



Converting Daily Rainfall Data to Sub-daily—Introducing the MIMD Method

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Abstract

One of the most important analysis in many hydrological and agricultural studies is to convert the daily rainfall data into sub-daily (hourly) because in many rainfall stations, only the daily rainfall data are available and for a comprehensive rainfall analysis, these data should be converted to sub-daily. Many experimental and analytical methods are available for this conversion but one of the simplest yet accurate ones has been proposed by the Indian Meteorological Department (IMD). Since the IMD method has shown low accuracy in some regions, in this study, the IMD method is modified to a single parameter equation, called Modified Indian Meteorological Department (MIMD) in order to improve the accuracy of the conversion. For this reason, the parameter is calibrated so that the maximum correlation between observed and estimated values is achieved. Five stations in different regions with different climatic conditions were selected so that the daily and sub-daily rainfall data were available in each of them. Then, the parameter of the MIMD method was derived for each station. The results were compared with both observed data and IMD method and it was shown that the mean correlation coefficient of MIMD and IMD methods were 0.9 and 0.73 respectively for 12-h rainfall depth which indicated that the accuracy of the MIMD method in estimation of sub-daily rainfall depths was significantly increased. Moreover, the results showed that the accuracy of the MIMD method decreases as rainfall duration decreases.

Keywords Modified Indian Meteorological Department (MIMD) · Daily to sub-daily rainfall conversion · Rainfall analysis · IMD method

1 Introduction

In many hydrological studies, rainfall analysis should be conducted to derive an Intensity–Duration–Frequency (IDF) relationship in order to derive the desired rainfall intensity from the corresponding rainfall duration and return period. To obtain IDF relationships with appropriate accuracy, long-term rainfall data (e.g., 30 consecutive years) with

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different sub-daily durations (i.e., 15, 30, 60, 120, 360, 720 and 1440 min) have to be available (Chow et al. 1988). Also, in agricultural studies especially in plant pathology, the meteorological data should be available at hourly time scale (Caubel et al. 2012).

In many rainfall stations, the rainfall is measured daily, and shorter-duration data are not available. Therefore, in order to derive an IDF relationship, first, the daily rainfall data should be converted to the desired shorter-durations. Several researchers have studied this issue, and proposed different analytical and experimental equations for different regions around the world. Although some of these equations have shown appropriate accuracy, the disadvantage is that either the calculation of short duration rainfall from them is very complicated, or the evaluation of the parameters involved is complex.

One of the earliest equations, was proposed by Hershfield (1961) for the USA, which was later modified and extended by Bell (1969) as the following:

$$P_T^t = (0.52 + 0.21 \cdot \ln(T)) (0.54t^{0.25} - 0.50) P_{10}^{60} \quad (1)$$

where P_T^t is the rainfall depth with a duration of t (minute) and return period of T (year). This equation which is still commonly used in water engineering projects, is only applicable for rainfalls with a duration in the range of 5 to 120 min and a frequency between 5 to 100 years. As it can be seen in Eq. (1), evaluation of P_{10}^{60} when there is only daily rainfall available, is very complicated (Mauriño 2004). Many other researchers by modifying and calibrating the coefficients of Eq. (1), proposed different equations for various regions in the world, other than the USA (Ghahraman and Abkhezr 2004; Vaziri 1991).

In spite of using daily rainfall depths for the calculation of short-duration rainfall, several studies attempted to relate short-duration rainfall intensity to different parameters, including: near surface temperature, dew point (Shaw et al. 2011; Utsumi et al. 2011; Schroerer and Kirchengast 2018; Ali and Mishra 2018), sea level pressure, relative humidity, wind, and geospatial height (Hertig and Jacobeit 2013; Lepore et al. 2016). In these studies, the researchers were focused on implementing a multivariate regression between various parameters to achieve equations with minimum error, which is very time-consuming and difficult.

