy budget, whereas the effect is opposite when rainfall occurs (Box et al., 2012). Besides, precipitation type is needed for the correction of precipitation gauge data, as the catch ratio of precipitation gauges depends on precipitation type (Yang et al., 1988, 1995; Rasmussen et al., 2012). Therefore, the differentiation of precipitation types is important for land hydrological process studies (Anderson and Mackintosh, 2012).

However, precipitation types are often not observed or not accessible. For example, the data of precipitation amount at more than 700 CMA (China Meteorological Administration) weather stations since 1950s can be obtained via the CMA National Meteorological Information Center (NMIC), but the data of precipitation types is not available for the years after 1979 (Han et al., 2010). So the discrimination of the precipitation types for the recent three decades mainly relies on empirical or semi-empirical relationships derived from other observations. Generally, the discrimination schemes are categorized into two classes according to the used variables.

One class is based on the temperature profile and other atmospheric conditions (e.g. Bocchieri, 1980; Ryzhkov and Zrnic, 1998; Rauber et al., 2001; Lundquist et al., 2008). Czys et al. (1996) presented a non-dimensional parameter (i.e. the ratio of the available time for melting to the required time for complete melting) to differentiate between freezing rain and ice pellets by using air temperature profile. Bourgouin (2000) used the area between the air temperature profile and the 0 °C isotherm on aerological diagrams to diagnose precipitation types. Schuur et al. (2012) employed the vertical profile of wet-bulb temperature derived from the rapid update cycle model (Benjamin et al., 2000) and polarimetric radar retrievals to classify the precipitation types. A challenging issue that hinders the applications of the above schemes is that air temperature profile is generally not available at weather stations.

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The other class of empirical schemes mainly employs surface air conditions. Their inputs are accessible and thus they are widely used for hydrological and land surface modeling. Among them, surface air temperature-based methods are most widely used for the identification of precipitation types (e.g., Auer, 1974; Kang et al., 1999; Gustafsson et al., 2001), including single threshold methods (Yang et al., 1997; Clark et al., 2006) and dual-threshold methods (Kang, 1994; Wigmosta et al., 1994; Chen et al., 2008). A single threshold method differentiates rain and snow with only one critical temperature. A dual-threshold method uses two critical temperatures to differentiate rain, snow, and sleet: rain occurs when air temperature is higher than an upper critical temperature; snow occurs when air temperature is lower than a lower critical temperature; sleet (as a mixture of rain and snow) occurs when air temperature is between the two critical temperatures. In addition, some schemes are developed to calculate the ratio of snow (or rain) amount to total precipitation amount (Zhang et al., 2013), instead of determining the precipitation type. Yamazaki (2001) used a scheme with the wet-bulb temperature as an indicator to calculate the ratio of snow amount to total precipitation amount for modeling land surface processes in Eastern Siberia. Dai (2008) proposed a method to calculate the frequencies of rain, sleet, and snow from their relationships with both surface air temperature and pressure over land and ocean. Table 1 shows the critical temperatures of nine schemes in the literature and the calculations of snow ratio as the ratio of the above two schemes; clearly, the critical temperature values are not unique in different regions, and all these schemes need validations for different climate regimes. Particularly, we have little knowledge on how elevations impact the precipitation types.

This study aims at developing a new scheme to discriminate precipitation types, based on more than 400,000 samples of precipitation types collected from different climate regimes and elevations in China. The remaining parts of this paper are organized as follows. Section 2 introduces the dataset and the data quality control procedures. Section 3 presents the dependence of precipitation types on surface wet-bulb temperature, relative humidity, and elevation. Based on their relationships, a new parameterization scheme is developed in Section 4 and its evaluation is presented in Section 5 by comparisons with 11 schemes in the literature. The results are summarized in Section 6.

2. Data

The dataset used in this study is the Version 3.0 of “Daily Surface Climate Variables of China”, which is provided by CMA NMIC. This dataset covers the period from 1951 to 1979, with precipitation type information available at daily scale. Therefore, daily weather data are used in this study, including daily mean air temperature (Ta), daily mean relative humidity (RH), daily mean surface pressure (ps), daily total precipitation (Ptot), and precipitation type of 824 stations. Elevation (Z) is also used so as to understand its role in the formation of precipitation.

