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Comparison of classification methods for the divisions of wet/dry climate regions in Northwest China

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ABSTRACT: Two distinct approaches can be employed in the classification and divisions of wet/dry climate. The first is the rule-driven strategy with predefined threshold values representing climate division boundaries, which is usually performed by Aridity Index (AI). The second is an automated method in a data-driven fashion, avoiding the direct specification of classification rules while utilizing some forms of cluster analysis. However, various methods for climate classifications raise issues on their applicability and quality. Therefore, evaluation and comparative studies are needed to handle such issues first, in order to analyze their performance and second, to better understand climate characteristics in a region. This article makes a comprehensive analysis and comparison among five classification methods, including four rule-driven methods based on different categories [Penman-Monteith (PM), Thornthwaite, Holdridge, Sahin's method] and one data-driven method (factor-cluster analysis). With the meteorological data for long-term period (1981–2010), the wet/dry climate divisions were performed for 191 meteorological stations in Northwest China (NW). The results indicated that the overall climate regimes were in agreement for five classifications, but boundaries of wet/dry climate divisions in a data-driven fashion showed a better consistency with topographic features. PM classifications displayed more arid climate types in NW, while the Thornthwaite approach showed an underestimate in arid environments. All wet/dry climate types corresponding to Holdridge and Sahin's classifications were represented in NW, but Holdridge classification is more easily affected by topography and elevation. Complete comparisons among rule-driven methods are difficult to conduct due to different class definitions and low coincident classes. Class definition of climate types for different rule-driven classifications thus needs further investigation. This article highlights the importance of acknowledging the limitations and advantages of different classification systems as well as the dry and wet climate conditions in NW in hope to provide a reference for a similar geographical region.

KEY WORDS classification; wet/dry climate; aridity index; rule-driven; data-driven; factor-cluster analysis; Northwest China

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1. Introduction

The climate of a geographic location is influenced by many factors. The diversity of global climate types makes it necessary to have a prior knowledge of the climatic conditions prevailing in a region. Climate classifications are an important tool and have often been employed to identify similar climate types or regional variability (Jacobeit, 2010; Bieniek *et al.*, 2012). A typical example is the global climate classification from Wladimir Köppen (1923). Among these climate elements, however, precipitation is indispensable in determining climate features of any locality or region (Sönmez and Kömüşcü, 2011; Sahin and Cigizoglu, 2012). Divisions of wet/dry climate zones are thus considered as one of the most basic contents in climate classifications.

It has long been believed essential to understand the wet/dry climate features of a geographic region for climatic research and agricultural water management. The Aridity Index (AI) which can be described by many empirical and semi-empirical formulas is important to classify climate types (Nastos *et al.*, 2013). The earliest study can date back to at least the early 1900s, when the ratio of annual potential evaporation to precipitation was proposed by Dokutchev in 1900 (Oliver, 2005). The concept was known as the aridity or dryness index after Budyko (1974) (Arora, 2002). However, the role of evapotranspiration was truly emphasized by Thornthwaite (1948) and Thornthwaite and Mather (1951) who considered it as an equally important climatic factor with precipitation in the wet and dry condition analysis of climate. Following this, computational methods of potential evapotranspiration (PET) arose and evolved constantly. Holdridge (1947) put forth a calculation formula with the biological significance. Penman (1948) established a semi-empirical physical-mathematical model.

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And Monteith (1965) derived an equation based on Penman's theory, referred to as Penman–Monteith equation (PM), which was revised and recommended as the sole standard by FAO afterwards (Allen *et al.*, 1998). However, all these methods have distinctive characteristics due to their different assumptions and input data requirements, or developed for specific climatic regions (Sahin, 2012). Even considered as the most reliable method, the application of PM was still limited because enormous meteorological data required may not be available everywhere. Therefore, Sahin (2012) defined a new AI by using specific humidity instead of PET, which only needed mean temperature, relative humidity and local pressure which are the most readily available variables. And it was found to be applicable for monitoring climate change and distribution of arid zones by an illustration in Turkey.

All these methods as mentioned above can be regarded as a 'rule-driven' strategy in which the climate types were first defined using the selected measures and then used to determine the classification of each locale for which the appropriate data are available, yielding the regionalization (Fovell, 1997). However, the process was partly subjective since thresholds were often predefined on the basis of discernible changes in some important components of the global ecosystem (e.g. alignment with major watersheds, agricultural administrative districts and geographic convenience) and expert judgment (Kostopoulou and Jones, 2007; Abatzoglou *et al.*, 2009; Jacobeit, 2010). As oppose to the 'rule-driven' strategy, the classification in a 'data-driven' fashion is objective and automated, and avoids the direct specification of classification rules, often utilizing some forms of multivariate statistical techniques, e.g. cluster algorithm (Fovell, 1997). In contrast, the implementation of the technique has allowed to classify climate without predefined thresholds by grouping individual objects (e.g. weather stations) into self-generating classes according to particular statistical criteria (Jacobeit, 2010). Fovell and Fovell (1993) have applied cluster analysis to identify climate zones in the United States based on the National Climatic Data Center (NCDC) dataset. The clustering algorithm has also been applied to diverse climates such as Turkey (Unal *et al.*, 2003) and Alaska (Bieniek *et al.*, 2012). Ahmed (1997) developed climate divisions for Saudi Arabia by using the factor-cluster analysis technique. Other techniques, e.g. principal component analyses (PCA), has also been considered in the field of climate classifications and delineation of climate zones (Bunkers *et al.*, 1996; Degaetano, 1996; Kostopoulou and Jones, 2007). However, it is necessary to understand and evaluate the performance of different classification systems.

In this article, five approaches were investigated by comparison, including four rule-driven methods representing different categories (Penman-Monteith, Thornthwaite, Holdridge and Sahin's method) and a data-driven method (factor-cluster analysis). Northwest China (NW) is considered as a case study in this article to further understand the distribution characteristics of wet/dry climate zones in order to formulate water resources management programmes in NW effectively and provide a reference for the regionalization of climate zones in a similar geographical region. The structure of this article is organized as follows: Section 2 describes the study area and data used in this study; the data analysis and description of methods are introduced in Section 3. The regionalization and classifications based on different methods are presented and compared in Section 4, and it also includes some discussions. Finally, some concluding remarks are provided in Section 5.

