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RESEARCH ARTICLE

Evaluation of spatio-temporal rainfall variability and performance of a stochastic rainfall model in Bangladesh

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Rainfall in Bangladesh exhibits persistent wet and dry anomalies associated with occurrence of floods and droughts. Assessing inter-annual variability of rainfall is vital to account these hydrological extremes in the design and operations of water systems. However, the inter-annual variability obtained from short record rainfall data might be misleading as it does not contain whole climate variability which signifies the utmost importance of stochastic rainfall models. Since the inter-annual variability and stochastic models have not been explored adequately for rainfall in Bangladesh, this study evaluated (a) the spatio-temporal variability of rainfall focusing on inter-annual variability, and (b) applicability of a stochastic daily rainfall model, referred as the Decadal and Hierarchical Markov Chain (DHMC) model. Daily rainfall data of 1973–2012 for 18 stations across Bangladesh were used to investigate the probability distributions and autocorrelations of rainfall, and the model performances. Results show a higher magnitude of inter-annual variabilities of rainfall depth (standard deviation 80–250 mm) and wet spells (standard deviation 4–6 days) in wetter months (June to September) across rainfall stations in the east region of the country. In contrast, higher rates of inter-annual variabilities (i.e., coefficients of variations) were observed in drier months across the west region. Spatially, the dry spells were observed consistent across the country. Monthly rainfall showed decreasing trend over the region from west to the middle part of the country, whereas monthly number of wet days showed increasing trend over the eastern part. The DHMC was found to preserve the observed variabilities of rainfall at daily to multiyear resolutions at all stations, except a tendency to underestimate the autocorrelation of monthly rainfall depth. Despite this limitation, DHMC can be considered as a suitable stochastic rainfall simulator for a tropical monsoon climate like Bangladesh.

KEYWORDS
DHMC, rainfall variability, stochastic simulation, wet–dry spell

1 | INTRODUCTION

As one of major regulating factors of hydrological processes, rainfall variability is linked to a wide-range of hydrological phenomenon such as flood and drought (Lehner *et al.,* 2006), urban water security (Lockart *et al.,* 2016), agricultural crop yield and food security (Murali and Afifi, 2014), and hydro-power generation (Kern and Characklis, 2017). Such influences of rainfall variability in Bangladesh, as a tropical and monsoonal rain-fed country, are inevitable. Heavy rainfall for a few hours often results into urban flash flood in its major cities such as Dhaka and Chittagong with apparent influence of impervious surfaces (Mark *et al.,* 2001; Yao *et al.,* 2016) and rainfall for several consecutive days often results into extreme floods with frequent influence of upstream flows of the Ganga-Brahmaputra-Meghna basin (Hopson and Webster, 2010; Masood *et al.,* 2015; Brammer, 2016). Therefore, evaluation of the rainfall variabilities may provide important information to optimize the design and planning of urban drainage and flood control systems of the country. Similarly, evaluation of the rainfall variabilities at monthly to multiyear resolutions is also important for sustainable design, planning and risk assessment of many water infrastructures that are responsive to the seasonal to multiyear variabilities of rainfall (Dai *et al.,* 1998; Sarker *et al.,* 2012). For example, the groundwater, on which most of the urban and irrigation water supply systems in Bangladesh are dependent, significantly varies over seasons (declines in dry winter months and recharges in wet monsoonal months). The overall aquifer level may exhibit an increasing or decreasing trend over multiple years with relation to the multiyear variabilities of wet–dry spells and rainfall intensities (Sciance and Nooner, 2018). Rainfall and its wet and dry spells are generally spatially non-uniform (Singh, 1997; Segond *et al.,* 2007). Particularly, there are contrasts of hydro-climatic conditions among different parts of Bangladesh, such as the crops in the northeast region of the country are often damaged by floods due to seasonal heavy rainfall (Ahmed *et al.,* 2017), while the crops in the northwest region are often affected by scarcity of irrigation water due to groundwater depletion during long dry spells (Kirby *et al.,* 2016).

Spatio-temporal variabilities of rainfall and their implications were widely studied in many countries and geographical regions. For example, Higgins *et al*. (2007) identified the frequency and inter-annual to inter-decadal variabilities of daily rainfall and wet periods over the United States, Beecham and Chowdhury (2010) and Rashid *et al*. (2015) statistically tested the temporal variability of rainfall in southeast Australia using measured point rainfall, Fang *et al*. (2011) used a tree-ring network to test the spatial variability of rainfall in northwest China, Kaptué *et al*. (2015) used Tropical Rainfall Measuring Mission (TRMM) estimations to assess the spatio-temporal variabilities over Africa continent. Similarly, in India and Myanmar, the neighbouring countries of Bangladesh along the Bay of Bengal, the variabilities of monsoonal rainfall were also widely investigated (Sadhukhan *et al.,* 2000; Mohapatra *et al.,* 2003; Shrivastava *et al.,* 2016; Thomas and Prasannakumar, 2016; Chaudhary *et al.,* 2017).

Several studies investigated the temporal and spatial variabilities of rainfall in Bangladesh (Sanderson and Ahmed, 1979; Ahmed and Karmakar, 1993; Ohsawa *et al.,* 2000; Singh, 2001; Ahmed and Kim, 2003; Islam and Uyeda, 2008; Shahid, 2008; Hossain *et al.,* 2014; Singh *et al.,* 2014). However, they mostly focused on the intra-annual seasonal variability, while only a few studies focused on the inter-annual variability of rainfall. Shahid and Khairulmaini (2009) examined daily rainfall data from 1969 to 2003 for 24 stations across Bangladesh and found seasonal variability of rainfall depth in all stations with a Coefficient of Variation (CV) greater than 24% and inter-annual variability with CV between 16% and 24%. Bari *et al*. (2017) investigated the monthly rainfall data from 1964 to 2013 for eight stations in the northern part of Bangladesh and they observed that the rate of inter-annual variability (i.e., CV) of winter (December to February) rainfall is higher than that of monsoon (June to September) rainfall. However, these studies did not explicitly investigate the inter-annual variability of wet and dry spells.

Spatial variability of rainfall in Bangladesh is primarily linked with the direction of monsoonal wind and local orography in the northeast (i.e., Sylhet) and southeast (i.e., Chittagong) regions. The monsoon wind is diverted by the Meghalaya plateau and Chittagong hill-tracks in the northeast and southeast regions, respectively, to pour highest rainfall in these two regions (Ahmed and Karmakar, 1993). Shahid (2010) examined daily rainfall data from 1958 to 2007 for 17 stations across Bangladesh and identified the spatial variability of rainfall as the wettest and driest condition observed in northeast (i.e., Sylhet) and central-west (i.e., Rajshahi) region, respectively. The mean annual rainfall depth gradually declines from around 4,300 mm in the east to around 1,400 mm in the west. Based on a seasonality index, Bari *et al*. (2017) showed that the length of dry periods is also shorter (i.e., longer wet period) in the northeast region compare to the northwest region. Shahid (2010) also identified a sub-region of south-to-north spatial distribution in the southeast part of the country where a relatively wet condition in the southeast coastline (i.e., Cox's Bazar) declines to a relatively dry condition in the north. However, in contrast to the mean rainfall depth, the rate of inter-annual variability (i.e., CV) of rainfall tends to decline from the west to the east of the country (Bari *et al.,* 2017). Shahid and Khairulmaini (2009) also found that the relatively dry northwest region exhibits a high rate of inter-annual variability compare to the relatively wet southwest region.

The above-mentioned studies on the spatio-temporal rainfall variability in Bangladesh used observed ground-based data of about 30 to 60 years at different spatial regions, either for the entire country or for a specific region. Most of the studies evaluated the variability of rainfall depth, but their wet–dry spells were not considered. In addition, these studies investigated the rainfall variability at monthly, seasonal, and annual resolutions, but not at the daily and multiyear resolutions. Since the understanding of spatio-temporal variability of rainfall is important for the country's sustainable management of water resources, including water supply and agriculture, the first objective of this study is to examine the variability of rainfall depth as well as their wet–dry spells at different temporal resolutions (from daily to multiyear) for the entire country.

A short record of rainfall data is often unable to represent full range of climate variability and generally not robust for planning, design and risk analysis of hydrological and agricultural infrastructures such as urban drainage, irrigation and hydro-power systems (Mortazavi-Naeini *et al.,* 2014). However, the short record data can be used to calibrate stochastic rainfall models to generate long (e.g., 1,000 years) synthetic data (Furrer and Katz, 2008; Chen *et al.,* 2010). Therefore, stochastic simulation is often performed in data scarce countries to generate synthetic rainfall time series in order to incorporate a wide range of climatic variability in hydrological and agricultural planning and design (Breinl *et al.,* 2017). This is particularly important for the study area, Bangladesh, where a long record of rainfall data is not available. Utilization of stochastic models in design and risk analysis depends on its ability to simulate rainfall statistics such as mean, standard deviation, autocorrelation, dry and wet spell at different temporal resolutions, ranges from daily to multi-year (Thompson *et al.,* 2007; Sivakumar, 2016).

There are several parametric and non-parametric approaches for the stochastic simulation of daily rainfall. Sivakumar (2016) provided a comprehensive discussion on different methods of stochastic simulation. A common parametric approach, primarily proposed by Richardson (1981), is to simulate the occurrence of wet and dry days by a low-order Markov Chain (MC) process and simulate the rainfall depth in wet days by using an exponential type probability distribution such as the single or mixed exponential distribution, gamma distribution, Weibull distribution and generalized Pareto distribution. A large number of studies (Wilks, 1999; Vrac and Naveau, 2007; Wang and Nathan, 2007; Srikanthan and Pegram, 2009; So *et al.,* 2015; Chowdhury *et al.,* 2017) used different variants of this approach to simulate daily rainfall in different parts of the world.