Generally, the precipitation type is recorded as one of three types (rain, sleet, and snow). Although the data quality has been preliminary controlled by the data provider, some stations recorded all precipitation events as rain throughout all years or some years, without discriminating precipitation types. In addition, erroneous or suspected classifications occur occasionally, since the precipitation type is based on manual judgment and recording. Therefore, the following data quality control procedures are adopted to remove erroneous and suspicious data.

1. Select qualified data according to the original quality control flag in the dataset. Herein, data are selected if the quality control flags of Ta, RH, ps, and Ptot are simultaneously marked as correct.

2. Search for erroneous and suspicious data records. A data record is regarded as abnormal if rain occurs when Ta < 0 °C, snow occurs when Ta > 8 °C, or sleet occurs when Ta < −1.6 °C or Ta > 9.6 °C, according to statistical results of the precipitation types; otherwise, the data record is regarded as normal. Then, we counted for each year of each station (i) the numbers of all samples of rain, snow, and sleet, recorded as Nrain, Nsnow, and Nsleet, respectively; and (ii) the numbers of all abnormal samples of rain, snow, and sleet, recorded as Nrain, wrong, Nsnow, wrong, andNsleet, wrong, respectively.

Table 1

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Thresholds of Ta or snow ratio</th>
<th>Model</th>
<th>Region and period being applied</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y97 (Yang et al., 1997)</td>
<td>2.2 °C</td>
<td>BATS model</td>
<td>Yershov, Uralsk, Urgutsovo, Kostroma, Khabarovsk and Tulun (48°N–57°N, 41°E–135°E), 1978–1983</td>
</tr>
<tr>
<td>L93 (Loth et al., 1993)</td>
<td>−1 °C, 4 °C</td>
<td>Snow cover model</td>
<td>German meteorological station Potsdam (52°23’, 13°04’), 1975–1980</td>
</tr>
<tr>
<td>W94 (Wigmosta et al., 1994)</td>
<td>−1.1 °C, 3.3 °C</td>
<td>DHSVM model</td>
<td>Middle Fork Flathead River basin in northwestern Montana (114°00’W, 48°29’N, 900 m–3000 m), Oct 1988–Oct 1991</td>
</tr>
<tr>
<td>K94 (Kang, 1994)</td>
<td>2.8 °C, 5.5 °C</td>
<td>Energy, water, mass balance and hydrological discharge model</td>
<td>Tianshan Mountain, China (43°06’N, 86°50’E, 3539 m–4010 m), 1986–1990</td>
</tr>
<tr>
<td>L97 (Lindström et al., 1997)</td>
<td>−1 °C, 1 °C</td>
<td>HBV model</td>
<td>Ten basins in Sweden, 1969–1989</td>
</tr>
<tr>
<td>C04 (Collins et al., 2004)</td>
<td>−5 °C, 0 °C</td>
<td>NCAR CAM3.0</td>
<td>Storglaciere, Sweden (67°55’N, 18°35’E, 1120 m–1730 m), 1993–1994</td>
</tr>
<tr>
<td>HH05 (Hock and Holmgren, 2005)</td>
<td>0.5 °C, 2.5 °C</td>
<td>Mass balance model</td>
<td>Tarim River Basin, China (35°N–43°N, 73°E–93°E, 2780 m–4800 m), 1961–2006</td>
</tr>
<tr>
<td>G10 (Gao et al., 2010)</td>
<td>−0.5 °C, 2 °C</td>
<td>Degree-day mass balance model</td>
<td>Qiyi Glacier in Qilian Mountains, China (39.5°N, 97.5°E, 4304 m–5158.8 m), Jun 30–Sep 5, 2010</td>
</tr>
<tr>
<td>W11 (Wang et al., 2011)</td>
<td>0 °C, 2 °C</td>
<td>Degree-day mass balance model</td>
<td>Lena River basin in Eastern Siberia, 1986–1994</td>
</tr>
<tr>
<td>Y01 (Yamazaki, 2001)</td>
<td>Snow ratio dependent on Ta</td>
<td>One dimensional land surface model</td>
<td>15,000 land stations global and many ships, 1977–2007</td>
</tr>
<tr>
<td>D08 (Dai, 2008)</td>
<td>Snow ratio dependent on Ta</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
(3) Search for abnormal years of each station. For each station, a year is regarded as abnormal if any of the following three conditions happens: (i) $N_{\text{rain, wrong}} / N_{\text{rain}} \geq 10\%$, (ii) $N_{\text{snow, wrong}} / N_{\text{snow}} \geq 30\%$, or (iii) $N_{\text{sleet, wrong}} / N_{\text{sleet}} \geq 30\%$. Then, we counted for each station (i) the number of years in which at least one precipitation type occurs, recorded as $Y_{\text{rain}}$, $Y_{\text{snow}}$, and $Y_{\text{sleet}}$, respectively; and (ii) the number of abnormal years for each type, recorded as $Y_{\text{rain, wrong}}$, $Y_{\text{snow, wrong}}$, and $Y_{\text{sleet, wrong}}$.