2. Study area and data

2.1. Study area

In this article, NW consists of six jurisdiction provinces (autonomous regions) including the autonomous regions of Xinjiang, Ningxia and Inner Mongolia, and the provinces of Shaanxi, Gansu and Qinghai (Figure 1). It covers an area of about 4.27×10^6 km^2, accounting for 44.5% of China's total area. The topography is complicated and changeable, and mountains range across its length and breadth in this region. Among three steps of China's terrain, the first (Qinghai–Tibet Plateau) and second steps (Inner Mongolia Plateau and Loess Plateau) are within the region (Wang *et al.*, 2005; Xu *et al.*, 2011). It is also the location of Tarim River, the largest inland river in China and the source regions of the Yangtze River and Yellow River.

The major source of moisture in NW is the Pacific Ocean. However, distance from the coast and terrains are the major factors affecting the climatic conditions and geomorphic features. Featured by a unique morphological complexity consisting of mountains, hills, plateau, basins and plains, the landscape of the region therefore generates the region's diverse biomes (forests, grasslands, deserts and oases) (Zhao *et al.*, 2011). The high mountains like Tianshan Mountains, Kunlun Mountains, Qilian Mountains and Da Hinggan Mountains block atmospheric circulation and thus create vast deserts, basins and plateau in the rain shadow, such as Tengger desert, Badain Jaran desert, the Tarim Basin, the Junggar Basin, the Qaidam basin, and Mongolian Plateau (Shi *et al.*, 2006; Yang *et al.*, 2008; Fang *et al.*, 2009). Meanwhile, the unique topography enables this region to reserve the rich melt water resources (Wang and Cheng, 2000).

Located in the center of the Eurasian continent, this region is dominated by a continental monsoon climate and is the typical arid and semi-arid climate. It is characterized mainly by low and irregular precipitation, high evaporation, large precipitation variation and pronounced periods of drought. The mean annual precipitation gradually decreases from southeast to northwest (from above 900 mm in the south of Qinling Mountains to 400 mm in the loess plateau and then to less than 50 mm in the Tarim Basin). Moreover, the annual precipitation is less than 400 mm in most areas. Meanwhile, about 70% of the annual precipitation in this region is in the

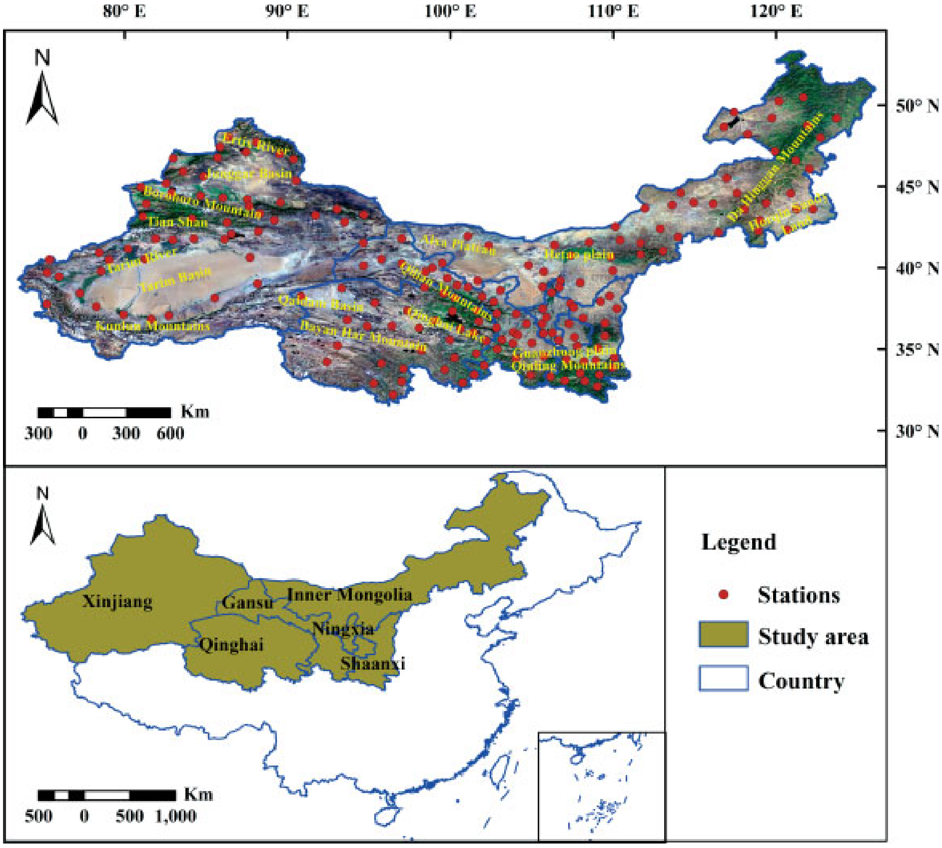

Figure 1. Locations of the study area and meteorological stations used in this study.

form of storm in the 4 months of June, July, August and September (Deng *et al.*, 2006). The climate makes the local ecological environment highly vulnerable. Rich though the land resources are, the regional agricultural production is seriously affected by water conditions, which as a result, restricts the economic and social development. In comparison with other regions in China, the economy in most of Northwest China is relatively undeveloped (Yang *et al.*, 2008).

2.2. Climate data

Station data for this study are from the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn), run by the National Meteorological Information Centre (NMIC). These data include the mean air temperature (T_m), maximum and minimum air temperature (T_{max} and T_{min}), relative humidity (R_h), wind speed (V), sunshine duration (S_d), precipitation (P_m) and air pressure (Pa) at a monthly time step, covering the time period between 1981 and 2010. The annual average precipitation (P_{ann}), potential evapotranspiration (PET), precipitation variability (P_v), relative humidity (RH) and annual temperature range (T_r) were calculated based on the above data for factor-cluster analysis. These variables were selected according to the consideration on the representative wet/dry climate elements.

There are 213 station data in the initial data set. Complete information table for these stations was omitted here due to the space limitation. Since these values are to be used for the determination of climate zones, all data should be obtained in the same period. Therefore, statistical information between 1981 and 2010 regarded as common for all data is given in Table 1.