The non-parametric approaches generally resample the historical data and generate a new synthetic data by using different techniques such as the k-nearest neighbour (Rajagopalan and Lall, 1999; Leander and Buishand, 2009; Caraway *et al.,* 2014), maximum entropy bootstrap (Srivastav and Simonovic, 2015), and coupling MC or a modified MC process with a resampling technique (Apipattanavis *et al.,* 2007; Mehrotra and Sharma, 2007; Steinschneider and Brown, 2013; Mehrotra *et al.,* 2015). However, overdispersion is a well-known problem of the stochastic daily rainfall simulation that refers to an underestimation of the observed rainfall variability when aggregated to higher scales (e.g., month and annual). Such underestimation of low-frequency variability may underestimate the extremes or overestimate the reliability of water resources. Many of the above-mentioned stochastic models addressed the underestimation of low-frequency variability by using different techniques, such as by using mixture of exponential-type distributions (Wilks, 1999; Vrac and Naveau, 2007; Rashid *et al.,* 2015), by adjusting the simulated daily data into monthly and annual models (Wang and Nathan, 2007; Srikanthan and Pegram, 2009), by correcting frequency spectrum (Chen *et al.,* 2010), by modifying MC parameters using memory of past wet and dry periods (Mehrotra and Sharma, 2007; Mehrotra *et al.,* 2015), and by using hierarchical parameterization technique (Chowdhury *et al.,* 2017). Nevertheless, each of these models has their own limitations to appropriately reproduce one or more critical characteristics of observed rainfall (overestimation of mean and underestimation of autocorrelation, for example), while application of some models might be site- or region-specific. Therefore, application of a stochastic model in a new climate condition is subjected to an evaluation of its suitability for that climate condition.

While generation of such synthetic rainfall time series using stochastic simulation is vital for Bangladesh due to its short record length of rainfall data, only a few studies (Rahman, 1999; 2000; Barkotulla, 2010; Hossain and Anam, 2012) have attempted to develop and evaluate stochastic rainfall models for the region. Rahman (2000) used a first-order MC and a skewed normal distribution (Arnold *et al.,* 1990) to simulate daily rainfall in the Barind Tract region at north-western part of Bangladesh. The model tends to overestimate monthly mean rainfall in almost all seasons, while the evaluation of the model to reproduce the rainfall variability at higher scales (i.e., annual to multiyear) and variability of wet–dry spells were not performed. Barkotulla (2010) fitted a MC-gamma model to 30 years (1980–2009) daily rainfall data for a rainfall station (Mahadevpur station) located in the north-western part of Bangladesh. The model well-reproduced the mean rainfall depth at daily and monthly resolution, and standard deviation (*SD*) at daily resolution, but underestimated the *SD* of monthly wet days. While it was not evaluated in the paper, the model is likely to underestimate the low frequency variability as a known limitation of such Richardson (1981) type MC-gamma model. Kumar *et al.* (2013) used the Long Ashton Research Station Weather Generator (LARS-WG) (Semenov and Barrow, 1997) to simulate daily rainfall data for 10 rainfall stations located in the Jamuneswari catchment of Teesta River basin. The model was found to well-reproduce the monthly mean and variance for most of the months, but could not satisfactorily reproduce the wet and dry spells for non-monsoon months (December to January). This suggests that the number and types of stochastic models tested for Bangladesh climate is limited, and there are significant limitations of the tested models. In addition, application of stochastic models for hydro-climatic impact studies is rare. Among only a few examples, Thurlow *et al.* (2012) used a stochastic model based on random perturbation of historical records to estimate and decompose agricultural damages from historical climate variability and future anthropogenic climate change. Alam *et al.* (2014) used a MC model to calculate seasonal and annual drought indices for Barind region of Bangladesh.

The above discussion suggests that the use of stochastic rainfall models is a seldom practice in Bangladesh. The available models were generally tested for local scale that did not represent the spatial rainfall variability of the country and almost all tested models failed to reproduce the wet–dry spells and low-frequency variability of rainfall depth. Accordingly, it can be assumed that the existing design and operation of water infrastructures of the country are based on the model results which are limited in reproducing hydrologically important climate variability. In such a case, application of stochastic rainfall models capable of incorporating a wide range of hydrologically important variability, might improve the design and operations of the water systems. Moreover, such practice could be even more useful for Bangladesh to face the future challenges of climate change with an existing increasing trend of rainfall in the recent decades which likely to be increased in future as found by several studies (Immerzeel, 2008; Caesar *et al.,* 2015).

With this background, in addition to the first objective to examine the spatio-temporal variability of rainfall depth and wet–dry spells, the second objective of this study is to calibrate a stochastic model to simulate daily rainfall at 18 stations across Bangladesh and evaluate its performance to preserve the observed variabilities at different temporal resolutions from daily to multiyear. We have calibrated and evaluated the Decadal and Hierarchical Markov Chain (DHMC) stochastic model, proposed by Chowdhury *et al*. (2017). The DHMC has been chosen because it was found to preserve the hydrologically important low to high temporal variabilities of observed rainfall for semi-arid climates in Australia (Chowdhury, 2017; Chowdhury *et al.,* 2017). Additionally, this study enables us to evaluate the model in a tropical climate condition in Bangladesh.

2 | DHMC MODEL

An overview of the DHMC model is available in Chowdhury *et al*. (2017). The model uses two MC parameters, transition probabilities of *dry-to-dry* and *wet-to-wet* days, in order to simulate the occurrence of wet and dry days. In a Monte-Carlo framework, rainfall depth in each wet day is simulated by a gamma distribution with two parameters, mean and *SD* of wet day rainfall depth. Both the MC and gamma parameters vary for each calendar month in order to incorporate the seasonal variability. On the other hand, in order to incorporate the low-frequency (annual to multiyear scales) variabilities, the MC and gamma parameters vary for each decade and year, respectively.

In the calibration of MC parameters, the transition probabilities of *dry-to-dry* and *wet-to-wet* days were calculated for every month of each decade. Whereas, the mean and SD of wet day rainfall depth were calculated for every month of each year for the calibration of gamma parameters. The DHMC model assumes that the yearly varying gamma parameters for each month are log normally distributed and exhibit a strong cross-correlation between the log-transformed values of the mean and *SD* for a month. Therefore, the following bivariate lognormal distributions were fitted to the calibrated mean and *SD* values for each calendar month *i*:

$$\log \text{mean}_i \sim N\left(\lambda_{\text{mean}_i},\ \zeta^2_{\text{mean}_i}\right), \tag{1}$$

$$\log SD_i | \log \text{mean}_i \sim N\left(\lambda_{SD_i} + \frac{\zeta_{SD_i}}{\zeta_{\text{mean}_i}} R_i \left(\log \text{mean}_i - \lambda_{\text{mean}_i}\right), \left(1-R_i^2\right)\left(\zeta_{SD_i}\right)^2\right), \tag{2}$$

where λ and ζ denote the lognormal parameters of mean and *SD* values for a month respectively, while R is the correlation coefficient between log mean and log *SD*.

In simulation of wet and dry days, the DHMC uses the monthly and decade-varied deterministic values of MC parameters. Although DHMC uses only the dry-to-dry and wet-to-wet transition probabilities, it accounts the dry-to-wet and wet-to-dry transitions as the counterparts of the two parameters, respectively. In simulation, within a Monte-Carlo framework, if the dry-to-dry transition is not true after a dry day, it is considered as a dry-to-wet transition, and the subsequent day is simulated as a wet day (similarly, wet-to-dry transition is related to the wet-to-wet transition). For the simulation of rainfall depth in wet days using gamma distribution, for every month of a year, the model uses gamma parameters that are stochastically sampled from the bivariate lognormal distributions shown in Equation 1 and 2.

3 | STUDY SITE AND DATA

This study has used daily rainfall data of 18 rainfall stations across Bangladesh (Figure 1) for the period 1973–2012, collected from the Bangladesh Meteorological Department (BMD, 2018). BMD operates a total of 36 rainfall stations across the country. The record length of most of the stations varies roughly between 35 and 60 years. Presence of missing data for almost all the stations was observed. A significantly high percentage of missing records was observed in years such as 1970–1972 (possible impact of the liberation war of Bangladesh), 1973–1976 and 1981 (see Supporting Information Table S1). After data screening, 18 stations were selected so that they cover all hydro-climatic regions of the country, and their missing data was less than 6% for the period from 1973 to 2012 (Figure 1). Missing data for each station were filled by available records for the respective days from the nearest neighbouring stations. More details about the filling of missing records are provided in Table S1. The rainfall depth presented in this paper are in millimetre (mm) unless otherwise specified.

