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Characterization of future drought conditions in the Lower Mekong River Basin

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ABSTRACT

This study evaluates future changes to drought characteristics in the Lower Mekong River Basin using climate model projections. The Lower Mekong Basin (LMB), covering Thailand, Cambodia, Laos and Vietnam, is vulnerable to increasing droughts. Univariate analysis was employed in this study to compare drought characteristics associated with different return periods for the historical period 1964–2005 and future scenarios (RCP 4.5 2016–2057, RCP 4.5 2058–2099, RCP 8.5 2016–2057 and RCP 8.5 2058–2099). Because a single drought event is defined by several correlated characteristics, drought risk assessment by a multivariate analysis was deemed appropriate, and a multivariate analysis of droughts was conducted using copula functions to investigate the differences in the trivariate joint occurrence probabilities of the historical period and future scenarios. The Standardized Precipitation Index (SPI) was selected as the drought index because of its ability to detect and compare metrological droughts across time and space scales. Historical precipitation data from 1964 to 2005 and future precipitation projections from 2016 to 2099 for 15 global circulation models (GCMs) obtained from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset were employed. In all future scenarios, the Lower LMB and 3S subbasins were expected to experience more severe and intense droughts. The multivariate drought risk assessment revealed an increase in drought risks in the LMB. However, the Chi-Mun subbasin may experience an alleviation of future drought characteristics. Because the basin was expected to experience an increase in average monthly precipitation in most months, the variability in magnitude suggested that the LMB region requires adaptation strategies to address future drought occurrences.

1. Introduction

Drought is a recurrent natural hazard that can occur in any climatic zone on the globe. Generally, droughts are divided into four categories according to their nature and effects as meteorological, hydrological, agricultural and socio-economic droughts (Wilhite and Glantz, 1985). Although drought lacks a universal definition (Mishra and Singh, 2010), the categorization helps in assessing droughts. A drought is described by multiple characteristics such as severity, duration, and intensity and hence is designated a complicated natural hazard (Mishra and Singh, 2010). Furthermore, compared with other natural disasters, droughts affect a wide areal extent (Wilhite et al., 2014). Hence, in a drought analysis, it is important to consider its multivariate nature and spatial variability. Climate change is expected to intensify the global hydrological cycle (Huntington, 2006; Milly et al., 2002), and the consequences can lead to an overall increase in extreme events such as droughts. Despite having relatively higher annual average precipitation, the Lower Mekong Basin (LMB), covering Thailand, Cambodia, Laos, and Vietnam, is vulnerable to increasing droughts, affecting the agricultural economy of the region (Adamson and Bird, 2010; Hung, 2017; MRC, 2005). This study seeks to understand future meteorological drought conditions in the LMB under climatic changes. Such knowledge would help to formulate adaptation strategies.

The LMB is an important area in Southeast Asia in which droughts regularly affect the socio-economic conditions of more than 60 million people (Joy, 2012). Although the LMB receives a high amount of precipitation during monsoon seasons, socio-economic activities are organized and adjusted for expected conditions, rendering such activities vulnerable to deviations from regular precipitation patterns (Adamson and Bird, 2010). The rain-fed agriculture-based rural economy in the region is considered to be a most vulnerable sector (Shimizu et al., 2006). Limited irrigation is practiced for rice farming, particularly in areas in northeastern Thailand and the Mekong Delta at the mouth of the river near the South China Sea, (Adamson and Bird, 2010; Thanopanuwat,