The station choice is based on the desire to have a widespread and availability of data. The initial quality control has been conducted by NMIC (Fan *et al.*, 2011). We further performed routine quality assessment and homogeneity test, according to two kinds of potential errors, i.e. outliers and inconsistency (Gao *et al.*, 2012). The missing data rate was generally controlled within the 5%. As a result, 22 meteorological stations were discarded. The missing data in the considered 191 stations was filled by using expectation maximization (EM) method (Sahin and Cigizoglu, 2012). The EM algorithm can be used both to compute the maximum likelihood estimates of the statistics of the data and to fill in missing values with their conditional expectation values given the available values and the estimated statistics. However, if an incomplete dataset, like most sets of climate data, has more variables than records so that it is rank-deficient, it cannot be used. The remained 191 stations had climatic time series for eight parameters in the time interval 1981–2010 based on the monthly data. It was thus performed for the missing data analysis. Properties and details of EM algorithm can also be found by Schneider

Table 1. Basic statistics of monthly data and total number of missing values after omitting 22 stations.

Variable	Mean	Maximum	Minimum	Median	St. Dev.	Missing	Percent (%)
T_m (°C)	6.4	33.9	−33.9	7.3	12.2	937	1.36
T_{max} (°C)	13.4	41.3	−27.9	14.3	12.1	937	1.36
T_{min} (°C)	0.4	27.2	−40.4	1.4	12.0	937	1.36
R_h (%)	53.7	93.0	13.0	53.0	15.0	939	1.37
V (m/s)	2.4	12.9	0.0	2.2	1.2	940	1.37
S_h (h)	230.7	403.9	4.4	232.3	56.5	944	1.37
P_m (mm)	24.4	689.9	0.0	8.3	37.8	936	1.36
P_a (Pa)	85156.7	103620.0	56980.0	87640.0	9780.3	939	1.37

'Missing' denotes the total number of missing values for 191 stations and 'Percent' denotes the percentage of missing values.

(2001). The geographic distribution of 191 stations and location of the study area is shown in Figure 1.

3. Methodology

3.1. Factor-cluster analysis (FC)

This method is an integrated statistical approach which is based on the factor analysis (FA) and cluster analysis (CA). Two steps are included for the application of the technique. The first step is to extract and integrate the overlapped information so as to realize the dimension reduction among original variables by using FA. In the second step, the resultant factor scores are taken as an input in a cluster analysis process to obtain climatic regions. The method has been employed for climatic classification of Saudi Arabia (Ahmed, 1997) and the regionalization of Iran's precipitation climate (Dinpashoh *et al.*, 2004).

Before using the FA, correlation structure between data should be evaluated and the adequacy of correlation level between indicators for using the FA should be determined. Two required basic assumptions, i.e. the Kaiser-Meyer-Olkin (KMO) statistic and Bartlett's test of sphericity, must be verified. The KMO is the sampling adequacy tests whether the partial correlations among items are small, and it was performed so as to decide whether each variable was appropriate for the factor analysis (Um *et al.*, 2011). The approved range of values of KMO (0.7–1.0) indicates the sample size sufficiency, though realistically it should exceed 0.80 if the results of the FA are to be more reliable (Table 2). The Bartlett's test is to give the information whether the correlation matrix is an identity matrix. Very small values of significance (below 0.05) for Bartlett's test demonstrates that the dataset is not an identity matrix and it is appropriate for the FA, whereas higher values (0.1 or above) indicate it is inappropriate (Um *et al.*, 2011).

The Kaiser criterion and Scree test are used to address the number of factors question. Accordingly all principal components (PCs) with eigenvalues >1.0 are extracted. Such an eigenvalue is generally employed for FA in order to estimate the appropriate number of factors (Kim and Mueller, 1978; Um *et al.*, 2011). The orthogonal Varimax normalized rotation is used for FA to improve the interpretation of the unrotated PCs results (Overall and Klett, 1972). The standardized PC scores are calculated using the regression method.

In this study, the hierarchical cluster technique, an ideal method for the exploratory stage of research (Unal *et al.*, 2003; Modarres and Sarhadi, 2011), was applied in order to classify the wet/dry climate homogeneous regions. In a first stage, the squared Euclidian distance is calculated based on the standardized PC scores from FA by using Ward's method. A dendrogram can be obtained for a visual guide for selecting the number of clusters and regions. The whole process was operated with the support of SPSS software tools.

3.2. PM equation

The PM equation is a semi-empirical model with the physical significance, and recommended by FAO (Allen *et al.*, 1998). Currently, it was often used as a standard and the most reliable method for calculating PET to verify other empirical methods (Chen *et al.*, 2005; Li, 2012). According to the FAO, PM for PET (or so-called reference evapotranspiration, ET_0, mm day^{-1}) can be expressed as:

$$ET_0 = \frac{0.408\Delta\,(R_n - G) + \gamma \frac{900}{T+273} u_2\,(e_s - e_a)}{\Delta + \gamma\,(1 + 0.34u_2)} \tag{1}$$

where R_n is the net radiation at the crop surface (MJ m^{-2} day^{-1}), G is the soil heat flux density (MJ m^{-2} d^{-1}), T is the air temperature at 2 m height (°C), u^2 is the wind speed at 2 m height (m s^{-1}), e_s is the saturation vapor pressure (kPa), e_a is the actual vapor pressure (kPa), $e_s - e_a$ is the saturation vapor pressure deficit (kPa), Δ

Table 2. The judging criterion of the KMO test (Kaiser and Rice, 1974).

KMO values	<0.5	0.6-0.7	0.7-0.8	0.8-0.9	>0.9
Factor analysis	Disagree	Unsuitability	Moderate	Suitable	Very suitable

is the slope vapor pressure curve (kPa°C^{-1}) and γ is the psychrometric constant (kPa°C^{-1}).

Due to the lack of directly measured data (e.g. R_n and G), however, we calculated ET_0 by CROPWAT model developed by FAO (1992, 2007) in this article. The input data required in the model includes the monthly maximum and minimum temperature, monthly relative humidity, wind speed and sunshine duration. The class definition of AI used in this article follows the rules given by CAS (1959) which is widely used for climate regionalization of China (The National Commission for Agricultural Regionalization, 1984; Chen and Zhang, 1996; Zheng *et al.*, 2010). The AI based on PM method (AI_p) is given by:

$$AI_P = \frac{PET_a}{P_a} \tag{2}$$

In which, P_a and PET_a are the average annual precipitation and potential evapotranspiration (mm), respectively.