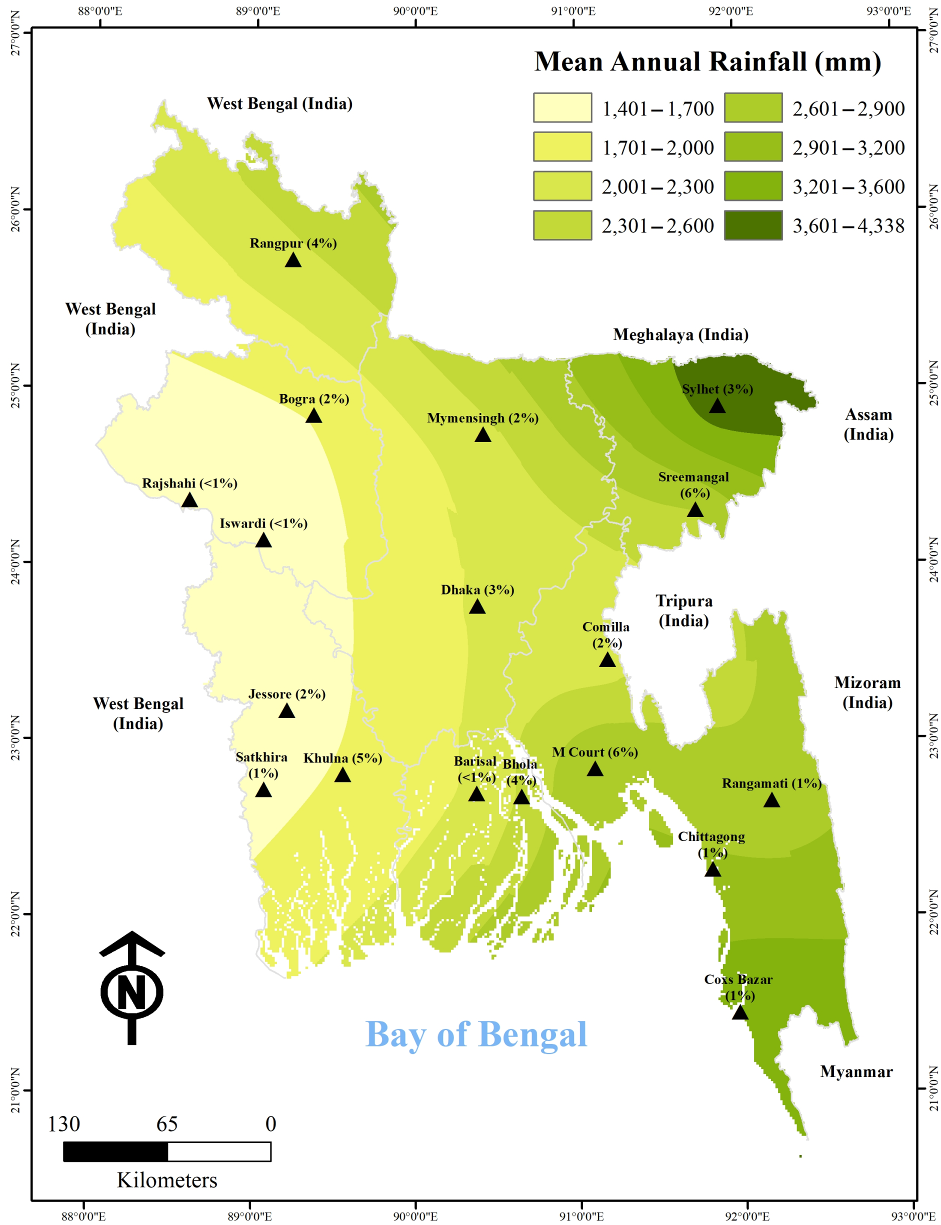

FIGURE 1 Location of 18 rainfall stations used in this study. The percentages of missing records in each station are shown in the parentheses. The colours indicate spatial distribution of annual mean rainfall (in mm) over Bangladesh produced by using empirical Bayesian kriging method in ArcGIS [Colour figure can be viewed at wileyonlinelibrary.com]

4 | METHODOLOGY

4.1 | Rainfall variability assessment

This study has assessed the distribution characteristics of rainfall depth using the first two moments such as mean and *SD*, while coefficients of variation (CV) was calculated as a ratio of *SD* and mean. In addition, the 95th percentile of rainfall depth was considered in order to include the extremes. Wet days were only considered in the estimation of rainfall depth statistics at the daily temporal resolution. In order to evaluate the seasonal variability, rainfall statistics were estimated for each calendar month at both daily and monthly resolutions. Whereas, for annual to multi-year resolutions, rainfall statistics were estimated for 1 to 10 overlapping years.

For wet and dry spells, this study has assessed the statistical moments (mean and *SD*) of the "average wet (and dry) spells" and the number of wet days. The 95th percentiles of the number of wet days and the mean of the "long wet (dry) spells" were also investigated. The statistics for wet and dry spells were evaluated at the monthly and annual resolutions assuming that the lengths of wet and dry spells do not significantly vary at higher scales, whereas the number of wet days were evaluated at the monthly, annual and multiyear resolutions.

The "average wet (dry) spells" and the "long wet (dry) spells" were defined by the average and 95th percentile of the length of wet (dry) spells (one or more consecutive wet (dry) days) at a temporal resolution. For example, at monthly resolution, first the wet (dry) spells were extracted for each month of every year. Then, for each month of every year, mean and 95th percentile of the lengths of the extracted wet (dry) spells were calculated that we defined as "average spell" and "long spell" respectively. Finally, for each calendar month, the mean and *SD* of the yearly varying average wet (dry) spells were estimated, whereas only the mean of the yearly varying long wet (dry) spells was estimated to check the climatological pattern of maximum lengths of wet (dry) spells. Similarly, the mean and *SD* of the average wet (dry) spells and mean of long wet (dry) spells were also estimated at annual resolution.

To examine the homogeneity and stationarity of rainfall time series, the Mann–Kendall test for trend (Mann, 1945; Kendall, 1975) at a 5% significance level was conducted for daily rainfall time series, and for monthly total rainfall and number of wet days for each month.

4.2 | Model calibration

In the calibration of MC parameters (i.e., probabilities of dry-to-dry and wet-to-wet day), this study has divided the 40-year data of each station into four decadal samples and calibrated the parameters of each calendar month to each decadal data, therefore there were 48 values (12 months × 4 decades) for each parameter. Whereas, in the calibration of gamma parameters (i.e., mean and *SD* of wet day rainfall depth), 12 values of each parameter were calculated for each year that provided a total of 480 values (12 months × 40 years) for each parameter. The spatial correlations of MC and gamma parameters between pairs of stations (e.g., correlation between 48 values of dry-to-dry probabilities of a station with the corresponding parameter values of each of the other 17 stations) were also examined.

4.3 | Model assessment

First, to test how well the DHMC model reproduces daily rainfall series, the Spearman's rank correlation coefficients (Spearman, 1904; Fieller *et al.,* 1957) were estimated between the observed and simulated daily rainfall. Simulated daily rainfall series was obtained as median of the 1,000 replicates of DHMC model. Then, performance of the DHMC model was assessed for selected statistics of rainfall depth and wet–dry spells at different time resolutions ranging from daily to multiyear. The selected statistics include mean and *SD*, 95th percentile and autocorrelation. The first two moments (i.e., mean and *SD*) were used to examine the ability of DHMC to reproduce the distributions of observed rainfall series. However, higher moments (e.g., skewness, kurtosis) were not examined as Wang and Nathan (2007) and Lombardo *et al*. (2014) showed that the first two moments generally provide enough information to understand the characteristics of the distributions, while use of higher moments may result in inappropriate inferences of model performance. Instead, this study used the 95th percentile to explicitly examine the ability of DHMC to reproduce the extreme events. The autocorrelation is checked because a stochastic model may underestimate the observed autocorrelation by introducing excessive variability to overcome overdispersion issue (Chowdhury, 2017). The above-mentioned statistics used to evaluate the performance of DHMC include most of the statistics of the extreme precipitation indices (Karl *et al.,* 1999; Rashid *et al.,* 2017).

The *Z* score (defined in Equation 3) was used to evaluate the model performance to reproduce the observed statistics of rainfall. First, the model was run for 1,000 times to generate 40-year long (consistent with the 40-year long observation from 1973 to 2012) 1,000 synthetic rainfall series. Then, the selected rainfall statistics were estimated for the synthetic rainfall series, which eventually produces 1,000 realizations for each of the selected rainfall statistics. Finally, statistical moments (mean and *SD*) were estimated from those 1,000 realizations. The *Z* score was estimated using the Equation 3.

$$Z\,\text{score} = \frac{\text{Obs}_S - \text{Exp\_synth}_S}{SD\_\text{synth}_S}, \tag{3}$$

where Obs_S represents the observed value of any rainfall statistic (95th percentile, for example), Exp_synth_S and SD_synth_S represent the mean and *SD* of corresponding rainfall statistics, respectively, obtained from the 1,000 synthetic rainfall series as described above.

The underlying assumption of the *Z* score calculation is that the values of a statistic from the 1,000 synthetic rainfall series are normally distributed with a mean equal to corresponding observed value of the statistic. Therefore, a *Z* score equal to zero for a statistic indicates that the statistic has been exactly reproduced by the model. The positive and negative values of the Z score indicate the tendency of the model to underestimate and overestimate the observed statistic, respectively. A value of Z score between −2 and + 2 for a statistic indicates that the observed value falls within the 95% confidence interval of the statistic values from 1,000 synthetic rainfall series. Accordingly, Z scores greater than +2 and less than −2 can be considered as significant underestimation and overestimation of the observed statistic by the model, respectively.

In addition to the *Z* scores, the distribution statistics at the annual resolution were shown by probability plots. Autocorrelations of monthly rainfall depth and the number of wet days were also used to evaluate the model performance. The month-to-month (January to February of same year, for example) and year-to-year (January of two successive years, for example) autocorrelations of the monthly rainfall depth and number of wet days were estimated from the observations and compared with the model outputs. Autocorrelations of modelled monthly rainfall depth and number of wet days were estimated as the average of 1,000 realizations obtained from 1,000 synthetic rainfall series as described earlier.

To examine the performance of DHMC to incorporate the variability of rainfall outside the calibration period, we performed a cross validation test. For the cross validation, 40 years rainfall (1973–2012) data were divided into two halved (1973–1992 and 1993–2012) of 20 years each. Then, the Spearman's rank correlation coefficients were estimated by calibrating the model to one half (e.g., 1973–1992) and comparing against another half (e.g., 1993–2012), and vice versa.

5 | RESULTS AND DISCUSSION

5.1 | Spatio-temporal variabilities of rainfall

Figures 2 and 3 show the transition probabilities of wet-to-wet days and boxplots of the mean of wet day rainfall depth, respectively. Transitional probabilities of dry-to-dry days and *SD* of wet day rainfall depth are shown in Figures S1 and S2. Figures 2 and 3 exhibit a strong seasonal variability of rainfall in all stations. With a relatively high wet-to-wet probabilities (around 0.5 to 0.85) and mean of wet day rainfall depth (around 15 mm to 30 mm per wet day), the pre- to post-monsoon months (i.e., March to November, will be referred as "monsoonal months" hereafter) indicate a wet season with the wettest condition in the monsoon months from June to September. The winter months from December to February are relatively dry. Figure 3 indicates that the dry months are extremely dry with almost zero mean of wet day rainfall depth for almost all stations (except for a few stations such as Jessore and Satkhira). The 95th percentiles of the mean of wet day rainfall depth (upper whiskers of the boxplots in Figure 3) for winter months indicate occasional dry season storms in few years. However, the above findings of seasonal variability are well-established in existing literatures (Ahmed and Karmakar, 1993; Ohsawa *et al.*, 2000; Ahmed and Kim, 2003).