Many studies are available which used statistical methods to obtain short-duration rainfall depths. Some of these methods are based on stochastic Bartlett-Lewis or Newman-Scott rectangular pulse models (Pui et al. 2012; Cowpertwait et al. 1996) in which, five to seven parameters are included in the calculations. Moreover, using many other statistical methods, the short duration rainfall can be estimated by statistical distribution fitting (Garcia-Bartual and Schneider 2001; Smithers and Schulze 2001; Haddad et al. 2011), logarithmic graph fitting techniques (Al Mamun et al. 2018), multivariate regression method (Koutsoyiannis et al. 2003) or L-moment method (Galoie et al. 2013a). Although these methods have represented satisfactory results, heavy statistical efforts are involved in them.

The K-nearest neighbor resampling (KNNR) method is one of the popular methods which is based on the nonparametric disaggregation technique. Although the application of this method in converting daily rainfall to sub-daily is not easy, a method based on three-day rainfall patterns was used by Park and Chung (2020) in order to improve the ability of the method. Also, some researchers used the random cascade model and method of the fragment (MOF) for converting the daily to sub-daily rainfall (Bakhshi and Al Janabi 2019; Li et al. 2018). The results showed that the accuracy of the method for different rainfall resolutions (e.g. 4-h, 1-h and 10-min) were different so that for 10-min rainfall the result was overestimated (Bakhshi and Al Janabi 2019).

One of the simplest and easy to use methods is an empirical equation proposed by the Indian Meteorological Department (IMD). It has been successfully used with significant

accuracy by a number of researchers in India (Palaka et al. 2016) and other regions of the world (Logah et al. 2013; Rashid et al. 2012; Chowdhury et al. 2007). This method is used for the conversion of maximum daily to hourly rainfall depths, as the following:

$$P^t = P^{24} \left(\frac{t}{24} \right)^{\left(\frac{1}{3}\right)} \tag{2}$$

where, P is the rainfall depth and t is the duration (hour). The IMD is a straightforward equation, but attempts to employ this method in some regions such as northern Graz in Austria showed that this equation with the “1/3” power gave low accuracy results (Galoie et al. 2013b). In that study, the researchers showed that by changing the power to “0.29”, the accuracy of the final results improved significantly.

According to the literature review, the simplest, yet accurate method for the estimation of sub-daily rainfall from daily data is the IMD method. In this study, the IMD equation is modified in a way that it can be calibrated for different locations worldwide, to obtain sub-daily rainfall depths with high accuracy.

2 Methodology

In this study, the IMD equation is modified to a single parameter equation, called Modified Indian Meteorological Department (MIMD), as the following:

$$P^t = P^{24} \left(\frac{t}{24} \right)^n \tag{3}$$

where, *n* is the regional coefficient which can be obtained by calibration. As it can be seen in this study, this coefficient in various regions can be varied even more than ±15% in comparison to the fixed power of IMD formula (0.33).

Five stations located in different regions with different climatic conditions were selected (Table 1), in order to find the corresponding “*n*” value for each region. The location of the stations is also shown in Fig. 1. For each of the selected stations, daily and sub-daily rainfall depths were available (i.e., 1, 6 or 12 h) in order to compare observed data with final modeled data. The climate classification in Table 1 is based on the Koppen method which is the most widely used method for climate classification (Beck et al. 2018).

Table 1 Selected stations and related information

Country: Station Code:	Austria (A)	Barbados (B)	China (C)	China (D)	Iran (E)
Latitude	47° 04' 00"	13° 05' 59"	30° 40' 00"	38° 02' 29"	35° 49' 57"
Longitude	15° 26' 59"	59° 37' 00"	104° 04' 00"	114° 28' 42"	50° 59' 29"
*Climate classification	Cfb	Am	Cwa	Bsk	Dsa
Data availability	1969–2019	1965–2019	1982–2019	1981–2019	1985–2020
Recorded interval (min)	60	60	360	720	720
Elevation (m)	375	10	505	78	1341

*Cfb: Temperate oceanic climate; Am: Tropical monsoon climate; Cwa: Monsoon-influenced humid sub-tropical climate; Bsk: Cold semi-arid climate; Dsa: Hot summer continental climate