3.3. Thornthwaite method

The Thornthwaite method derived an empirical correlation between PET and air temperature T from measurements in different climatologic regions (Shuttleworth, 1992; Thi *et al.*, 2012). An assumption based on a standard month of 30 days, each day with 12 h of photoperiod was proposed for computing the monthly PET. The Thornthwaite formulae for the calculations are as follows (Thornthwaite and Mather, 1955; Kafle and Bruins, 2009; Anayah, 2012):

$$AI_T = 100\left(\frac{P_a}{PET_a} - 1\right) \tag{3}$$

$$PET_m = 16C\left(\frac{10T_m}{I}\right)^a \tag{4}$$

$$C = \frac{S}{360} \tag{5}$$

$$I = \sum_{Jan}^{Dec}\left(\frac{T_m}{5}\right)^{1.514} \tag{6}$$

$$a = 6.75 \times 10^{-7}I^3 - 7.71 \times 10^{-5}I^2 + 1.79 \times 10^{-2}I + 0.492 \tag{7}$$

where AI_T is the aridity index of Thornthwaite, PET_m is the monthly potential evapotranspiration (mm), T_m is the average monthly temperature (°C), C is the daylight coefficient, S is the actual photoperiod (h) for a given month, a is an exponent derived from the thermal index (I).

3.4. Holdridge Method

The Holdridge method is an empirical equation with biological significance. It is based on a correlation between PET and bio-temperature BT from measurements in different climatologic regions. Its hypothesis is that the range of the mean temperature from plant vegetative stage is 0–30 °C. The temperatures that are below 0 °C or above 30 °C are eliminated, and supposed as 0 and 30 °C, respectively (Holdridge 1947, 1967).

$$AI_H = \frac{PET_a}{P_a} \tag{8}$$

$$PET = 58.93 \times BT \tag{9}$$

$$BT = \frac{\sum T_m}{12} \tag{10}$$

where AI_H is the aridity index of Holdridge, BT is the average annual bio-temperature (°C).

3.5. Sahin's method

Sahin's Aridity Index (I_q) is a method based on specific humidity (S_h), instead of PET. It can be considered a new simplified method, which avoids the disadvantage caused by the unavailability of the climatic data required. Therefore, it can be more easily applied globally and regionally with a very high number of meteorological stations and has the potential that replaces PM method. The basic equation of I_q is defined as follows:

$$I_q = \frac{\overline{P}}{\overline{S_h}} \tag{11}$$

where P and S_h are the long-term average of the annual precipitation total (mm) and the annual mean specific humidity (g kg^{-1}), respectively.

The specific humidity data is calculated on the basis of the formula given by Gill (1982). The formula is as follows:

$$q_a = \frac{0.622e_a}{p_a - 0.378e_a} \tag{12}$$

where q_a is the specific humidity (kg kg^{-1}), e_a is the vapor pressure of the air (Pa) and P_a is the local pressure (Pa). The formula of vapor pressure of the air e_a is also given by Gill (1982):

$$e_a = r_h 10^{[(0.7859+0.03477T_a)/(1.0+0.004212T_a)+2]} \tag{13}$$

In which, T_a and r_h are the monthly mean temperature (°C) and relative humidity (%), respectively.

S_h is the average of long time-series data. In this article, S_h data were calculated for 191 stations between the time period 1981 and 2010.

Table 3 shows the specific definition of climate classifications based on different methods.

4. Results and discussion

4.1. Classification system established by using FC

The correlation matrix was first inspected based on the KMO statistic and Bartlett's test. As shown in Table 4, all of the variables over the entire matrix showed high values of correlation coefficient, except for annual temperature range (T_r) which had low correlation with all other

Table 3. The definition of climate classifications using different methods.

Class definition		AI_{PM}	AI_H	I_q	AI_T
Hyper-arid		>16	>8.0	<20	<−100
Arid		4.0 to 16.0	4.0 to 8.0	20 to 35	−100 to −67
Semi-arid		1.5 to 4.0	2.0 to 4.0	35 to 60	−67 to −33
Sub-humid	Dry	1.0 to 1.5	1.0 to 2.0	60 to 90	−33 to 0
	Wet				0 to 20
Humid		0.5 to 1.0	0.5 to 1.0	90 to 120	20 to 100
Very humid		<0.5	<0.5	>120	>100

Table 4. Correlation matrix based on the FA.

Correlation	P_{ann}	PET	P_v	RH	T_r
P_{ann}	1.000	−0.615	−0.683	0.725	−0.496
PET	−0.615	1.000	0.565	−0.764	0.232
P_v	−0.683	0.565	1.000	−0.537	0.334
RH	0.725	−0.764	−0.537	1.000	−0.155
T_r	−0.496	0.232	0.334	−0.155	1.000

Table 5. Total variance explained of the run of the FA.

Component	Initial eigenvalues			Extraction sums of squared loadings		
	Total	% of Variance	Cumulative (%)	Total	% of Variance	Cumulative (%)
1	2.949	73.715	73.715	2.949	73.715	73.715
2	0.532	13.311	87.026			
3	0.337	8.434	95.461			
4	0.182	4.539	100.000			

variables. Therefore, the T_r was removed (Um *et al.*, 2011). After discarding the T_r, the KMO statistic (0.744) met the middling standard (Kaiser and Rice, 1974) and thus is more appropriate for the FA. Consequently, the significant level (below 0.05) for Bartlett's test and the value of KMO statistic satisfied the prerequisite of FA.

According to Table 5, the first component of common factors explained 74% of total variance. The eigenvalue is 2.9. The eigenvalue of second component is less than 1.0. A break point with the values of variance of the first and second components can be also found in Scree plot. One component was thus determined. It means that these variables have great similarity, all of which explain a common climate phenomenon, i.e. the dry/wet climate conditions. Therefore, this factor is interpreted to reflect the comprehensive features of the wet and dry climate in NW. The linear model of factor scores was expressed as follows:

$$F = 0.299P_{ann} - 0.291\text{PET} - 0.272P_v + 0.301\text{RH} \tag{14}$$

The computed factor scores (F) from 191 stations are grouped on a basis of the hierarchical clustering. Seven resultant regions were presented. The value of climate classes was defined from high to low, depending on the climatic characters from arid to humid. Locations of seven climate classes are shown in Figure 2.