Figure 2 indicates similar seasonality in the decadal wet-to-wet probability values for all four decades with nominal inter-decadal variabilities (mostly overlapped) for all stations. However, inter-decadal variabilities of wet-to-wet probabilities were found slightly higher in the drier months (December to February) compare to the variabilities in the wetter months (March to November) (although there might be some inconsistencies in wet-to-wet probabilities of 1973s in some stations such as Bhola, Cox's Bazar, and Comilla with possible link to data inconsistencies as discussed in Section 3). On the other hand, the probabilities of dry-to-dry days (Figure S1) indicates some higher inter-decadal variabilities in the wetter months compare to the drier months. This suggests an existence of inter-decadal variability of wet and dry spells in the dry (winter) and wet (monsoon) seasons, respectively. Similarly, relatively high CVs were observed for monthly rainfall depth and wet spells in dry winter months (around 100–200% and 85–150% as shown in Figure 4(a) and (b), respectively). In contrast, relatively high *SD*s were observed for monthly rainfall depth and wet spells

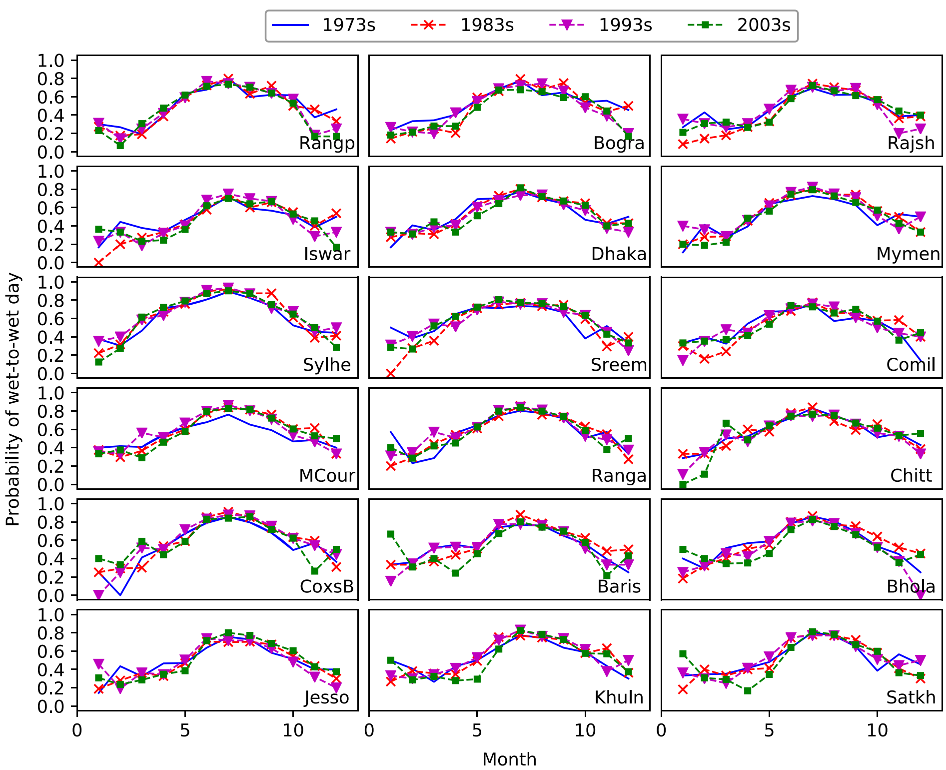

FIGURE 2 Transitional probabilities of wet-to-wet day for each calendar month and for each of the four decades between 1973–2012. The stations are denoted by their first five characters of full name (Mymensingh = Mymen, for example) [Colour figure can be viewed at wileyonlinelibrary.com]

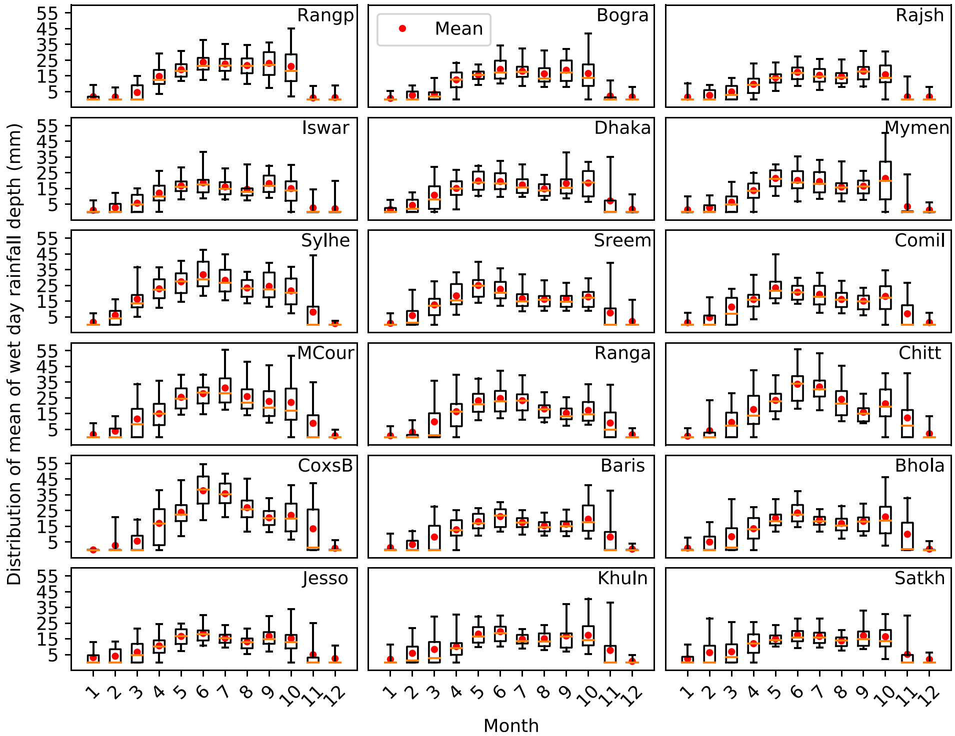

FIGURE 3 Distribution of the mean of wet day rainfall depth over the data period from 1973 to 2008. Each boxplot shows the quartiles including median with fifth and 95th percentiles as lower and upper whiskers, respectively. The solid circles are mean of the yearly-varied values of mean of wet day rainfall depth [Colour figure can be viewed at wileyonlinelibrary.com]

in wet monsoonal months (around 80–250 mm and 4–6 days per month as shown in Figure 4(a) and (b), respectively). While the mean and *SD* of monthly dry spells were found to be complementary to the respective wet spell statistics, the CVs of monthly dry spells were found higher (around 65–100%) in the pre- and post-monsoon months compare to the monsoon and winter months (Figure S3).

The above results suggest that the rates of inter-annual variability (i.e., variability as a percentage of mean as denoted by the CVs) of rainfall depth and wet spells are higher in the dry winter months with a potential link to the inter-decadal variability of wet-to-wet transition probabilities, but the magnitudes of these inter-annual variability (as denoted by the *SD*s) are higher in the wet monsoonal months (and vice versa in case of dry spells). Since the dry winter months are extremely dry with less than 5% of annual rainfall, the higher rate of inter-annual variability of rainfall depth and wet spells in the dry winter months likely to have nominal impacts on the hydrological systems. Instead, the higher magnitude of inter-annual variability of rainfall depth and wet spells in the wet monsoonal months might be of greater interest for design and operation of water systems. This understanding is a clear advancement in the relevant scientific knowledge as the existing literatures (Bari *et al.,* 2017, for example) are mostly based on CVs of monthly rainfall depth and only focused on the higher inter-annual variability in the dry winter months.

The spatial variability of rainfall over Bangladesh is mainly driven by the monsoonal rainfall. Figure 4(a) and (b) indicates the existence of an east-to-west gradient of wetness with the wettest condition in the Sylhet station of north-east region with a relatively high mean monthly rainfall depth (around 850 mm) and wet spell (around 11 days) in the monsoon, whereas the driest condition is observed in the stations located in central-west region such as the Rajshahi and Iswardi stations with a lower mean monthly rainfall depth (around 250 mm) and wet spell (around 4 days) in the monsoon. Figure 1 shows an overall spatial distribution of the annual mean rainfall depth that indicates a gradual dryness from the northeast to the central-west region and from the southeast coastline to the further north (note that our Figure 1 is comparable to the Figure 1(a) of Shahid (2010)). The wet conditions in the northeast and southeast region are linked with the topographic lifting effects of the Meghalaya plateau and Chittagong hills, respectively (Ahmed and Karmakar, 1993). In the west, the Rangpur station in the northwest region is wetter than the central-west region with a possible influence from the Himalayan foothills, whereas the Khulna and Satkhira stations in the southwest region are also found wetter than the central-west region with possible influence of the vicinity to the Bay of Bengal. Such findings of spatial variability of rainfall depth and wet–dry spells are mostly consistent with the findings of relevant previous studies (Ohsawa *et al.,* 2000; Shahid, 2010).

As a new finding on spatial variability, this study has observed that the mean and 95th percentile of wet-day rainfall depth (Figure 3 and S4) in some winter months (December–February) in the stations of southwest to south-