(4) Search for abnormal stations. A station is regarded as abnormal if any of the following four conditions happens: (i) $Y_{\text{rain, wrong}} / Y_{\text{rain}} \geq 50\%$, (ii) $Y_{\text{snow, wrong}} / Y_{\text{snow}} \geq 50\%$, (iii) $Y_{\text{sleet, wrong}} / Y_{\text{sleet}} \geq 50\%$, or (iv) $Y_{\text{snow}} + Y_{\text{sleet}} = 0$.

(5) Remove abnormal data found in Step (2–4). Firstly, remove all data from abnormal stations. Secondly, remove all data from abnormal years for each station. Thirdly, remove all abnormal data records that still remain after the preceding steps.

After all the above quality control steps, the data records with $-10^\circ\text{C} < T_a < 10^\circ\text{C}$ are selected, because this temperature range is concerned in terms of precipitation type discrimination.

The sample size of the precipitation data after the quality control is 459,766 collected at 709 stations. The station distribution is shown in Fig. 1. All these stations are separated into a calibration (or analysis) group and a validation group. The calibration group includes 609 stations (containing about 85% of all data) and is used for both the analysis of factors controlling the precipitation types and the development of a new discrimination scheme. The validation group includes 100 stations (containing about 15% of all data) and is used for testing the performance of the scheme in different regions, and its calculation is given in the Appendix A. Since precipitating droplets (including rain, sleet, and snow) have a temperature closer to $T_a$, it is reasonable to use $T_a$ for the validation of the new scheme. These calibration stations are selected randomly with consideration of spatial homogeneity. To test the performance of the scheme in different regions, all the stations are separated into four sub-regions: the Tibetan Plateau, Northwest China, Northeast China and the rest of China. The ratio of the calibration stations to the validation stations is about 14–20% of the samples in each bin.

3. Factors controlling precipitation types

3.1. Dependence on daily mean wet-bulb temperature ($T_w$)

$T_w$ contains air temperature, humidity, air temperature, and wet-bulb temperature, and its calculation is given in the Appendix A. Since precipitating droplets (including rain, sleet, and snow) have a temperature closer to $T_a$, it is reasonable to use $T_a$ for indicating the precipitation type. This is also suggested in Fig. 2c and d.

According to Fig. 2c, 99.5% of rain samples occur when $T_a \geq 0.5^\circ\text{C}$, and 98.7% of snow samples occur when $T_a \leq 5^\circ\text{C}$. In the overlapping range of $T_a [0.5^\circ\text{C}, 5^\circ\text{C}]$, there are 60,799 rain samples, 22,360 snow samples, and 27,222 sleet samples. However, according to Fig. 2d, 99.3% of rain samples occur when $T_w < -0.7^\circ\text{C}$, and 99% of snow samples occur when $T_w \leq 2.5^\circ\text{C}$. In the overlapping range of $T_w [-0.7^\circ\text{C}, 2.5^\circ\text{C}]$, there are 31,600 rain samples, 20,520 snow samples, and 24,258 sleet samples. So, the number of rain samples and snow samples in the overlapping range in terms of $T_w$ is much less than that in terms of $T_a$. In other words, it is reasonable to use $T_w$ instead of $T_a$ to discriminate precipitation types, as has been suggested by Yamazaki (2001).