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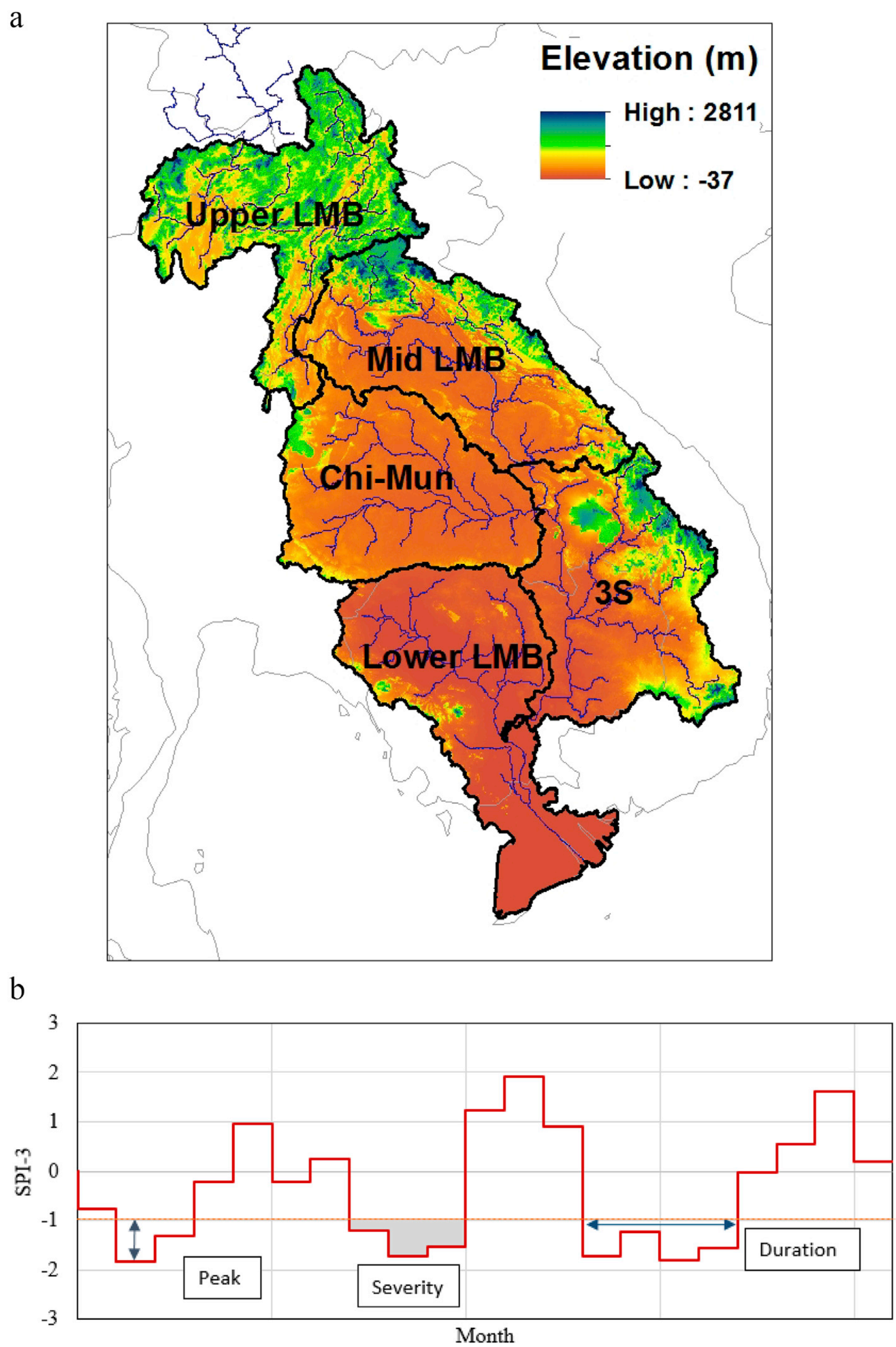

Fig. 1. (a) Map of the Lower Mekong Basin with the subbasins and elevation. (b) Definition of drought events and characteristics using the theory of runs.