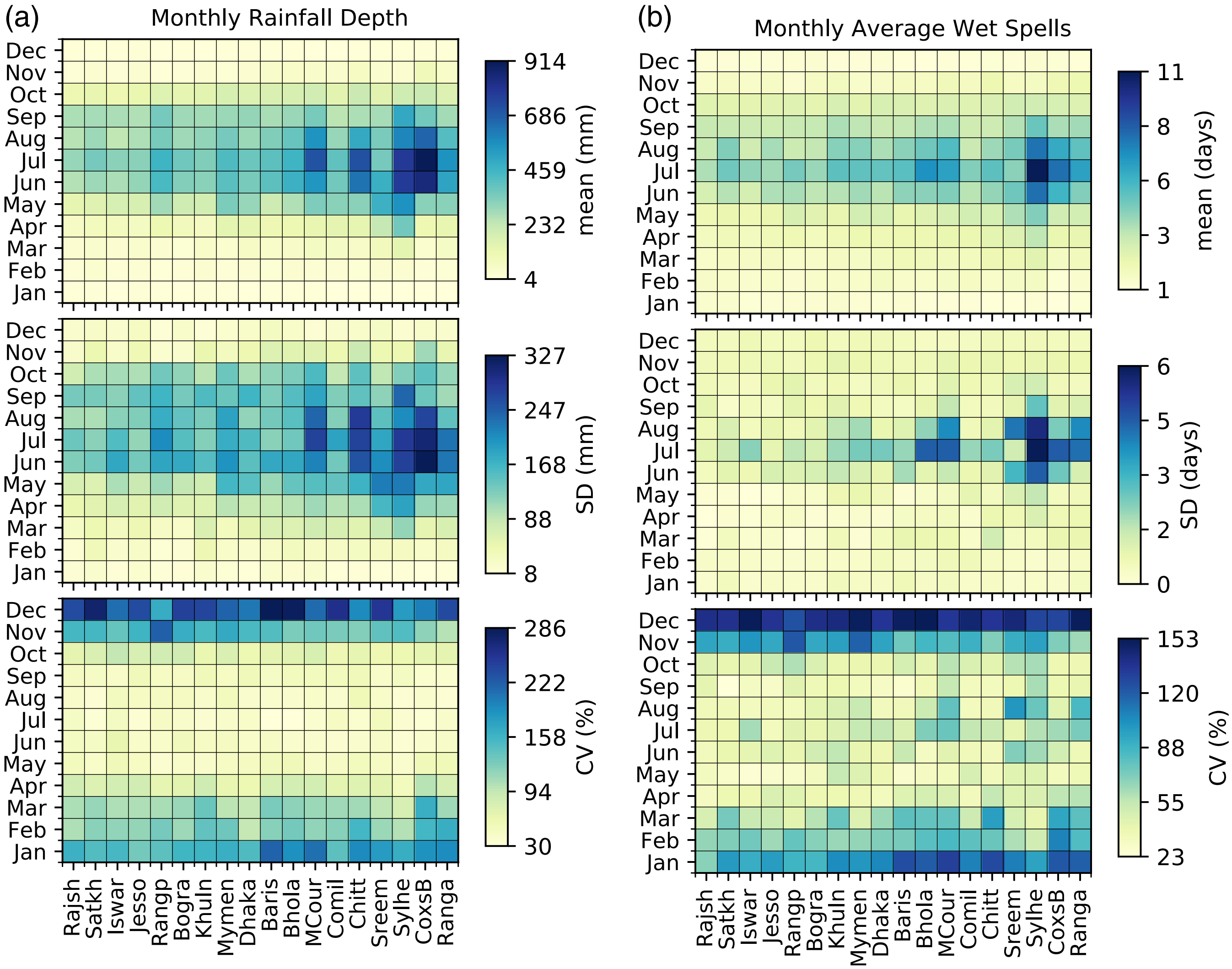

FIGURE 4 Mean, *SD*, and CV of (a) monthly rainfall depth and (b) monthly average wet spells. In each X-axis, the stations are arranged from left to right according to an approximate geographical direction from west to east. Please note the scale of colour bars in each subplot is different [Colour figure can be viewed at wileyonlinelibrary.com]

central regions (e.g., Jessore, Khulna, Satkhira, Barisal, Bhola) are as high as the pre- and post-monsoon months, while the mean (and 95th percentile) of monthly rainfall depth for the respective months indicate drier conditions (Figure 4(a)). Such months of these stations probably receive small size storms (mean wet day rainfall depth below 5 mm as shown in Figure 3) for short wet spells (mean length of wet spells below 2 days as shown in Figure 4(b)) during winter which contribute to their wet-day rainfall depth to be higher than the respective dry winter months of other stations. The average length of dry spells in winter months are also slightly shorter (around or below 20 days as compare to 25–30 days in other stations) in those stations of southwest and south-central regions (Figure S3) that supports the above observation of short-duration winter storms in that region. The short duration winter rainfall events are likely to be generated by weak tropical depressions in the Bay of Bengal (origin of most of the storms in Bangladesh) (Ahmed and Karmakar, 1993), which mostly fall on the coastal districts of southwest and south-central regions, but do not progress further north to the inland regions.

As shown in Figure 4(a) and (b), the magnitude of inter-annual variabilities (*SD*s) of rainfall depth and wet spells declines from east to west, while the rate of inter-annual variabilities (CVs) show an opposite trend. This is an enhanced understanding of the spatial distribution of the inter-annual variability of rainfall depth and wet spells in Bangladesh. Previous studies (Bari *et al.,* 2017), which are mostly based on spatial distribution of CVs, concluded that the inter-annual variability of rainfall declines from west to east.

The autocorrelations of monthly rainfall depth and wet days (Figure 5; also see Figures S5 and S6) indicate that the patterns of seasonality of rainfall depth and wet spells are similar in all stations throughout the country exhibiting relatively strong correlations at lag-1 (around 0.5 to 0.7), lag-6 (around −0.5 to −0.7) and lag-12 (around 0.55 to 0.75). This might be because the storms that mostly originated in the Bay of Bengal and flow from south to north, maintain a

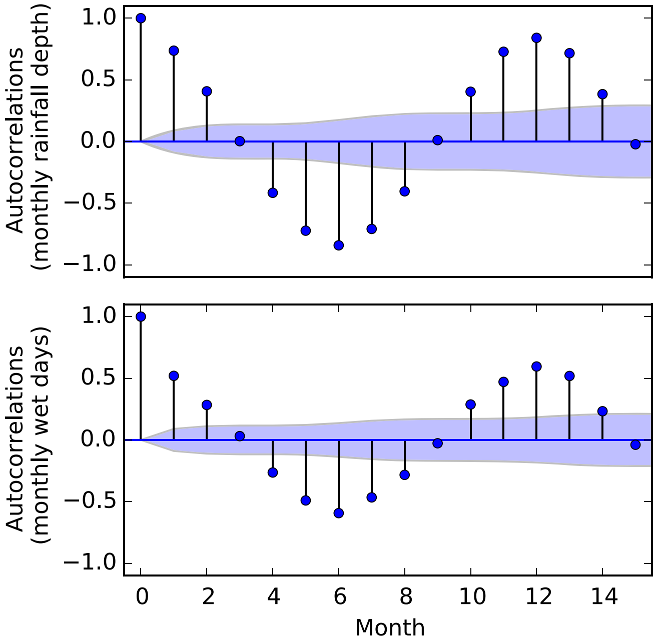

FIGURE 5 Autocorrelation of monthly rainfall depth and wet days for Sreemangal as a typical station (autocorrelations of all other stations are similar as shown in Figure S5 and S6). The shades indicate 95% confidence interval [Colour figure can be viewed at wileyonlinelibrary.com]

similar interval of arrival and withdrawal dates over the entire country, while the intensity of rainfall and length of wet spells vary over space due to the direction of monsoon winds and local orography.

The spatial variabilities are clearer in the rainfall depth and wet spells compare to the dry spells. This observation is supported by the spatial correlations of DHMC parameters between station-pairs as shown in Figure 6. In Figure 6(a), the right triangle shows the correlation coefficient (r) values for dry-to-dry probabilities (correlations of the 12×4 values of the parameter in two stations) and the left triangle shows the r values for wet-to-wet probabilities. Figure 6(b) shows the r values for mean and *SD* of wet day rainfall depth (two Gamma parameters) in right and left triangles, respectively. The spatial correlations of dry-to-dry probabilities are strong ($r \approx 0.90$–0.95) for almost all station-pairs indicating high similarity of dry spell occurrence in entire country. The correlations of wet-to-wet probabilities are weaker than that of dry-to-dry probabilities, but still strong for most of the station-pairs ($r \approx 0.70$–0.90). This might indicate that most of the storms produce rainfall over the entire country. However, the correlations are only moderately strong for the mean and *SD* of wet-day rainfall depth ($r \approx 0.45$–0.65) indicating that although a storm might cause rainfall over the entire country, the rainfall depth could significantly vary spatially.

Note that the spatio-temporal variability of long wet–dry spells and multiyear variabilities of rainfall depth and wet days are also investigated by this study. The findings are consistent with the spatio-temporal variabilities as discussed (Figure S7 and S8).

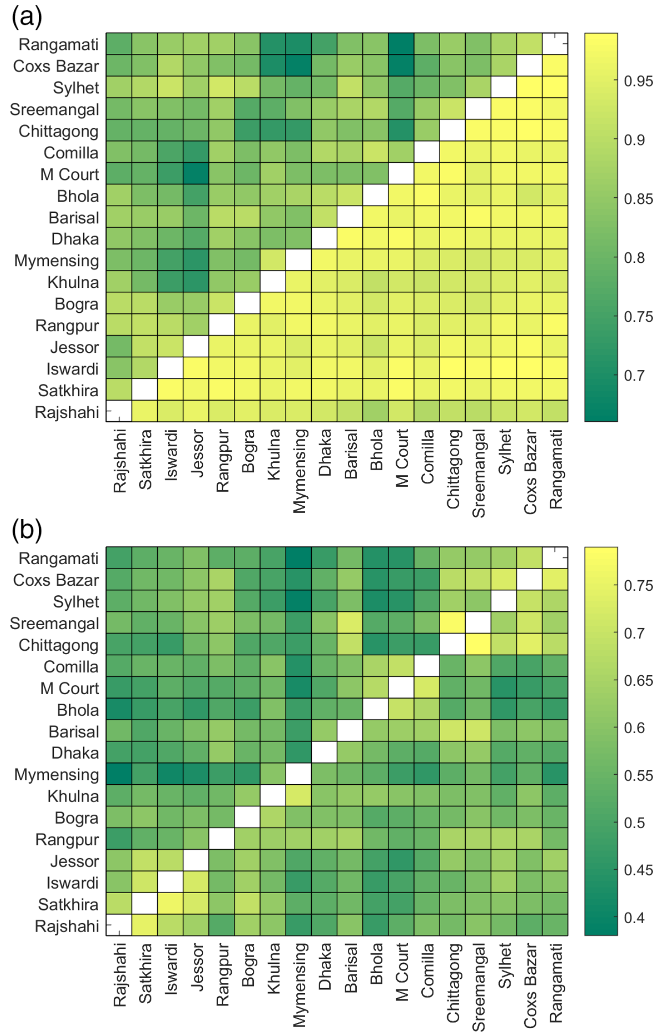

FIGURE 6 Correlation coefficients (r) of DHMC parameters between station-pairs—(a) r values for dry-to-dry (right triangle) and wet-to-wet (left triangle) probabilities and (b) r values for mean (right triangle) and *SD* (left triangle) of wet-day rainfall depth [Colour figure can be viewed at wileyonlinelibrary.com]

Table 1 shows the results of Mann–Kendal test for daily rainfall series, and for monthly total rainfall and monthly number of wet days for each month. For daily rainfall, stations across the western region were found trendless whereas significant (at 5% significance level) increasing and decreasing trends were observed in stations across the eastern and southern coastal regions (e.g., Barisal and Bhola), respectively. In case of monthly rainfall depth, significant decreasing trends were observed over the region from west to the middle part of the country, particularly in the monsoonal months. In contrast, number of wet days in monsoonal months showed increasing trends over the eastern region of the country.

The above results of this study have provided enhanced understandings of the spatio-temporal variabilities of rainfall depth and wet–dry periods over Bangladesh. These understandings are important in terms of stochastic simulation of rainfall that the stochastic model(s) should preserve these rainfall characteristics.