To quantify the dependence of the occurrence frequency of each precipitation type on $T_w$, the precipitation samples for snow, sleet, and rain are counted, respectively, for each $0.2^\circ\text{C}$ bin of $T_w$. Fig. 3 shows the ratio of rain, sleet, and snow samples to their total in each bin with dark grey, white, and light grey, respectively. This ratio may be regarded as the probability of the occurrence of each type. As expected, with the increase of $T_w$, the probability of snowfall decreases, the probability of rainfall increases.

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Fig. 1. The distribution of the selected 709 CMA meteorological stations in China. The white marks represent the calibration group that comprises 609 stations for data analysis and scheme development, and the black ones represent the 100 stations for scheme validation. All the stations are separated into four sub-regions: the Tibetan Plateau (round), Northwest China (pentagram), Northeast China (square) and the rest of China (triangle).

Fig. 2 shows the sample distribution of rain, sleet, and snow within the calibration group with respect to elevation, relative humidity, air temperature, and wet-bulb temperature. The validation group has a similar distribution as in Fig. 2, with about 14–20% of the samples in each bin.
increases, and the probability of sleet occurrence first increases and then decreases.

3.2. Dependence on elevation and relative humidity (RH)

To explore the impact of other parameters on precipitation types, the ANN (Artificial Neural Network) is used to analyze the dependence of the precipitation types on several meteorological and geographic parameters (wind speed, specific humidity, RH, air pressure, station elevation, and latitude), and it is found that elevation and RH play much more important roles in determining the precipitation types.

To investigate the relationship between elevation and precipitation types, the total elevation range is divided into 6 sub-ranges (0–500, 500–1000, 1000–2000, 2000–3000, 3000–4000, and 4000–5000 m). The sample size of each type (rain, sleet, and snow) in each sub-range is shown in Fig. 2a, and the ratio of each type to the total (within each 0.5 °C bin of $T_w$) in each elevation sub-range is shown in Fig. 4a–f. It is clearly seen that, along with the increase of elevation, both the bound between snow ratio and sleet ratio and the bound between sleet ratio and rain ratio move toward higher temperature. As a result, a higher temperature threshold is needed for discriminating snow and rain over a higher elevation.

Similarly, the total RH range is divided into 5 sub-ranges (0–60%, 60–70%, 70–80%, 80–90%, and 90–100%), and Fig. 4g–k shows the ratio of each precipitation type to total (within each 0.5 °C bin of $T_w$) in each RH sub-range. A striking result is that the probability of sleet occurrence significantly increases with the increase of RH.

The dependence of precipitation types on elevation and RH can be explained through the energy exchange between precipitation droplets and the ambient air during the falling process. Precipitation droplets generally fall down in a near-surface heating environment, so the precipitation type relies on how many snow droplets can melt away before landing.
A higher elevation implies an environment with lower pressure and thinner air, leading to less drag force on the snow droplets. Thus the droplets can land faster in such an environment, causing the less amount of energy exchanged for melting snow droplets. So the snow droplets tend to keep their original type at a higher elevation. This explains why there is an increasing trend of the temperature threshold for discriminating snow and rain over high-elevation regions (Fig. 4a–f).

Different from the effect of elevation on landing speed of snow droplets, RH mainly affects the speed of the melting process. With the increase of RH, the vapor pressure difference between the surface of the snow droplet and the ambient air decreases, so the evaporation of the droplets becomes slower, and the evaporative cooling effect on the droplets becomes smaller during the falling of the droplets. This is favorable for the transition from snow to rain. Meanwhile, the temperature difference between the snow droplets (close to Tw) and the air (Ta) becomes smaller, so the heat absorbed by the droplets decreases, which may suppress the transition rate of droplets from snow to rain. As a result, the droplets can have a higher probability to appear as sleet in a humid environment than in a dry one (Fig. 4g–k).