2010). The basin-wide extreme drought in 1992 caused 210 million USD in damage in Thailand, and similar extreme drought events occurred in 1997–98 and 2004 (Prapertchob et al., 2007). Widespread drought conditions during 1997–98 in Vietnam affecting 3 million people resulted in an estimated total loss of 400 million USD in agricultural production (Shaw and Nguyen, 2011a). A similar drought during 2002 in Cambodia affected southern provinces, affecting more than 2 million people and destroying 100,000 ha of paddy fields (Shaw and Nguyen, 2011b). Several studies have attributed these drought occurrences primarily to extreme weather events, mentioning concerns that drought effects may be exacerbated by upstream hydrological alterations such as dams (Lu et al., 2014; MRC, 2005). Meteorological droughts may occur with the precipitation shortfall relative to average conditions in the area and can be identified using climatological drought indices. This study identified the historical droughts that occurred in 1992, 1997, 1998, 2002 and 2004 in the LMB using a climatological drought index for further evaluation with a high-resolution historical precipitation dataset. Because the precipitation patterns in the Mekong Basin are expected to change with climatic changes (MRC, 2005; Kiem et al., 2008; Lauri et al., 2012; MRC, 2012; Piman et al., 2013; Tatsumi and Yamashiki, 2015), an assessment of how the future climatic changes may affect meteorological drought conditions is important.

Global climate models (GCMs) are considered to be the most reliable tools with which to obtain global climate projections hundreds of years into the future (Sehgal et al., 2016). Numerous studies have evaluated climate change effects over the Mekong Basin using future projections from a single GCM (Hoanh et al., 2010; Kiem et al., 2008; Västilä et al., 2010). For example, Västilä et al. (2010) reported a 4% increase in the annual streamflow and an increase in the annual average temperature between 1° and 2 C^{o} by the 2040s in the Mekong Basin using the dynamically downscaled data from the ECHAM4 model. Kingston et al. (2011) conducted a hydrological effect assessment using seven different GCMs and concluded that multi-model assessments are important because of the existing differences in the precipitation projections among multiple GCMs. Thompson et al. (2013, 2014) used the climate data from seven GCMs and concluded that inter-GCM precipitation differences are a prominent source of uncertainty compared with potential evapotranspiration and the choice of hydrological modeling techniques. Thus, great uncertainty in precipitation projections among GCMs necessitates multi-model assessments to address the uncertainty in precipitation and hence drought estimation.

The majority of the Mekong-related studies have used the climatic projections from GCMs from Coupled Model Intercomparison Project Phase 3 (CMIP3) (Meehl et al., 2007). Compared with its predecessor, Coupled Model Intercomparison Project Phase 5 (CMIP5) (Guilyardi et al., 2013; Taylor et al., 2012) demonstrated substantial developments in resolution and model physics (Taylor et al., 2012). Hasson et al. (2016) revealed the higher efficacy of CMIP5 GCMs during the Asian monsoon region including the Mekong Basin. Moreover, the Special Report on Emission Scenarios (SRES) (Nakicenovic et al., 2000), used frequently in earlier studies, was replaced by Representative Concentration Pathways (RCPs) scenarios (Clarke et al., 2007; Nakicenovic et al., 2000), describing radiative forcings and concentrations of greenhouse gasses by the year 2100. Despite the improvements in model resolutions of CMIP5 GCMs compared with CMIP3, the lack of spatial specificity and accuracy hinders regional climate change effect assessments (Wood et al., 2004). This study used the newly available NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) (Thrasher et al., 2013) to conduct the climate change effect assessment, which brings novelty to our approach in evaluating evolving conditions. The NEX-GDDP dataset was produced by downscaling CMIP5 GCMs using a Bias-Correction Spatial Disaggregation (BCSD) method, which sought to address prevailing limitations in GCM outputs (Maurer and Hidalgo, 2008; Stackhouse et al., 2004; Wood et al., 2004, 2002). The NEX-GDDP dataset was bias-corrected by adjusting the CDFs of climatic projections to that of the historical data while preserving the long-term trends (Thrasher and Nemani, 2015). Furthermore, spatial disaggregation algorithms employed in the NEX-GDDP dataset can preserve the spatial details of the data more effectively than simple linear interpolation.