TABLE 1 Results of Mann–Kendal test for daily rainfall series, and for monthly total rainfall and monthly number of wet days for each month

Station name	Daily rainfall (mm)	Monthly total rainfall (mm)												Monthly number of wet days											
		J	F	M	A	M	J	J	A	S	O	N	D	J	F	M	A	M	J	J	A	S	O	N	D
Rajsh			D																						
Satkh																									
Iswar						D																			
Jesso																									
Rangp																			I						
Bogra			D					D												D					
Khuln						D																			
Mymen																									
Dhaka						D									D										
Baris	D																								
Bhola	D								D									D							
Mcour	I										I								I	I	I	I			
Comil																					I	I			
Chitt																									
Sreem	I																		I		I				
Sylhe																			I						
CoxsB	I									I		D									I	I			
Ranga	I																					I	I		

Notes. The blank cells indicate no trend, while the "I" and "D" signs indicate increasing and decreasing trends, respectively. The stations are arranged from top to bottom according to an approximate geographical direction from west to east

5.2 | Model performances

The Spearman's rank correlation coefficients between the observed and modelled daily rainfall time series were found above 0.9 in all stations (see Table S2) indicating satisfactory performance of DHMC to reproduce the daily rainfall series. Figures 7 and 8 show the performances of DHMC to simulate the distribution statistics (i.e., mean, *SD*, and 95th percentiles etc.) of wet day rainfall depth and monthly wet spell lengths, respectively. The typical results for monthly rainfall depth, number of wet days, and dry spell lengths are shown in Figures S9, S10, and S11, respectively. Then, in Table 2, the overall performances of the model for the rainfall depth and wet–dry spell statistics are shown as average of the absolute values of respective Z scores in each of the four seasons. Table 2 does not include the relevant statistics for 95th percentiles of rainfall depths and mean of long wet–dry spells (i.e., extreme events) because the performance of DHMC for the extremes is similar to its respective performance for mean and *SD* (Figures 7 and 8).

The DHMC has satisfactorily preserved the mean, *SD* and 95th percentiles of wet day rainfall depth for the wetter months of pre- to post-monsoon (March to November) as Z scores are mostly between −2 and +2 indicating observed statistics are within the 95% confidence interval of the DHMC simulated values. However, the model tends to underestimate the statistics for the wet day rainfall depth in relatively dry months of winter (December to February) with Z scores greater than +2 (Figure 7). The likely reason of this underestimation is that the drier months receive nominal rainfall with almost no wet days in most of the years except some occasional storms in some years (as shown in Figure 3 and discussed in above section), while the generation of rainfall depth in DHMC by a stochastic process using gamma distribution cannot reproduce the occasional storms. However, the underestimation of DHMC for such occasional wet day rainfall in the drier months might be negligible for hydrological systems. Note that the model underestimates the mean of wet day rainfall depth of November for some stations of relatively dry west regions such as Rajshahi, Satkhira, Iswardi etc. (Figure 7 and Table 2). It indicates that the dry season is probably extended from November to February in these relatively dry regions, although November is defined as a post-monsoon month. The performance of DHMC for the mean, *SD,* and 95th percentiles of monthly rainfall depth is consistent with the respective performance for wet day rainfall depth (Figure S9 and Table 2). The above results are mostly similar for all stations irrespective of the spatial variabilities discussed in the previous section.

The DHMC has satisfactorily reproduced the statistics of wet spell length in all stations for all months except underestimation of the *SD* of average wet spell length in a few stations for some of the wetter months such August of Sreemangal and May of Khulna etc. (Figure 8 and Table 2). However, these rare failures of the model can be associated with potential inconsistencies in the observed data. The performance of DHMC for the monthly number of wet days is similar to its respective performance for monthly wet spells (Figure S10). The DHMC has also satisfactorily reproduced the statistics of dry spell length in all stations for all months with a tendency to underestimate the dry spells in the pre-

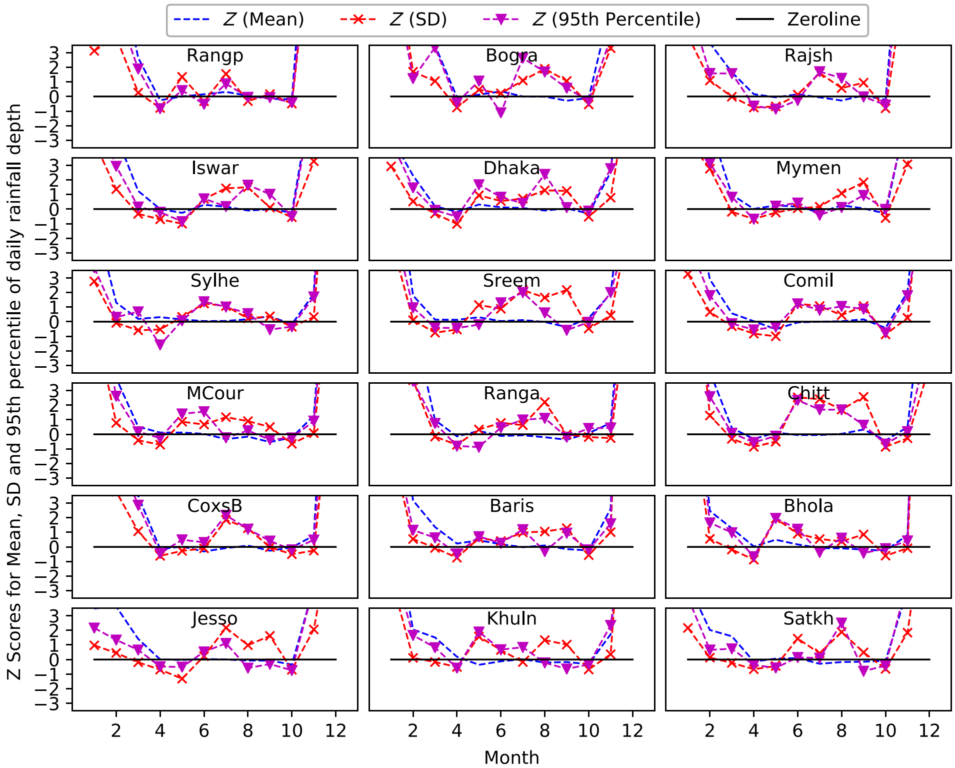

FIGURE 7 *Z* score for mean, *SD*, and 95th percentile of daily (wet days) rainfall depth. *Z* scores outside of −3 and +3 limit are not shown [Colour figure can be viewed at wileyonlinelibrary.com]

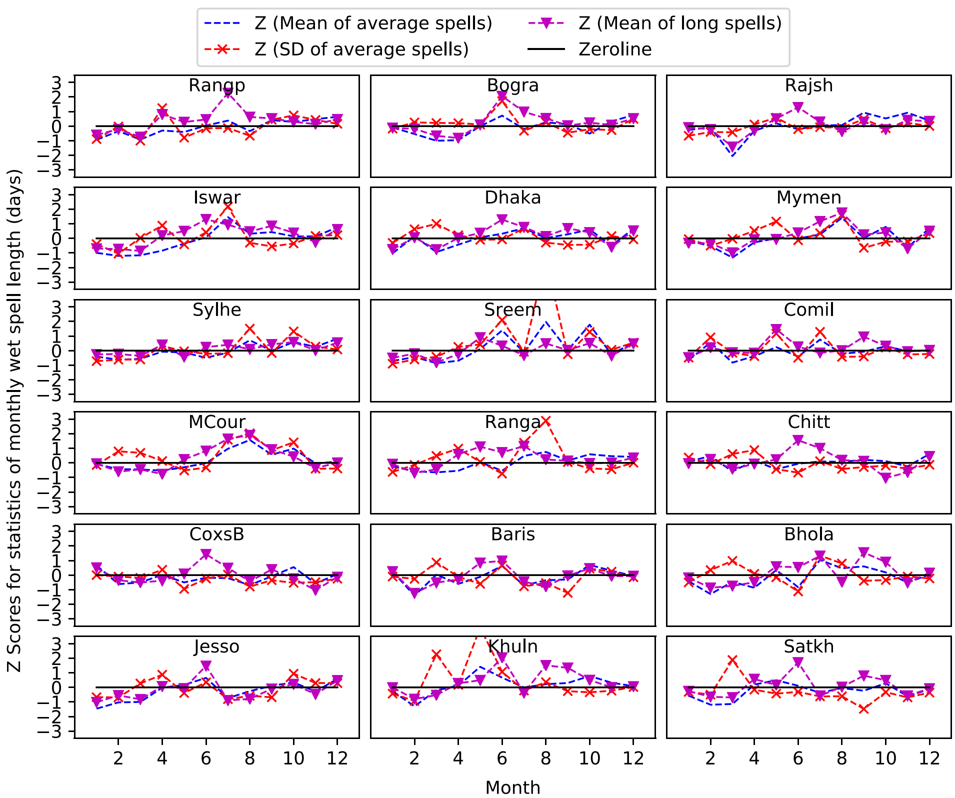

FIGURE 8 *Z* score for mean and *SD* of monthly average wet spell lengths and mean of long wet spells [Colour figure can be viewed at wileyonlinelibrary.com]

monsoon months of March to May (Figure S11). Despite these limitations, the overall performance of DHMC is satisfactory to preserve the distribution of monthly wet and dry spells.