4. A new parameterization scheme for precipitation type discrimination

4.1. Parameterizing the occurrence probability of precipitation types

The relationship between the precipitation types and Tw presented in Fig. 4 may be described with three parameters defined in Fig. 5. In Fig. 5, the bound between light grey and white represents the occurrence probability of snow (P₁), and the bound between white and dark grey represents the cumulative probability of snow and sleet (P₂). A centralized curve between these two bounds is parameterized by:

\[
P_c(T_w) = \frac{1}{1 + \exp\left(\frac{T_w - T_0}{\Delta S}\right)}
\]  

Then, the \(P_1\) and \(P_2\) relationships can be expressed as:

\[
P_1(T_w) = \frac{1}{1 + \exp\left(\frac{T_w - T_0}{\Delta S}\right)}
\]  

\[
P_2(T_w) = \frac{1}{1 + \exp\left(\frac{T_w - T_0 - \Delta T}{\Delta S}\right)}
\]

where \(T_0\), \(\Delta T\), and \(\Delta S\) are parameters to be determined; \(T_w\) is the wet-bulb temperature (°C); \(P_c\), \(P_1\), and \(P_2\) all range from 0 to 1.
Once \( P_1(T_w) \) and \( P_2(T_w) \) are determined, the occurrence probabilities of snow (\( F_{\text{snow}} \)), sleet (\( F_{\text{sleet}} \)), and rain (\( F_{\text{rain}} \)) at \( T_w \) can be calculated as:

\[
F_{\text{snow}}(T_w) = P_1(T_w),
\]

\[
F_{\text{sleet}}(T_w) = P_2(T_w) - P_1(T_w),
\]

\[
F_{\text{rain}}(T_w) = 1 - P_2(T_w).
\]

In Eqs. (1)–(3), \( T_0 \) is the temperature at which \( P_1(T_w) \) is equal to 0.5; it approximately represents the center of the range in which snow/rain transition happens. \( \Delta T \) is the temperature difference between \( P_2 \) and \( P_1 \) (or \( P_2 \) and \( P_1 \)) that gives \( P_1 = P_2 = 0.5 \), and \( 2\Delta T \) shows the temperature range in which sleet mainly occurs. \( \Delta S \) represents a temperature scale. With the increase of \( \Delta S \), the temperature range for snow/rain transition widens. The parameterizations of \( \Delta T \) and \( \Delta S \) are estimated from the relationship of precipitation types with elevation and \( RH \) based on the analysis in Section 3.2.

According to the relationship of precipitation types with \( T_0 \) and elevation (Fig. 4a–f), the three parameters (\( T_0 \), \( \Delta T \), and \( \Delta S \)) are obtained in each elevation sub-range. The relationships of the three parameters with the average elevation are shown in Fig. 6a–c. It is seen that \( T_0 \) has an overall increasing trend with elevation, while \( \Delta T \) and \( \Delta S \) do not have obvious changes with elevation.

Similarly, the three parameters (\( T_0 \), \( \Delta T \), and \( \Delta S \)) are obtained from Fig. 4g–k in each \( RH \) sub-range, and their relationships with the average \( RH \) are shown in Fig. 6d–f. With the increase of \( RH \), an increasing trend in \( \Delta T \) and a decreasing trend in \( \Delta S \) are pretty clear. Also, \( T_0 \) changes with \( RH \).

Since both \( \Delta T \) and \( \Delta S \) change with \( RH \) but not much with elevation, the parameterizations of \( \Delta T \) and \( \Delta S \) are developed by their dependences on \( RH \) and given by:

\[
\Delta T = 0.215 - 0.099 \times RH + 1.018 \times RH^2,
\]

\[
\Delta S = 2.374 - 1.634 \times RH,
\]

where \( RH \) is relative humidity and it ranges from 0 to 1. As \( T_0 \) depends on both elevation and \( RH \), it is a function of both elevation and \( RH \). Given the values of \( \Delta T \) and \( \Delta S \) from Eqs. (7) and (8), the value of \( T_0 \) is optimized using the shuffled complex evolution method (Duan et al., 1993) to maximize the accuracy of discriminating the precipitation types. The final result is given by:

\[
T_0 = -5.87 - 0.1042 \times Z + 0.0885 \times Z^2 + 16.06 \times RH - 9.614 \times RH^2,
\]

where \( Z \) denotes station elevation (km).