Extreme events play a key role in changing climates; however, the existing literature does not present much insight into the frequency analysis of droughts in the Mekong Basin. Hoang et al. (2016) conducted a frequency analysis of extreme high and low flows in the Mekong Basin and revealed that climatic changes indicate a reduction in the frequency and magnitude of extremely low flows because of increased flows during dry seasons from five downscaled CMIP5 projections. However, insights into the loss of short-term storage and water supplies, including soil moisture that may occur because of the climatic changes, were not available, which is more important for agriculture (Mishra and Singh, 2010). Moreover, because drought is a relative condition rather than an absolute condition (Svoboda et al., 2012), our study addresses the dynamic anomalies using the Standardized Precipitation Index (SPI), which can capture the characteristics of meteorological droughts relative to the alternate climatic conditions imposed by climatic change.

Currently, the majority of the research on droughts in the LMB has focused on drought management (Bastakoti et al., 2013; Hundertmark, 2008; Marks, 2011) and monitoring (Son et al., 2012). ICEM (2013) analyzed agricultural droughts from the perspective that drought occurs when monthly precipitation is less than 50% of evapotranspiration and reported that a significant increase in drought duration is expected in the southern and eastern portions of the Lower Mekong Basin by 2050 using downscaled datasets from six CMIP3 GCMs. Their estimation was based on the number of drought months, which does not address the other characteristics of drought, such as severity and intensity. Univariate frequency analyses of drought characteristics have been used in research to compare different periods or scenarios (Ge et al., 2016; Masud et al., 2016). However, simultaneous assessment of the multiple characteristics is important in the evaluation of drought risk because of the multivariate

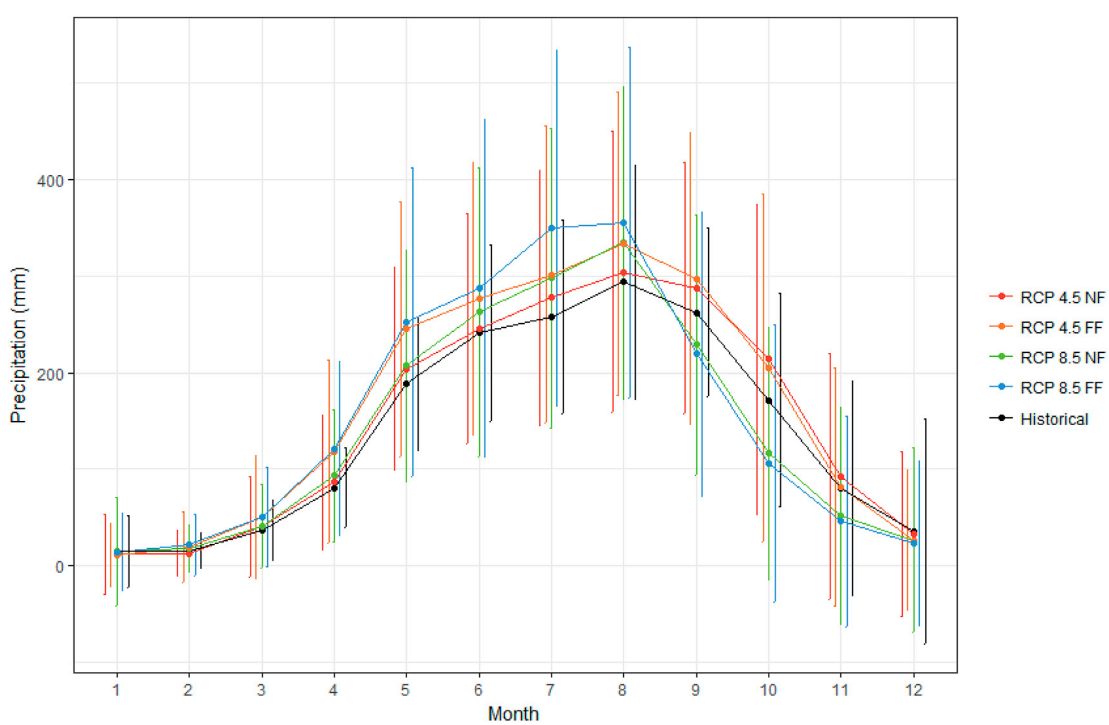

Fig. 2. The mean monthly precipitation with error bars showing one standard deviation (Historical indicates the period between 1963 and 2005, NF indicates near future (2016–2057), FF indicates far future [2058–2099]).