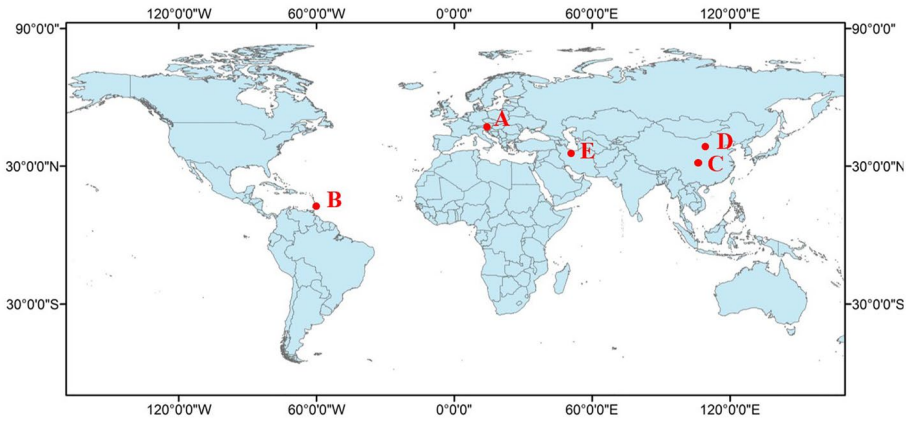


Fig. 1 The location of the selected stations in the world (A, B, C, D, and E denote the station codes)

2.1 Statistical Analysis

According to Table 1, the sub-daily rainfall depths are available for all stations. The return period of maximum annual values can be calculated using the Weibull equation as the following (Ragunath 2006):

$$Tr = \frac{N + 1}{m} \tag{4}$$

where, Tr is the return period (year); N is the number of data availability years; m is the rank of observed rainfall values when arranged in descending order. Using Eq. (4), the computed return periods are limited to the duration of data available. In order to estimate rainfall depths in longer return periods, the type I generalized extreme value (GEV-I) distribution (Gumbel) is used as the following (Gumbel 1954; Singh 2013):

$$x = \bar{x} + \frac{\sigma}{\bar{\sigma}_N} (y - \bar{y}_N)$$

$$y = -\ln\left(-\ln\left(\frac{Tr}{Tr - 1}\right)\right) \tag{5}$$

where, \bar{x} and σ are the mean and standard deviation, respectively; $\bar{\sigma}_N$ and \bar{y}_N can be obtained from GEV type I tables, based on the number of sample data (Singh 2013).

Analysis of variance (ANOVA) in most cases is done when two or more than two sets of sample data are compared together as a test of hypotheses. In this analysis, the student’s t-test is commonly used for comparing the true difference between two groups with 95% confidence interval (Landau and Everitt 2004). The 95% limit is not mandatory and can be changed according to the test accuracy but in practical, the 95% is very commonly used. The t-test assumes that the two groups are normally distributed with equal variances. If the variances are unequal, the Welch’s t-test should be used (Welch 1947). However, if the two groups have the same sample sizes and variances, Student’s t-test and Welch’s t-test will give the same results. The t-test formula can be expressed as follow (Landau and Everitt 2004):

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{6}$$

where, \bar{X} is the sample mean, s is the sample variance, n is the sample size and subscripts 1 and 2 refer to the sample groups. The analysis can be performed manually or conveniently with statistical software (e.g. R, SPSS, Excel and etc.).

Also, it should be noted that correlation coefficient (r test) is one of the most famous tests for every researcher in order to evaluate the similarity or deviation between two sets of data. Therefore, in order to evaluate the accuracy of the estimated values, the Root Mean Square Error (RMSE) (Eq. 7), and the sample Pearson correlation coefficient (Eq. 8) were used. The RMSE is frequently used to measure the average magnitude of error, and the sample Pearson correlation coefficient is used to evaluate the degree of agreement between the observed (P_o) and estimated (P_m) values.