4.2. A scheme for determinant parameterization of precipitation types

From Eqs. (2)–(9), the occurrence probability of each precipitation type can be calculated by inputting \( T_w \), \( RH \), and elevation. For land hydrological modeling, it is usually not sufficient to give the probabilities of the precipitation types; instead, the type for a specific precipitation event must be given. In other words, a determinant identification rather than the probability of a precipitation type is needed. Therefore, two threshold temperatures (\( T_{\text{min}} \) and \( T_{\text{max}} \)) are defined such that the precipitation type is decided by:

\[
type = \begin{cases} 
\text{snow, if } T_w \leq T_{\text{min}}; \\
\text{sleet, if } T_{\text{min}} < T_w < T_{\text{max}}; \\
\text{rain, if } T_w \geq T_{\text{max}}.
\end{cases}
\]

According to the \( P_1-T_w \) and \( P_2-T_w \) relationships in Fig. 5, \( T_{\text{min}} \) is the temperature value at which the occurrence probabilities of snow and sleet are equal to each other, and \( T_{\text{max}} \) is that for the equal occurrence probabilities of rain and sleet. These can be expressed as

\[
F_{\text{snow}}(T_{\text{min}}) = F_{\text{sleet}}(T_{\text{min}}),
\]

\[
\text{Fig. 6. The relationships of } T_0, \Delta T, \text{ and } \Delta S \text{ with average elevation (Z) in each Z sub-range (a)–(c), and their relationships with average relative humidity (RH) in each RH sub-range (d)–(f).}
\]
5. Scheme evaluations

The new parameterization scheme developed in Section 4 is evaluated in different regions and periods against the 609 stations in the calibration group and the 100 stations in the validation group (Section 5.1). In addition, all data are used to compare the performance of this scheme with 11 schemes that have already been used in land hydrological models, and this section presents the performances of 11 schemes in the literature in comparison with the present scheme. Table 1 lists the 11 schemes in the literature. Among them, nine schemes are used for precipitation-type classification: Y97 is a single threshold method; L93, W94, ...

5.2. Scheme inter-comparisons

A number of schemes for precipitation-type discrimination have been used in land hydrological models, and this section presents the performances of 11 schemes in the literature in comparison with the present scheme. Table 1 lists the 11 schemes in the literature. Among them, nine schemes are used for precipitation-type classification: Y97 is a single threshold method; L93, W94, ...

Fig. 7. (a) Accuracy of the present scheme and nine threshold schemes (first nine in Table 1) over the air temperature range [0 °C, 4 °C] in China, the Tibetan Plateau (TP), Northwest China (NW), Northeast China (NE), and the rest of China (Rest) for the whole period. The white bars denote the discrimination accuracy for the calibration group, and the black ones denote that for the validation group. Against the calibration group, the average accuracy of this scheme for the mainland of China exceeds 88% over [−10 °C, 10 °C] of $T_a$. Furthermore, its accuracy exceeds 86% for all the four sub-regions. It can be seen that the accuracy over the TP is slightly higher than the other three sub-regions, which implicates a better performance of the scheme in highland regions.

In order to investigate the time stability of the present scheme, the whole study period is divided into three sub-periods: 1951–1960, 1961–1970, and 1971–1979. The white bars in Fig. 7b show the performance of the present scheme in each sub-period over the $T_a$ range [−10 °C, 10 °C]. The accuracy of the scheme is about 88% for the whole period, and it is quite stable for the three sub-periods, indicating that the new scheme has a robust performance.

The performance of the new scheme against the independent validation data is very close to and even slightly better than the one against the calibration data, as shown in Fig. 7. This further proves the general applicability of the present scheme in China.
K94, L97, C04, HH05, G10, and W11 are dual-threshold methods. Other two schemes (Y01 and D08) are used to calculate the ratio of snow (or rain) amount to total precipitation amount with input of \( T_a \) or \( T_w \). The specific temperature thresholds to discriminate precipitation types or the variable used to estimate the snow ratio for these schemes are summarized in Table 1.