nature of droughts (Shiau and Modarres, 2009). Since drought characteristics may follow different marginal distributions and exhibit a significant correlation with one another, copula functions can be used for multivariate analysis of droughts. Numerous studies have investigated drought using copula functions in various portions of the world (Abdi et al., 2016; Chen et al., 2013; Hao et al., 2015; Liu et al., 2016; Masud et al., 2016; Yusof et al., 2013). Considering previous research, drought evaluation in the Mekong region based on data-driven approaches is quite limited. Our study addressed this gap using both univariate and multivariate frequency analyses of drought characteristics that are quantified based on the theory of runs (Yevjevich, 1967) over the LMB region.

The objectives of this study were to investigate the characteristics of droughts using SPI for the historical period and to analyze drought in a changing climate using univariate and multivariate analyses. Primarily, univariate analysis was used to calculate drought characteristics for two return periods (i.e., 20- and 50-year) during the historical and future climate periods. Historical droughts were assessed using the Global Meteorological Forcing Dataset (GMFD) (Sheffield et al., 2012, 2006). The future climate scenarios were obtained from 15 GCMs of the NEX-GDDP dataset. As a secondary analysis, copula functions were used to calculate multivariate probabilities using pre-defined thresholds of drought characteristics. Next, the probabilities obtained from the historical period were compared with future scenarios in the LMB region and presented spatially.

2. Background

2.1. Standard Precipitation Index

Mckee et al. (1993) introduced the Standard Precipitation Index (SPI), which requires only precipitation as input. The SPI is calculated based on the long-term precipitation record for a desired period in a particular location, typically for at least 30 years. The SPI can be calculated over a range of time scales such as 1, 3, 6, 9 and 12 months. Different time scales can indicate the effects of drought differently, and the end user can choose the right time window for decision-making. For example, soil moisture variability responds to short-term precipitation anomalies whereas streamflow and groundwater levels react to long-term anomalies. The SPI is calculated by fitting the long-term precipitation record to an appropriate distribution and transforming it into normal distribution to calculate the mean SPI value as zero (Edwards and McKee, 1997).

2.2. Copulas

The primary advantage of copulas is that the dependence structure between variables can be constructed even if the marginal distribution type for each variable is not identical. Copula functions can be used effectively in combining several marginal distributions into a joint distribution. According to Sklar (1959) and Nelsen (2006), if there are n correlated random variables of $X_1, X_2, \ldots, X_n$ and their marginal