4.2. Comparison of climate classifications

4.2.1. Spatial distribution of climate variables used in this study

Before comparing the performance of different wet/dry climate classification systems in NW, it is instructive to consider maps of NW on distributions of main climate variables involved, including annual mean air temperature (T_{ann}), annual temperature range, and precipitation, potential evapotranspiration, precipitation variability, relative humidity and specific humidity.

As shown in Figure 3(a), four distinct regions for air temperature, including two high value regions and two low value regions, can be found in NW. For regions with high temperature, it can be known that it is mainly caused by a large area of deserts and exposed land surface in the Tarim Basin, where covers the biggest desert of China (i.e. Takla Makan Desert), whereas it is related to latitude in the south-central part of Shaanxi which is dominated by subtropical climate. For regions with low temperature, the south of Qinghai which locates in the Qinghai-Tibet Plateau is mostly affected by high-altitude, whereas it is attributed to latitude as well in the northeast Inner Mongolia which lies in the northernmost regions of China.

In terms of the spatial distribution of annual temperature range (T_r), it is clear that T_r is significantly related to latitude (Figure 3(b)). The value of T_r increases gradually with the latitude increasing. It can be noticed that temperature variables have a close relationship with latitude.

Among several climate elements employed in the FC, some similar spatial patterns can be observed, according to Figure 4. A clear southeast–northwest gradient exists in Figure 4(a)–(c). The Tarim basin, the Qaidam Basin and the Alxa Plateau is a core area with the characteristic dryness, where annual precipitation is the lowest, PET is the largest and air humidity lowest, so that it was clustered as a homogeneous region. The characteristic wetness is presented in the southeast of Qinghai and Gansu, and the south of Shaanxi (mainly localized in the south of Qinling Mountains). Another humid region in the northeast of Inner Mongolia is also detected. Some differences exist between precipitation

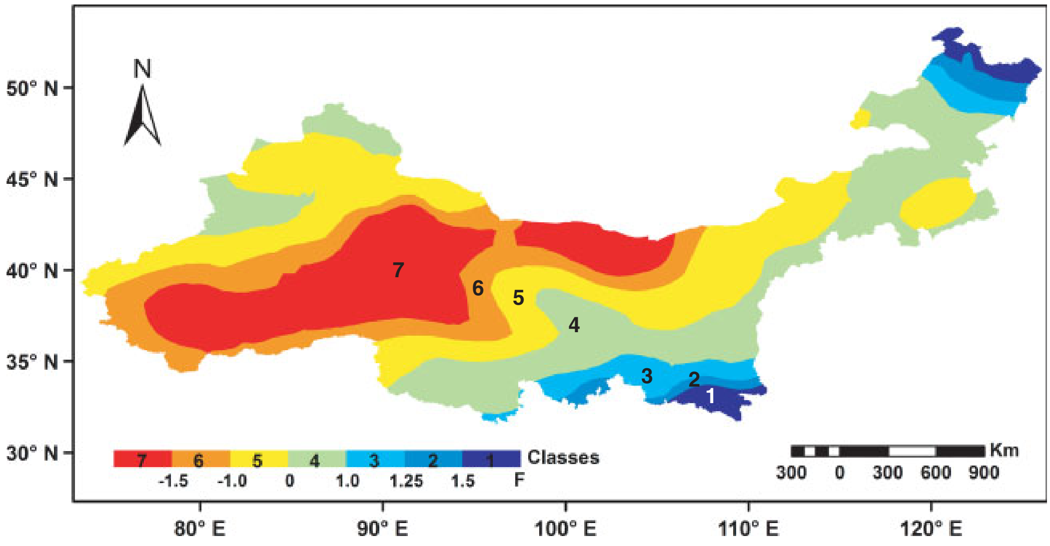

Figure 2. Map of climate classes according to FC.

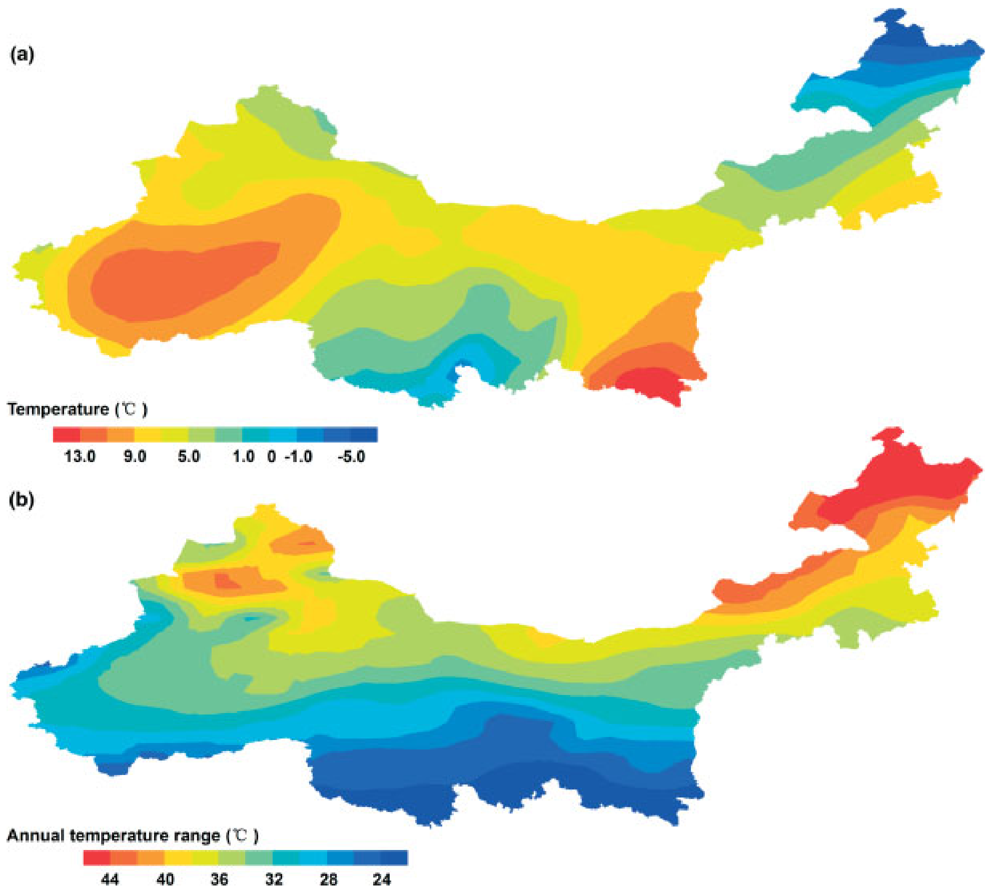

Figure 3. Distribution maps of the temperature variables [(a) annual mean temperature (°C) and (b) annual temperature range (°C)].

variability and other three variables. The areas with the largest precipitation variability appear in the west of the Tarim basin and the region of Kunlun Mountains. Precipitation variability is the smallest in southern Qinghai Plateau, not in the south of Shaanxi and northeast of Inner Mongolia. However, it can be found that there is a characteristic aridity belt in the southwest–northeast direction, which connects four regions of Xinjiang, Qinghai, Gansu and Inner Mongolia, according to the spatial distributes of four climatic elements. The overall patterns indicate the general characteristics of dry/wet climate in NW.