TABLE 2 Average of the absolute values of Z scores (for selected statistics) in four seasons, namely monsoon (Mon, June–Sep), pre-monsoon (prmon, Mar–May), post-monsoon (pomon, Oct–Nov), and winter (win, Dec–Feb)

Variable and season		Raj	Satk	Iswa	Jess	Rang	Bog	Khul	Mym	Dhak	Bari	Bhol	MCou	Comi	Chit	Sree	Syl	Coxs	Ranga
Mean of wet day rainfall depth	Mon	0.1	0.2	0.1	0	0.2	0.2	0.1	0.2	0.1	0.1	0.1	0.3	0.1	0.1	0.1	0.2	0.2	0.2
	Prmon	0.6	0.6	0.5	0.5	1	1.2	0.7	0.4	0.2	0.7	0.6	0.3	0.4	0.3	0.2	0.2	1.2	0.4
	Pomon	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	1	**>2**	1.4	1.4	0.5	0.8	1.2	0.5	1.1	1	0.4	0.4
	Win	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**
SD of wet day rainfall depth	Mon	0.8	1.1	0.9	1.2	0.6	1.1	0.8	0.8	0.9	0.9	0.7	0.8	1	**>2**	1.7	0.7	0.8	0.9
	Prmon	0.5	0.4	0.7	0.7	0.8	0.8	0.8	0.4	0.8	0.5	1	0.7	0.7	0.6	0.8	0.5	0.7	0.4
	Pomon	**>2**	1.2	1.9	1.4	**>2**	1.9	0.5	1.8	0.7	0.8	0.3	0.4	0.6	0.6	0.4	0.3	0.4	0.2
	Win	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**
Mean of monthly rainfall depth	Mon	0.1	0.1	0.1	0	0.1	0.2	0.1	0.2	0.1	0.1	0.1	0.2	0.1	0.1	0.1	0.2	0.2	0.2
	Prmon	0.6	0.6	0.5	0.5	0.9	1.1	0.6	0.4	0.2	0.6	0.6	0.2	0.3	0.3	0.2	0.2	1.2	0.4
	Pomon	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	1	**>2**	1.3	1.3	0.5	0.7	1.1	0.4	1	0.9	0.4	0.4
	Win	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**
SD of monthly rainfall depth	Mon	0.9	1	0.5	0.6	0.8	0.7	0.8	0.5	0.7	0.7	0.9	1.1	0.9	0.6	0.6	0.7	1.3	1.1
	Prmon	0.7	0.8	0.7	0.8	0.7	0.7	0.7	0.5	0.6	0.3	0.5	0.7	0.9	0.7	0.5	0.4	0.8	0.5
	Pomon	**>2**	1	1.5	1.2	**>2**	1.6	0.6	1.4	0.8	0.7	0.6	0.5	0.6	0.7	0.5	0.7	0.6	0.6
	Win	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**	**>2**
Mean of average wet spell length	Mon	0.3	0.2	0.6	0.4	0.3	0.3	0.3	0.4	0.3	0.5	0.7	0.8	0.4	0.1	0.9	0.3	0.3	0.5
	Prmon	0.9	0.6	0.8	0.4	0.5	0.7	0.6	0.5	0.5	0.2	0.6	0.4	0.5	0.4	0.6	0.3	0.3	0.4
	Pomon	0.7	0.4	0.1	0.3	0.4	0.4	0.6	0.7	0.6	0.5	0.3	0.5	0.2	0.2	1	0.4	0.6	0.5
	Win	0.2	0.6	1	1	0.6	0.5	0.5	0.5	0.6	0.6	0.6	0.2	0.4	0.4	0.6	0.6	0.5	0.4
SD of average wet spell length	Mon	0.2	0.8	0.9	0.6	0.3	0.7	0.5	0.7	0.4	0.8	0.9	1.2	0.7	0.4	**>2**	0.5	0.4	1.3
	Prmon	0.4	0.8	0.4	0.5	1	0.2	**>2**	0.6	0.4	0.5	0.4	0.4	0.6	0.6	0.4	0.3	0.5	0.5
	Pomon	0.2	0.5	0.3	0.6	0.6	0.2	0.3	0.2	0.3	0.3	0.2	0.9	0.2	0.3	0.7	0.8	0.5	0.4
	Win	0.4	0.4	0.6	0.5	0.4	0.3	0.5	0.3	0.3	0.2	0.4	0.4	0.5	0.2	0.7	0.5	0.1	0.3
Mean of average dry spell length	Mon	0.4	0.3	0.2	0.3	0.5	0.3	0.5	0.8	0.3	0.3	0.5	0.3	0.2	0.4	0.8	0.7	0.2	0.5
	Prmon	1.3	1	1.3	1.8	0.9	1.4	1	1.5	1.4	1.4	1.2	1.5	1.5	1.4	1.4	0.8	1	1.9
	Pomon	0.4	0.5	0.2	0.4	0.5	0.4	0.5	0.6	0.3	0.1	0.2	0.2	0.2	0.2	0.1	0.2	0.1	0.1
	Win	0.9	0.5	0.8	0.7	0.8	0.7	0.4	0.3	0.7	0.4	0.4	0.7	0.5	0.5	0.5	0.5	0.4	0.8
SD of average dry spell length	Mon	0.3	0.8	0.4	0.9	0.7	0.9	1.3	**>2**	0.7	0.5	0.7	0.7	0.4	1.7	**>2**	0.9	0.7	0.8
	Prmon	**>2**	1.4	**>2**	1.8	1.3	1.7	1.7	**>2**	**>2**	**>2**	1.6	1.6	**>2**	1.3	**>2**	1.7	0.9	**>2**
	Pomon	0.8	1.2	0.4	0.9	0.5	1	0.9	1	0.7	0.3	1	0.2	0.3	0	0.4	0.5	0.2	0.3
	Win	0.5	0.8	0.9	0.8	0.4	0.8	0.5	0.3	0.5	0.9	0.9	0.9	0.5	0.4	0.4	0.1	0.7	1.1

Notes. Values greater than two (>2) indicate failure of DHMC to preserve the respective observed statistics within the 95% confidence interval of simulated statistics. The stations are arranged from left to right according to an approximate geographical direction from west to east.

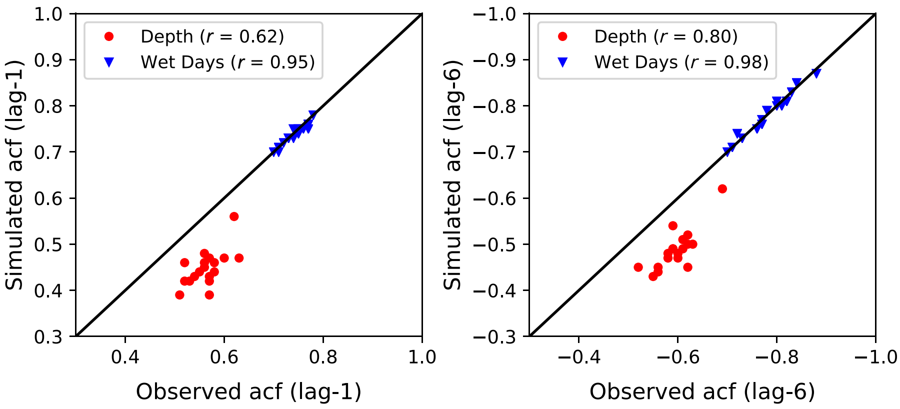

FIGURE 9 Autocorrelations of monthly observed and simulated rainfall depth and monthly number of wet days at lag-1, lag-6, and lag-12 for all stations. Values in the parenthesis indicate correlation coefficients (r) between observed and simulated autocorrelation values at each lag [Colour figure can be viewed at wileyonlinelibrary.com]

In addition to the above-mentioned distribution statistics, this study has also investigated the DHMC performance to preserve the autocorrelations of the observed rainfall. Figure 9 shows the performance of DHMC to reproduce the autocorrelations of monthly rainfall depth and number of wet days at lag-1, lag-6, and lag-12 (lags with relatively strong observed autocorrelations) in all stations. It indicates that the DHMC has preserved the autocorrelations of monthly wet days at all three lags with r value of above 0.95 for lag-1 and lag-6, and 0.89 for lag-12. However, the model shows a consistent tendency to underestimate the autocorrelations of monthly rainfall depth at all lags with the r values of around 0.6 for lag-1 and lag-12, and 0.8 for lag-6. Such tendency of DHMC to underestimate the autocorrelations of monthly rainfall depth is likely to be linked with the hierarchical generation process of rainfall depth by using bivariate lognormal distributions of gamma parameters that incorporate excessive variability of rainfall depth in the model.

Figure 10 shows the performance of DHMC to reproduce the rainfall depth, number of wet days, and average length of wet–dry spells at annual resolution for Sreemangal and Bogra as representative stations of relatively wet and dry regions respectively (plots for all other stations are provided in Figures S12 to S15). It indicates that the distributions of rainfall depth and wet–dry periods at annual resolution have been preserved well by the DHMC for all stations irrespective of spatial variability of rainfall among the stations. The Z scores of DHMC for SDs of rainfall depth and wet days at multiyear resolutions (i.e., at 2, 5, and 10 multiple overlapping years) are also mostly between −2 and +2 as shown in Figure 11. However, the model shows a consistent tendency to overestimate the variability of rainfall depth at multiyear resolutions (negative Z scores for SDs of rainfall depth in most of the stations), while SDs of wet days at multiyear resolution are well-preserved with slight tendency of underestimation at 2-year resolution (mostly positive Z scores). Despite these limitations, we conclude that the performance of DHMC to preserve the low-frequency variabilities (i.e., variabilities at annual and multiyear resolutions) of rainfall in Bangladesh is satisfactory considering the well-known challenge of over dispersion of daily rainfall models.

In cross-validation, the Spearman's rank correlation coefficients between observed rainfall outside of calibration period and simulated rainfall were found very strong (above 0.9, see Table S2). This indicates that the DHMC can incorporate the characteristics of rainfall outside of its calibration period.

The above findings indicate that the DHMC can satisfactorily simulate the daily rainfall in stations across Bangladesh (irrespective of underlying spatial variabilities) by preserving the key statistical characteristics of rainfall depth and wet–dry periods at both high and low temporal frequencies (i.e., daily to multiyear resolutions). The only critical limitation of the DHMC is that the model tends to underestimate the autocorrelations of monthly rainfall depth particularly at lag-1 and lag-12, which could be due to the excess variabilities introduced by the hierarchical stochastic generation process of rainfall depth. Despite that, the DHMC can be considered as a suitable stochastic rainfall simulator to use in the planning and operations of various water infrastructures in Bangladesh.

6 | CONCLUSION

This study evaluated the spatio-temporal variability of rainfall and the potential of using a stochastic rainfall model (known as DHMC) to simulate daily rainfall in a tropical monsoon climate, that is, Bangladesh. Rainfall depth and wet–dry periods were investigated at different temporal resolutions using the daily rainfall data of 18 rainfall stations across the country. In light of the observed rainfall variability, the performances of the DHMC model were assessed.