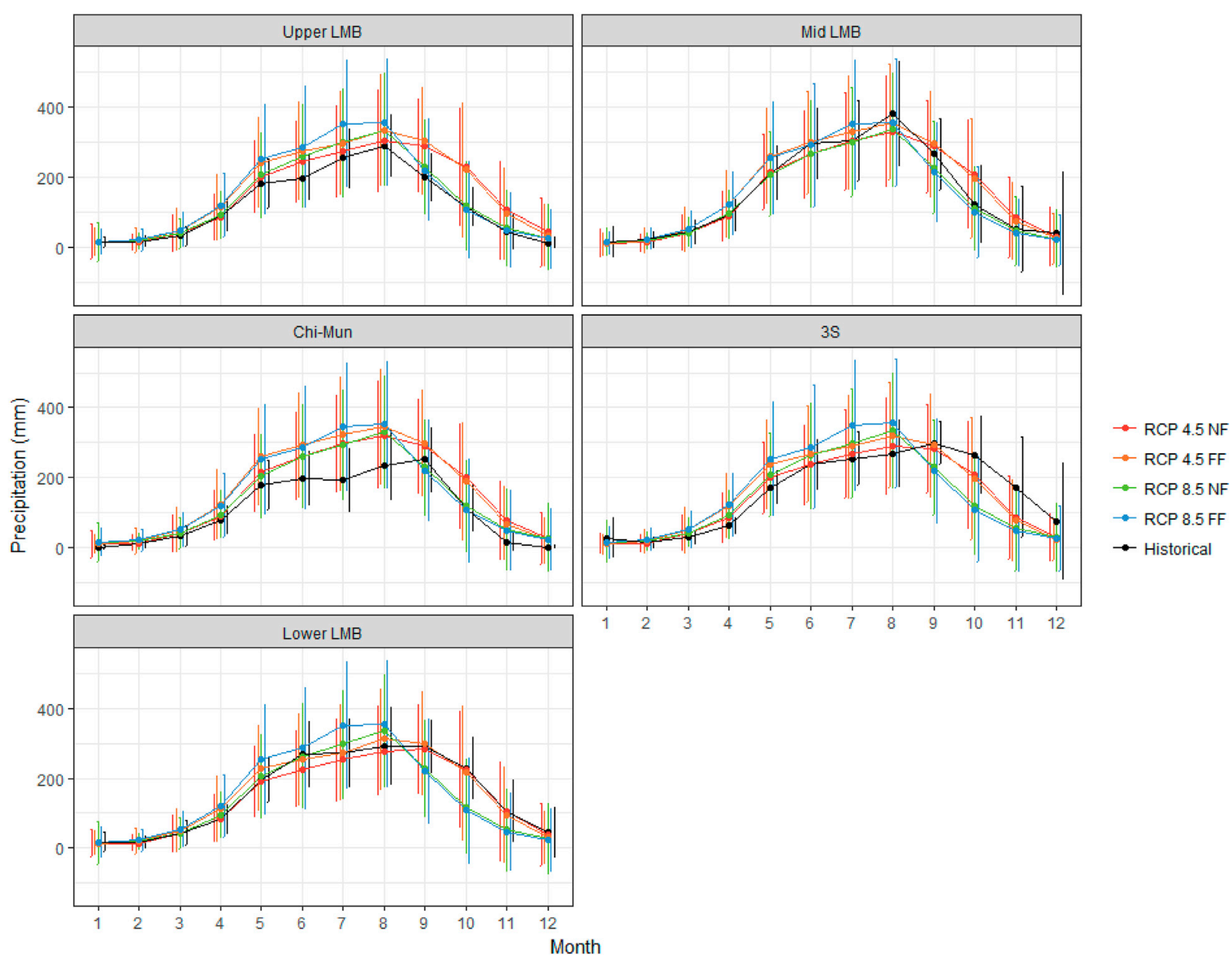

Fig. 3. The mean monthly precipitation with error bars showing one standard deviation in the historical period (1964–2005) in each subbasin (Historical indicates the period between 1963 and 2005, NF indicates near future (2016–2057), FF indicates far future [2058–2099]).

cumulative distribution functions are $F_1(x_1),\ F_2(x_2),\ldots,\ F_n(x_n)$, n-dimensional joint distribution (H) is defined as in Equation (1):

$$H(x_1, x_2, \ldots, x_n) = C[F_1(x_1),\ F_2(x_2), \ldots,\ F_n(x_n)] \tag{1}$$

where C is defined as the copula function that describes the dependent structure. The marginal distributions should be continuous to analyze the variables using copula functions. Archimedean copulas have been widely used in research related to hydrology and drought in bivariate analyses. However, in multivariate analyses, which involve more than two variables, the symmetric Archimedean copulas with a single parameter are not appropriate for modeling asymmetries because all of the pairs of variables are forced to have the same dependence structure. This can be avoided using a hierarchical structure of Archimedean copulas, which is obtained by combining Archimedean copulas. These Archimedean copulas are also known as nested copulas (Hofert and Maechler, 2011). For example, if there are three correlated random variables of $X_1, X_2,\ X_3$, the nested copula function can be illustrated as in Equation (2):