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (P_o - P_m)^2}{N}} \tag{7}$$

$$r_{P_o P_m} = \frac{N \sum P_{o_i} P_{m_i} - \sum P_{o_i} \sum P_{m_i}}{\sqrt{N \sum P_{o_i}^2 - (\sum P_{o_i})^2} \times \sqrt{N \sum P_{m_i}^2 - (\sum P_{m_i})^2}} \tag{8}$$

where, N is the sample size, P_o and P_m are observed and estimated rainfall depths, respectively. The closer the value of RMSE is to 0, the better the model performance is. The value of r is always between -1 and $+1$. If $r = +1$ or $r = -1$, it means that there is a perfect linear correlation between P_o and P_m . For $r = +1$, P_m increases as P_o increases and for $r = -1$, vice versa. Also, a value of 0 implies that there is no linear correlation between the variables (Holmes et al. 2017).

3 Results and Discussion

The MIMD equation (Eq. 3) was used for the selected stations, and regional coefficients (n) that resulted in the best correlation between observed and estimated values were obtained. Table 2 summarizes the final estimations of regional coefficients (n) and the corresponding RMSE and correlation coefficients.

Moreover, Fig. 2 represents the observed and estimated maximum 12-h rainfall depths for each stations data.

Table 2 Regional coefficient (n) and corresponding RMSE and correlation coefficient for maximum 12-h rainfall depths

Station	A	B	C	D	E
Regional coefficient (n) – MIMD method	0.29	0.31	0.32	0.35	0.35
RMSE—MIMD	0.062	0.134	0.091	0.177	0.162
Correlation coefficient (r) – MIMD method	0.95	0.89	0.92	0.87	0.88
Correlation coefficient (r) – IMD method	0.69	0.66	0.88	0.70	0.72