There are some similarities and differences between S_h and climatic variables used for FC. The change of spatial

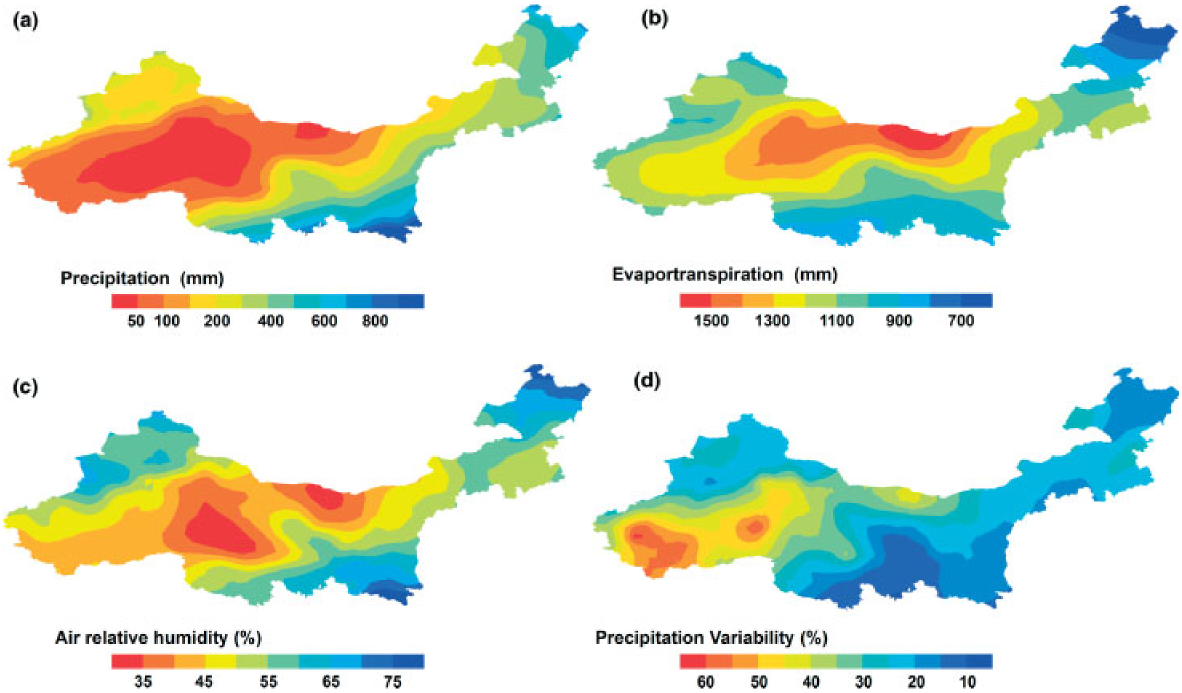

Figure 4. Distribution patterns of four variables used in FC [(a) Annual mean precipitation (mm), (b) PET, (c) Relative humidity and (d) Precipitation variability].

patterns is in agreement among them. The S_h still shows a downtrend from southeast to northwest. However, three specific regions can be distinctly identified, as shown in Figure 5. The Qaidam Basin, the northwest of Gansu and the northern half of Inner Mongolia are the lowest regions of S_h. The southern of Xinjiang formed the medium and the south of Shaanxi is the high value area of S_h. The distribution characteristics showed a close relationship between S_h and physical geography attributes, including altitude, topography and landscapes and so on.

Spatial distributions of the above climate variables indicated that it has good consistency among climate elements employed in the FC and specific humidity, but temperature elements (i.e. T_m and T_r) are different from them. It suggests that temperature variables and dry/wet climate variables should be two different aspects of climate features. They represented thermal and water conditions respectively. In fact, Kafle and Bruins (2009) also has confirmed that there was not significant correlation between PET and temperature by analyzing their trends in Israel during the period 1970–2002, and P/PET (i.e. the Aridity Index) trends were not sufficiently affected by the warming trend. Ultimately, this also demonstrates the reasonability of discarding temperature variables in FC analysis for characterizing the wet/dry climate divisions.

4.2.2. *Rule-based methods and comparisons*

Most of these classifications bear some subjective similarities. The climate has an obvious transition from humid zones in the southeast to arid zones in the northwest (Figure 6). The core area of dry climate in NW locates in the Tarim Basin, east Xinjiang basin (Turpan–Hami Basin), Qaidam Basin in Qinghai and Alxa Plateau in Inner Mongolia. In its southeast, the middle of Qinghai, Hexi Corridor of Gansu, Ningxia plain, the Ordos plateau and the Hetao plain of Inner Mongolia constitute a climate class. The next class mainly occurs in the west of Da Hinggan Mountains, the Loess Plateau of northern Shaanxi, the loess hilly region of central Gansu, the district around Qinghai Lake, the upper reaches of Huangshui Valley and source regions of Yangtze and Yellow Rivers in Qinghai. The Guanzhong plain of Shaanxi and the mountainous region of southern Gansu with the similar climate conditions are another class of climate zone. The south of Qinling Mountains, the most humid region in NW, is a distinct climate type. Among four rule-based classifications, the climate regimes based on PM and Thornthwaite classifications showed the best similarity. The next is Sahin's classification. Holdridge classification shows the biggest differences with other three methods, which mainly occurred in the northwest of Xinjiang, the middle and south of Qinghai and the south of Qinling Mountains.

Considering the characteristics of climate classification systems, the differences among four methods can be viewed from two aspects. One is class definition, and the other is the boundary of climate zones. From the view of class definition, there are different climate zones in NW for different methods (Table 6).