Fig. 8a compares the accuracy between the present scheme and the nine threshold schemes (the first nine schemes in Table 1) over the \( T_a \) range \([0 \degree C, 4 \degree C]\) in China and the four sub-regions of China (TP, NW, NE, and Rest). It is seen that the accuracy of all schemes for the \([0 \degree C, 4 \degree C]\) range is worse than that for the \([-10 \degree C, 10 \degree C]\) range (Fig. 7), indicating that the discrimination of precipitation types for the \([0 \degree C, 4 \degree C]\) range is more difficult. Perhaps, precipitation types over this temperature range are more sensitive to ambient air conditions. Nevertheless, the accuracy of the present scheme is clearly better than that of the nine schemes for the whole region and each of the four-sub-regions, as also indicated in Table 2. Among the nine schemes, Y97 scheme shows better performance in the four sub-regions; K94 scheme also has good performance for TP and NW but not so for NE and Rest, perhaps because K94 scheme is obtained from high-elevation observations; other seven schemes generally perform better for the low-elevation regions than the high-elevation regions, perhaps because they focus more on low-elevation regions or estimate the threshold temperatures by experiences. In turn, this demonstrates the dependence of precipitation types on elevation. The difference in the accuracy between the present scheme and Y97 scheme is nearly 7.9% for China (59.3% and 51.4% for the two schemes, respectively), 12.5% for TP (66.1% and 53.6%, respectively), 6.3% for NW (60.1% and 53.8%, respectively), 4.8% for NE (53.1% and 48.3%, respectively), and 7.3% for Rest (57.8% and 50.5%, respectively), as shown in Fig. 8a. The accuracy difference between the present scheme (66.1%) and K94 scheme (57.2%) for TP is nearly 8.9%, and that between the present scheme (57.8%) and HH05 scheme (51.6%, the best one among the nine schemes) for Rest is about 6.2%. To show the performance of the present scheme more clearly, Fig. 8b compares the accuracy distribution of this scheme with Y97 scheme and HH05 scheme (the best two schemes among the nine) with respect to \( T_w \) for China. Again, it can be seen that the present scheme performs better at any specific \( T_w \) value.

Fig. 9a shows the comparison of \( P_{1-T_a} \) and \( P_{2-T_a} \) relationships from observed data (obs), their fitted curves (fit) according to Eqs. (2) and (3), and the \( P-T_a \) relationship \( (P \) is the ratio of snow amount to total precipitation amount) given by Y01 scheme; (b) the \( P_{1-T_a} \) and \( P_{2-T_a} \) relationships between the observed and D08 scheme.

### Table 2

<table>
<thead>
<tr>
<th>Country</th>
<th>Present (%)</th>
<th>Y97 (%)</th>
<th>L93 (%)</th>
<th>W94 (%)</th>
<th>K94 (%)</th>
<th>L97 (%)</th>
<th>C04 (%)</th>
<th>HH05 (%)</th>
<th>G10 (%)</th>
<th>W11 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>China</td>
<td>59.3</td>
<td>51.4</td>
<td>29.4</td>
<td>37.2</td>
<td>35.7</td>
<td>41.3</td>
<td>39.6</td>
<td>47.4</td>
<td>42.6</td>
<td>43.7</td>
</tr>
<tr>
<td>TP</td>
<td>66.1</td>
<td>53.2</td>
<td>24.1</td>
<td>24.1</td>
<td>57.2</td>
<td>19.7</td>
<td>20.3</td>
<td>33.8</td>
<td>20.9</td>
<td>22.8</td>
</tr>
<tr>
<td>NW</td>
<td>60.1</td>
<td>53.8</td>
<td>28.1</td>
<td>34.0</td>
<td>45.3</td>
<td>32.2</td>
<td>29.4</td>
<td>43.9</td>
<td>35.5</td>
<td>37.0</td>
</tr>
<tr>
<td>NE</td>
<td>53.1</td>
<td>48.3</td>
<td>34.3</td>
<td>40.6</td>
<td>34.8</td>
<td>41.5</td>
<td>36.9</td>
<td>48.4</td>
<td>44.1</td>
<td>45.1</td>
</tr>
<tr>
<td>Rest</td>
<td>57.8</td>
<td>50.5</td>
<td>30.4</td>
<td>40.9</td>
<td>27.5</td>
<td>49.3</td>
<td>47.8</td>
<td>51.6</td>
<td>50.0</td>
<td>50.7</td>
</tr>
</tbody>
</table>

6. Conclusion and remarks

Precipitation type is an important input for the study of land hydrological processes, and usually determined by static temperature thresholds in most current hydrological models. To better discriminate rain, sleet, and snow, this study presented the relationships of precipitation types with elevation and meteorological variables based on CMA station data during 1951–1979, and then a new parameterization scheme was developed.