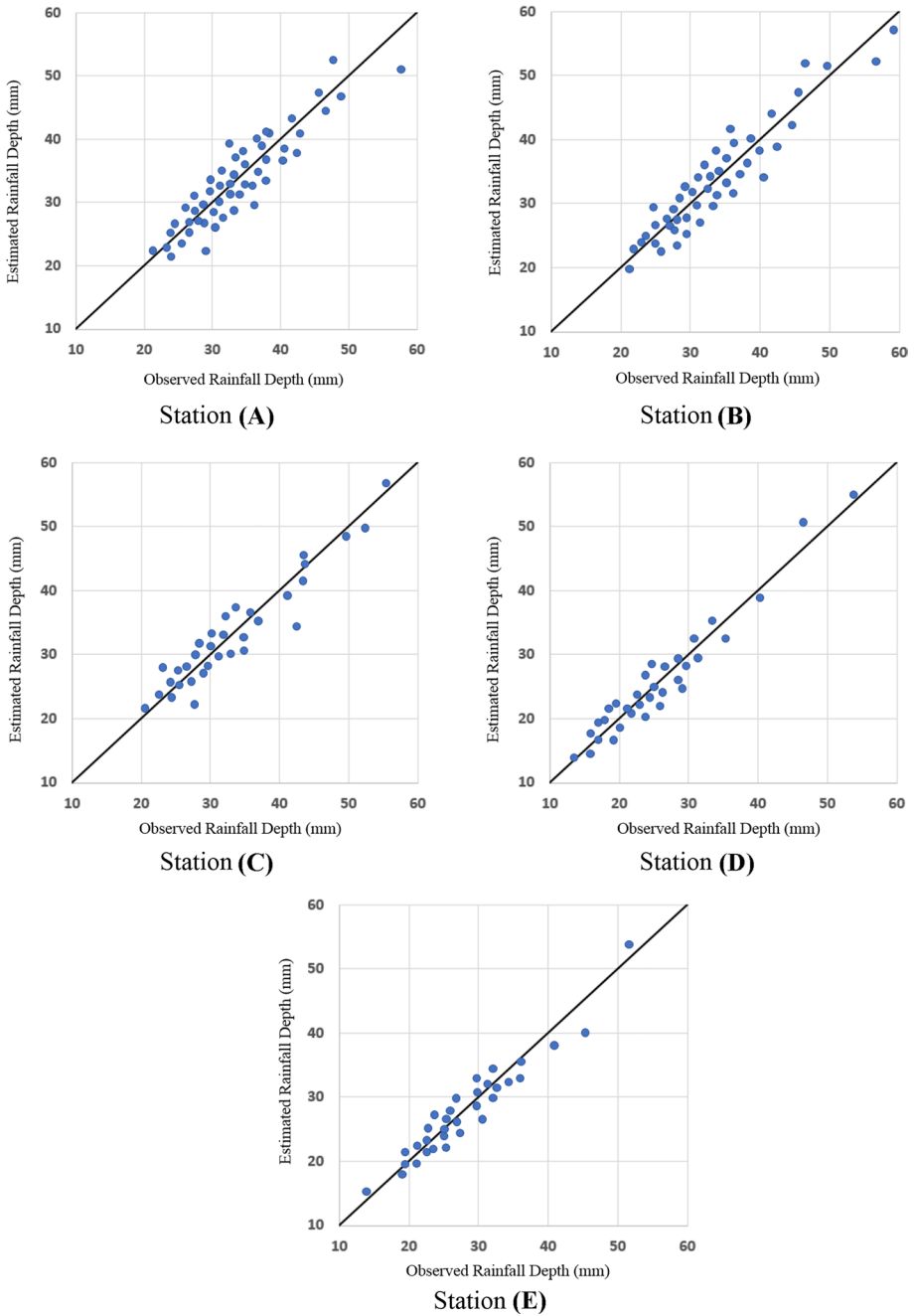


Fig. 2 Observed and estimated 12-h rainfall depths based on estimated regional coefficient (n) of the MIMD equation (the station codes are represented in each panel)

Table 3 The t-test outputs for observed and modeled data in SPSS software

Station	Sample size	t	p-value (sig.)
A	50	-0.305	0.762
B	54	-0.488	0.628
C	37	0.381	0.661
D	38	-0.512	0.587
E	35	0.494	0.598

According to Table 2 and Fig. 2, for all stations, the correlation coefficient of MIMD method is between 0.8 and 1.0 which can be described as a very strong positive association. Also, the regional coefficient (n) is not equal to 0.33 for any of the stations, which is the power of the IMD equation (Eq. 3). Moreover, Table 2 represents that the regional coefficient (n) in regions with humid climate is smaller than regions with dry climate.

To make a comparison between IMD and MIMD method, the correlation coefficients are calculated for IMD method and they are represented in Table 2. As it can be seen, by modification of IMD method and employing only one parameter as regional coefficient in MIMD method, the results are improved considerably in comparison with IMD method.

Also, the hypothesis testing of means was performed using t-test for observed and modeled data in SPSS software (Table 3). The analysis in all modeled data showed that the p-value (in SPSS denotes as sig) is more than 0.05 which represents that there was no significant difference between the modeled and observed data (Cleophas and Zwinderman 2016).

Since sub-daily data less than 12-h were not available for stations (D) and (E), the correlation coefficients for 1- and 6-h rainfall depths were calculated for stations (A) and (B) in which, both 1- and 6-h data were available. Also, the correlation coefficients for 6-h rainfall depth was calculated for stations (C) in which, 6-h data were available.

The analysis showed that the estimated regional coefficients (n) are still valid for a short duration but the correlation coefficients are less than the values obtained for 12-h rainfall depths. This means that as the rainfall duration decreases, the accuracy of MIMD decreases as well. Table 4 summarizes the final analysis of short-duration rainfall.

In order to show the accuracy of MIMD, this method is compared with observed data and the Bell method. Figure 3 represents the final results for the station (E). As can be seen in this figure, the MIMD method can estimate the intensity better than the Bell method. The correlation coefficient (r) of the Bell method is 0.71 which is much less than the MIMD method calculated as 0.88 for the station (E).