Four climatic zones in NW in PM classifications were comprised: hyper-arid, arid, semi-arid, and sub-humid. As shown in Figure 6, the north of Qinling Mountains is the sub-humid climate type in PM classifications, while it is classified as humid and very humid zone in Sahin and Thornthwaite classifications, as well as sub-humid zone in Holdridge classification. Humid and very

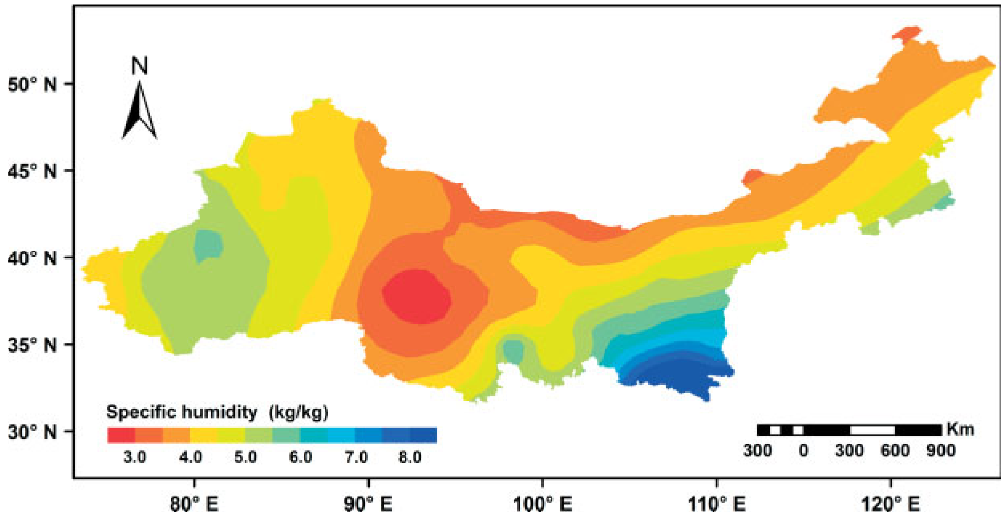

Figure 5. The spatial distribution of specific humidity in NW.

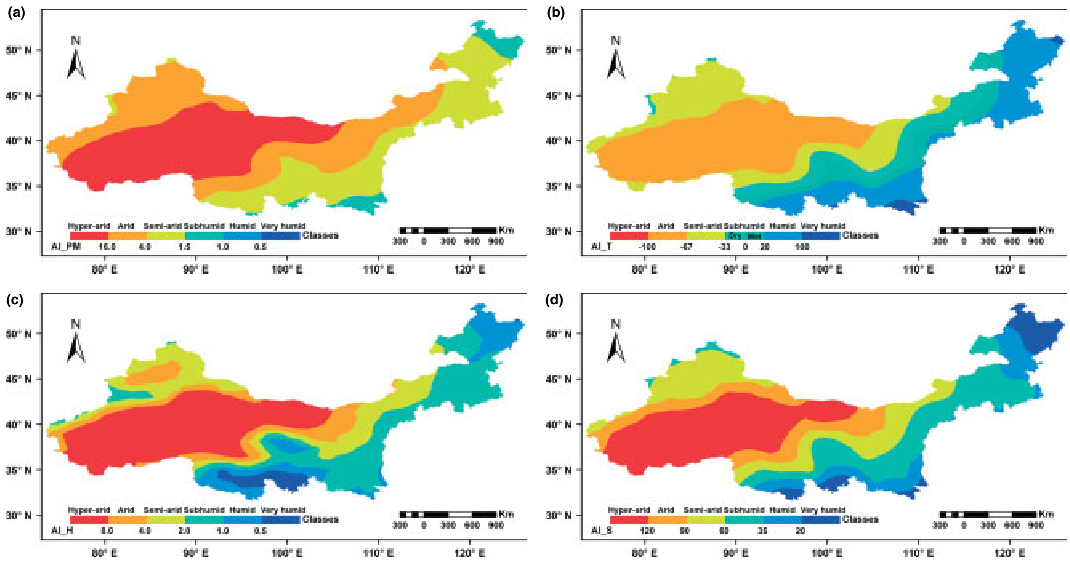

Figure 6. Climate classifications for NW according to different rule-based methods [(a) PM method, (b) Thornthwaite method, (c) Holdridge method, (d) Sahin method].

Table 6. Climate zones in NW defined by different classification methods.

Climate zones	Hyper-arid	Arid	Semiarid	Sub-humid	Humid	Very humid
PM (CAS)	+	+	+	+	−	−
Thornthwaite	−	+	+	+	+	+
Holdridge	+	+	+	+	+	+
Sahin	+	+	+	+	+	+

'+' denotes the climate zone included in NW; '−'denotes that the climate zone does not exist in NW.

humid zones do not prevail in NW according to PM classifications. Overall, major discrepancies occurred in humid and wet environments between PM and other three classifications. On the contrary, the Thornthwaite method shows a marked difference in arid climates. It is the only classification system in which the hyper arid zone does not prevail in NW. The driest regions, i.e. the Tarim basin, the Qaidam Basin and the Alxa Plateau are defined as arid zone, while they fell in the range of the hyper-arid zone in three other classification systems. An obvious underestimate for arid environments in Thornthwaite classification should exist, due to a systematical underestimate in dry climates and overestimate in moist and wet environments on PET (Pereira and Pruitt, 2004; Kafle and Bruins, 2009). Another difference is that two sub-regions of sub-humid climate, i.e. dry sub-humid and wet sub-humid zones, were developed by Thorthwaite, while other classification systems did not make the further subdivision for it. In contrast, it shows the most strongly correspondence between Holdridge and Sahin's classifications, which all the climate types can be comprised in NW in two classifications.

In terms of the boundary of climate zones, Holdridge and Sahin classifications still agreed well and provided the similar boundaries in the hyper-arid, arid and semiarid zones, but except for the northwest of Xinjiang. More obvious differences between them exist in the sub-humid and humid zones, including the district around Qinghai Lake, and the north plateau of Qinghai and south of Qinling Mountains with high elevation. It should be related to the assumption based on the bio-temperature in Holdridge method, so that it is more easily affected by altitude. Thornthwaite and PM classifications had remarkably differences with other two methods due to the discrepancy of class definition. However, the two classifications bear some subjective similarities in the divisional boundaries. In the core area of arid climates, PM's hyper-arid zone matches for Thornthwaite's arid zone; arid zone for dry sub-humid zone; and sub-humid zone for very humid zone. When considering the overall climate classifications, however, it is difficult to make more detailed comparison as the coincident classes and the agreements are low.