It is found that wet-bulb temperature is a better indicator of precipitation types than air temperature although the latter is more widely used in discriminating precipitation types. Precipitation types are also highly dependent on elevation and humidity. Over higher-elevation regions, snow droplets can land faster and thus absorb less heat from the ambient air. So the droplets tend to stay as snow at high elevations and a higher threshold temperature is needed for discriminating snow and rain. In a humid environment, small humidity difference between droplets and ambient air leads to small evaporative cooling and thus is favorable for the phase transition from snow to rain, but the intensity of the
transition is suppressed by the small heat transfer from the air to the snow droplets, resulting in more sleet.

Based on these findings, a new parameterization scheme was developed to discriminate rain, sleet, and snow. In this scheme, the threshold temperatures dynamically change with humidity and elevation. The dynamic threshold method tends to be a dual-threshold method in a humid environment and a single threshold method in a dry environment. Several evaluations show consistent good performance of the new scheme in different regions and periods, and also indicate that the new scheme performs better than other schemes in the literature.

Finally, it is worthy to note that the scheme was only evaluated for China territory, and further evaluations for other regions are needed. Furthermore, the new scheme was developed based on daily meteorological data, and thus it may be different from schemes developed based on hourly data. As the temperature during precipitation hours is usually lower than the daily mean temperature, the threshold temperature needed for identifying hourly precipitation types is expected to be lower than the values given by the present scheme.

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Appendix A. Wet-bulb temperature \( (T_w) \)

\( T_w \) is the temperature of a parcel of saturated air if the saturation is due to evaporation into it, with the latent heat supplied by the parcel itself. This process can be expressed as:

\[
\exp \left( \frac{L_v}{p_s} (e_s - e_{w, sat}) \right) = 0, \quad (A.1)
\]

where \( c_p = 1004 \text{ J K}^{-1} \text{ kg}^{-1}, \epsilon = 0.622, L_v = 2.5104 \times 10^6 \text{ J kg}^{-1}, p_s \) is air pressure [h Pa], \( T_a \) is air temperature [°C], \( T_w \) is wet-bulb temperature [°C], \( e_s \) is vapor pressure [h Pa], and \( e_{w, sat} \) is the saturated vapor pressure [h Pa] at \( T_w \).

From the above equation, \( T_w \) can be deduced as:

\[
T_w = T_a - \frac{e_{w, sat}(T_a)(1 - RH)}{0.000643p_s + \frac{L_v}{c_p}}, \quad (A.2)
\]

where \( RH \) is relative humidity and it ranges from 0 to 1; \( e_{w, sat}(T_a) \) is the saturated vapor pressure [h Pa] at \( T_a \) and is given by Tetens's empirical formula (Murray, 1967) as:

\[
e_{w, sat}(T_a) = 6.1078 \exp \left( \frac{17.27T_a}{T_a + 237.3} \right). \quad (A.3)
\]

Appendix B. Deduction of the constraint for the optimal threshold temperatures

There are two constraints for Eqs. (13) and (14), as given below:

\[
\exp \left( \frac{\Delta T}{\Delta S} \right) - 2 \exp \left( - \frac{\Delta T}{\Delta S} \right) > 0, \quad (B.1)
\]

and

\[
T_{min} < T_{max}. \quad (B.2)
\]
in which, Eq. (B.1) is a constraint required by the logarithmic term in Eq. (13), and Eq. (B.2) is a physical constraint. Putting Eqs. (13) and (14) into Eq. (B.2), we have

\[
\Delta S \ln \exp \left( \frac{\Delta T}{\Delta S} \right) - 2 \exp \left( - \frac{\Delta T}{\Delta S} \right) > 0, \quad (B.3)
\]

where \( \Delta S \) is a function of \( RH \) (Eq. (8)) and gives a value consistently larger than 0 over the \( RH \) range [0, 1]. So Eq. (B.3) is equivalent to

\[
\exp \left( \frac{\Delta T}{\Delta S} \right) - 2 \exp \left( - \frac{\Delta T}{\Delta S} \right) > 1, \quad (B.4)
\]

which also satisfies Eq. (B.1).

Eq. (B.4) can eventually be simplified as:

\[
\frac{\Delta T}{\Delta S} > \ln 2, \quad (B.5)
\]

which is the constraint for Eqs. (13) and (14).

References