Results indicate existence of short wet spells of small-size storms during the dry winter months in the southwest to

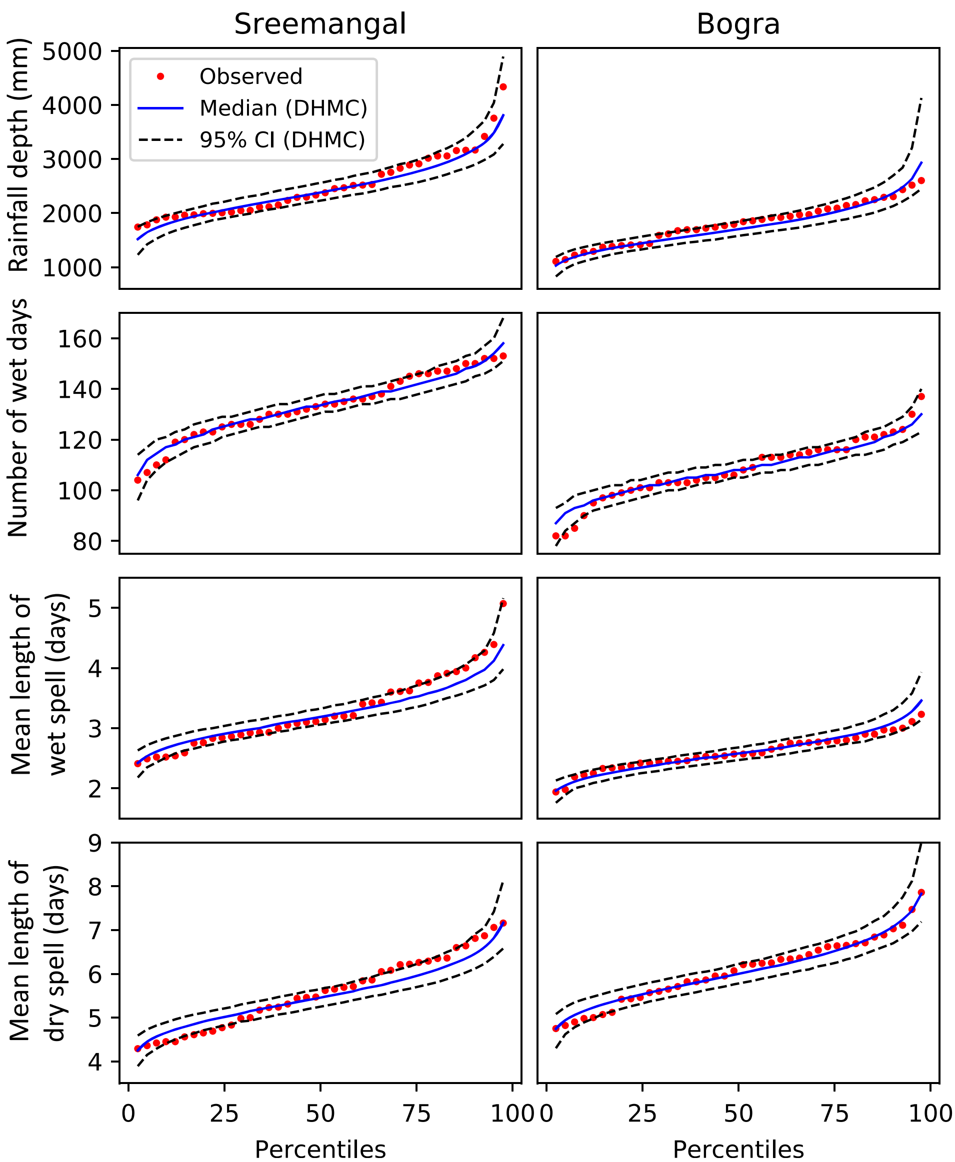

FIGURE 10 Observed and simulated probability distributions of rainfall depth (mm), number of wet days, mean length of wet spell, and mean length of dry spell at annual resolution in Sreemangal and Bogra as representative stations of relatively wet and dry regions, respectively (plots for all other stations are provided in Figure S12–S15). The dots are observed values and the solid and dashed lines are the medians and 95% confidence intervals (CI) of the 1,000 realizations of DHMC simulation [Colour figure can be viewed at wileyonlinelibrary.com]

south-central regions of the country. For inter-annual variability of rainfall, magnitude of inter-annual variability (i.e., *SD*) was found higher in wetter months (i.e., June to September) over the south and northeast regions, whereas the rate of inter-annual variability (i.e., CV) shows a contrasting pattern. Since the dry winter months contribute around 5% of annual total rainfall, the higher rate of inter-annual variability of rainfall in these months likely to have nominal impacts on the hydrological systems. Instead, the higher magnitude of inter-annual variability (i.e., *SD*s) of rainfall in the monsoon might be of greater interests that can critically influence the water systems. However, understanding of the higher rate of inter-annual variabilities (i.e., CVs) in the relatively dry west region is also critical to monitor the potential drought conditions (including groundwater depletions) for agricultural and domestic water supply in that region.

Dry spells are found consistent over the entire country followed by wet spells of slightly weaker spatial correlations, while the correlations for mean and *SD* of wet day rainfall depth are only moderately strong. This probably indicates that most of the storms occur rainfall over the entire country, while the intensity of rainfall may significantly vary over space.

The trend analysis shows significant decreasing trend of monthly rainfall over the relatively dry western region and increasing trend of monthly wet days in relatively wet eastern region. Such trends indicate enhanced risks of drought and flood in the west and the east part of the country, respectively, in the face of a changing climate.

The results of DHMC show that the model can satisfactorily preserve the variabilities of rainfall depth and wet–dry periods at both high- and low-temporal frequencies in all stations irrespective of spatial variabilities. However, DHMC

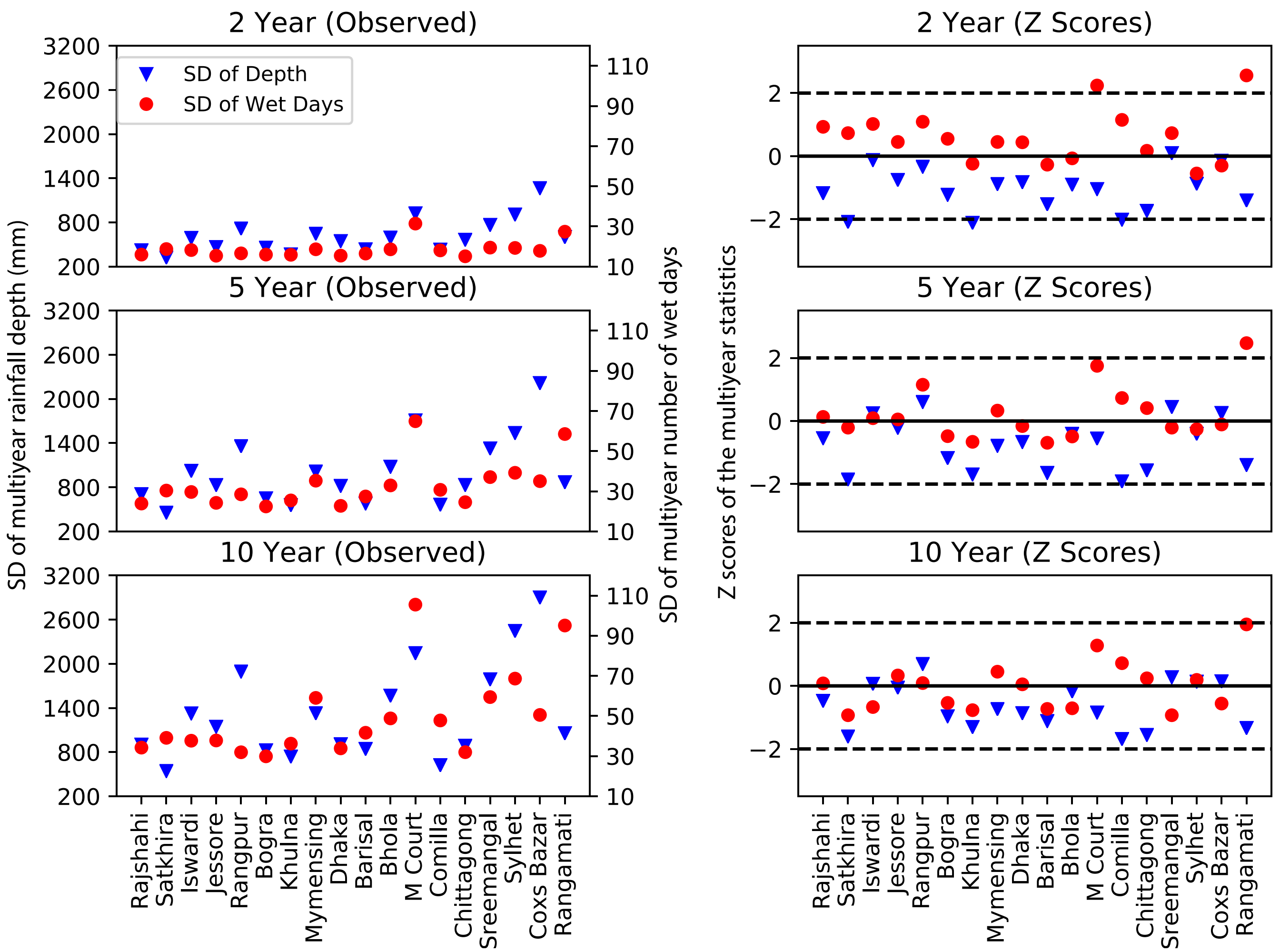

FIGURE 11 The observed statistics (left panels) and corresponding *Z* scores (right panels) for *SD*s of rainfall depth and wet days at multiyear resolutions. Statistics are shown for 2, 5, and 10 overlapping years [Colour figure can be viewed at wileyonlinelibrary.com]

shows a tendency to slightly underestimate the autocorrelations of rainfall depth that might be linked with the hierarchical stochastic generation process of rainfall depth that incorporate excessive variabilities in the model. Despite this, the DHMC has performed reasonably well to be considered as a suitable tool for stochastic simulation of daily rainfall in Bangladesh. The model can be used in future impact studies such as water security assessment for urban and agricultural supply.

Unavailability of high-quality long record data was a limitation of this study. At the time of this study, we only obtained data until 2012, and therefore, it was not possible to include more recent data. Additionally, the record length of the data was limited to 40 years because of unavailability of longer record and high percentage of missing record before 1973. Moreover, in some stations such as Cox's Bazar, Bhola, and Comilla, the data for 1973s contained high percentage of missing record, which slightly affected the MC parameters of DHMC for that decade but did not affect the overall performance of the model.

The overall findings of the study are expected to be useful for the hydrological and agricultural design and operations of the country. In addition, since the DHMC was previously tested for Australian climate conditions only (Chowdhury *et al.,* 2017), results of this study suggest the suitability of the model in a different climate. Such findings are likely to be of interest for many relevant international studies to consider the DHMC as a stochastic simulator.

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