Table 4 Statistical analysis of 1-, 6- and 12-h rainfall depths

Station	A	B	C
Correlation coefficient (r): 12-h rainfall	0.95	0.89	0.92
Correlation coefficient (r): 6-h rainfall	0.89	0.83	0.88
Correlation coefficient (r): 1-h rainfall	0.81	0.78	-

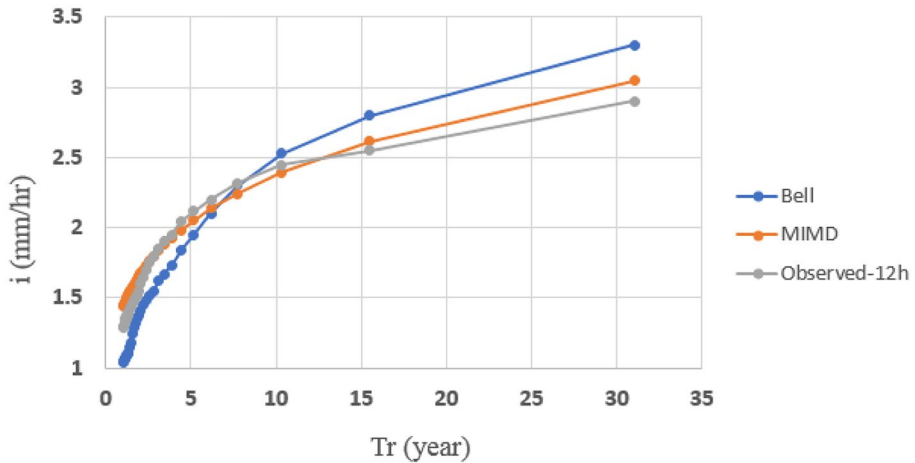


Fig. 3 A comparison between MIMD and Bell methods (station E)

4 Conclusion

Rainfall analysis is one of the most common processes in most water engineering projects and hydrological studies. In many rainfall stations, the rainfall depths are only available as daily and in order to estimate an IDF relationship, the daily rainfall data should be converted to sub-daily, such as 1-, 2-, 6- and 12-h. Many different methods have been suggested by a number of researchers which can be used for conversion of daily to sub-daily rainfall depth but most of them need intensive efforts to complete. Indian Meteorological Department (IMD) method is one of the simplest methods for converting daily to sub-daily rainfall depth but accuracy of this method in some regions is not acceptable. This study aimed to propose a modified form of IMD method, say Modified Indian Meteorological Method (MIMD) in order to increase the accuracy of IMD method. Five stations were selected in different countries with different climates so that in each of which, sub-daily rainfall data were available. The annual maximum values of daily and corresponding sub-daily rainfall depths were extracted and various return periods were calculated using Weibull and Gumbel methods. In this study, the IMD method was modified to a single parameter equation and then the parameter was calibrated for each station. The final results were compared with observed data and it showed that the accuracy of MIMD method in estimation of sub-daily (especially 6- and 12-h) rainfall depths was considerably increased (mean correlation coefficients as 0.9) in comparison to IMD method (mean correlation coefficient as 0.73). Also, the t-test analysis which was performed by SPSS software between observed data and MIMD outputs showed that the p-value for all stations was more than 0.05 which indicated that there was no significant difference between the modeled and observed data. The regional coefficient of the MIMD method for these five stations ranged between 0.29 to 0.35 while the coefficient of the IMD method is fixed as 0.33. Also, the results showed that the accuracy of the MIMD method was decreased as rainfall duration was decreased (less than 6-h).

For future studies, it is suggested that, more than one parameter is applied in MIMD method as regional coefficients so that the method increases the accuracy of the results for converting the daily to 1-h or less duration rainfall.

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Authors' Contributions Author 1: Majid Galoie (30%) Conceived and designed the analysis, Collected the data, Contributed data or analysis tools, Performed the analysis and Wrote the paper; Author 2: Fouad Kilanehei (30%) Conceived and designed the analysis and Wrote the paper; Author 3: Artemis Motamedi (30%) Collected the data, Contributed data or analysis tools and Performed the analysis; Author 4: Mohammad Nazari-Sharabian (10%) Other contribution (Reviewing the paper- Grammar Checking).

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Declarations

Ethics Approval Not applicable.

Consent to Participate Not applicable.

Consent to Publish Informed consent was obtained from all individual participants for whom identifying information is included in this paper.

Competing Interests Not applicable.

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