In addition, it can be noticed that when considering the entire climate classifications (Table 6), the coincident classes and the agreements are very low between PM and other three classifications. However, the AI calculated by PM method is better reasonable due to most reliable potential evapotranspiration calculation (Thi *et al.*, 2012), so that it is expected that particular predefined threshold values are worthwhile to further discuss for PM classifications. Sahin's classification presents a consistent spatial pattern with other classifications. The result shows no especial defects in wet/dry climate classifications in NW. This also confirmed that it is applicable for monitoring the distribution of arid zones, as indicated by Sahin (2012).

4.2.3. *Comparison of FC and rule-based methods*

Seven classes were identified according to the result from FC analysis. The F value of factor scores progressively decreased from classes 1 to 7, the climate characteristics following from humid to arid (Figure 2). Divisional boundary lines were drawn by identifying major terrain features. These boundaries formed by FC method were well in agreement with natural barriers between regions. The major topography, including the Kunlun Mountains in Class 7, Tarim River, Bogda Mountain and Burhan Budai Mountains in Class 6, Tian Shan, Borohoro Mountain, Ertix River and Qilian Mountains in Class 5, the delimitation between loess plateau and Guanzhong plain in Class 4, and the Qinling Mountains in Class 2, are the important boundaries of climate classifications.

The overall distribution pattern of climate clusters showed that the wet/dry climate zones by using FC method varied and mainly distributed along mountains, rivers and desert borders. Divisional boundaries are greatly influenced by natural features or barriers between regions. The similar conclusion was also drawn by Bieniek *et al.* (2012) that climate-division boundaries relied heavily on following the major terrain features surrounding the grouped stations by applying cluster analysis. Meanwhile, Arias (1942) also indicated that minor topographic variations can often cause great differences in a meso-climatic region, even if in two adjacent regions. It is influenced more easily by topographic features of the earth or large areas with different land conditions, such as extensive woods, swamps, deserts, etc. Therefore, it can be confirmed the application of FC method for the wet/dry climate zoning in NW.

In contrast, there are some similarities to rule-driven classifications. The overall agreement in the wet/dry climate regime can be considered as good, especially to PM classifications. Given that a better consistency in the distribution patterns of climate zones exists among four rule-driven classifications, the most common PM classifications was considered to illustrate the similarities and differences between FC and rule-based classifications. When looking across classes, class 6 matches for the hyper-arid of PM method, class 1 and sub-humid zone. Class 5 is associated with arid zone of PM classification. The climate zones integrated with classes 4, 3 and 2 shows slightly better correspondence with PM's semi-arid zone. The main differences exist in the Ili area located in the northwest of Xinjiang which is called a 'humid island' in arid regions (Zhang, 2006) and the Horqin Sandy Land in the northeast of Inner Mongolia which is one of the four largest desertification regions in China (Zhang *et al.*, 2012). In addition, the regions in class 7 bearing the driest climate, where the long-term average annual precipitation is less than 50 mm, is terminated an individual class, and no climate zone in rule-driven classifications matching for it. The north and south of Qinling Mountains are respectively separated as class 3 and class 1 according to FC method, and this mountain range formed a particular climate class (i.e. class 2). Among rule-driven classifications, however, a notable exception is that Holdridge classification shows the modest association with FC analysis in the northwest of Xinjiang.

The above analysis showed that FC method can perform better than four rule-driven classifications, in particular for unique natural features, e.g. the oasis in arid regions (Ili River Valley) and sandy land (Horqin area). Rule-driven classifications may be sub-optimal for applications that are sensitive to topographic diversities due to rigid boundary criteria, because there may be a strong internal variability of important climate elements in the regions with diverse natural landscape features, even if in the same climate class (Triantafyllou and Tsonis, 1994; Sparovek *et al.*, 2007). However, FC method can overcome the issue, and identify the great variability within the region. Zscheischler *et al.* (2012) also has indicated that statistical performances (k-means clustering) clearly outperformed classical climate classifications. On the other hand, however, Arias (1942) stated that the macro-climate is less influenced by topography and more stable since it concerned with the climatic character of the geographic region. Climate classifications using the rule-driven strategy may be therefore more reasonable at the macroscale.

5. Conclusions

Two very distinct approaches were performed for wet/dry climate classifications in this article. The overall climate regimes were in agreement for them, but the wet/dry climate zoning in a data-driven fashion showed a better consistency with topographic features.

Among five methods, FC method performed better than four rule-driven classifications in NW. Different methods should be employed depending on different regional scales and research objectives, however. The data- and rule-driven classifications can be seen as two complementary strategies of climate classifications, which were used in the meso and macroscales, respectively. As a result, climate divisions in a data-driven fashion can complement the defect of the rule-driven strategy to characterize the dry/wet climate in a macro-geographical region in more details. However, further study is still needed due to lack of the analysis on climate classifications at different geographic scales in this article.

In terms of rule-based methods, PM classifications displayed more arid climate types in NW, while the Thornthwaite approach showed an underestimate in arid environments. All wet/dry climate types corresponding to Holdridge and Sahin's classifications were represented in NW, but Holdridge classification was more easily affected by topography and elevation. The more complete comparisons are difficult to conduct due to different class definitions and low coincident classes. It also suggested that the wet/dry climate zones of a geographical region are difficult to divide accurately and thus should be used with caution for climate classification systems. Moreover, class definition of climate types for different rule-driven classifications needs further investigation.

The goal and format of this article prevents a full exploration of FC analysis. However, the distribution of climate variables indicates that there are obvious differences between water and thermal elements. They formed comprehensive climate properties. Although whether four elements selected in this article is sufficient and reasonable for the delineation of wet/dry climatic zones remains to be confirmed, we can found the conclusion reasonable that divisional boundary lines were drawn by following major surrounding topographic and geomorphology boundaries. It also implied that there is a need for objectively analyzing the relationship between topography and water conditions in the future climate classifications so as to further investigate the effect of topography on wet/dry climate classifications. This article performed a comparison of different methods for classifications of wet/dry climate in NW. It is expected to provide a reference for a similar geographical region.

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