$$C[F_1(x_1), F_2(x_2), F_3(x_3)] = C[F_1(x_1),\ C[F_2(x_2), F_3(x_3); \psi_1];\ \psi_0];\ \ \psi_0 > \psi_1 \tag{2}$$

ψ_0 and ψ_1 are the parameters of the parent (root) Archimedean copula and the child Archimedean copula, respectively. The meta-elliptical copula family is the extension of the multivariate Gaussian distribution, and unlike Archimedean copulas, these copulas can preserve the pairwise dependencies by a correlation matrix (Kao and Govindaraju, 2008).

3. Study area and datasets

3.1. Description of study area

The Mekong River is a major transboundary river basin located in Southeast Asia (Fig. 1a). The Lower Mekong Basin (LMB) lies in Laos, Thailand, Vietnam and Cambodia, and a partnership among those countries exists. The LMB extends to approximately 597,000 sq.km in an area that covers approximately three-quarters of the entire Mekong Basin. The LMB is an important region because it is in one of the largest transboundary basins in the world. The southwest monsoon primarily dominates the precipitation pattern in the LMB. The monsoon season begins in May and lasts until late September or early October (MRC, 2005). Elevation in the basin varies from 2800 m in the highlands in Laos to the mean sea level at the delta in southern Vietnam. Average annual precipitation from 1964 to 2005 in the basin ranged from 850 mm to 2500 mm. To perform a comprehensive spatial analysis, the LMB area was divided into five main subbasins, the Upper LMB, Mid LMB, Chi-Mun, 3S, and Lower LMB, which contain nearly 150–180 grids at 0.25° resolution (Fig. 1a). While dividing the subbasins, first hierarchical clustering (Murtagh and Legendre, 2014) was employed for the historical average annual precipitation data to identify the clusters of adjacent grids. Subsequently, the borders of clustered regions were adjusted considering the subbasin borders, which facilitated the divisions based on physiogeographical features.

3.2. Datasets

Precipitation data for the period of 1964–2005 were obtained from the GMFD gridded dataset available at 0.25° resolution (Sheffield et al., 2012, 2006). The GMFD dataset was compiled by merging multiple observed and reanalysis datasets such as the NCEP–NCAR reanalysis (Kalnay et al., 1996), CRU TS3.0 (Mitchell and Jones, 2005), the GPCP (Huffman et al., 2001), the TRMM (Huffman et al., 2002) and the NASA Langley SRB (Stackhouse et al., 2004). Daily precipitation projections obtained from 15 GCMs in the NEX-GDDP dataset for the period of 2016–2099 (84 years) were used in the study. The spatially downscaled and bias-corrected NEX-GDDP dataset is available in two RCP scenarios as RCP 4.5 and RCP 8.5 scenarios (Thrasher et al., 2013). It should be noted that the NEX-GDDP dataset has been bias-corrected using the GMFD dataset; hence, the selection of these datasets provides a harmonious analysis.

4. Methods

4.1. Characterization of droughts

The SPI was selected as the drought index considering its ability to detect and compare metrological droughts across time and space scales (Svoboda et al., 2012). The SPI was calculated based on the long-term precipitation record for the desired period in a particular location. For our analysis, a long-term record of monthly precipitation was fitted to a gamma distribution, which was then transformed to a normal distribution so that the mean SPI for the location and desired period was zero (Svoboda et al., 2012). Gamma distribution is commonly used for computing the SPI (Mckee et al., 1993; Angelidis et al., 2012; Naresh Kumar et al., 2009; Stagge et al., 2015; Yacoub and Tayfur, 2017). The SPI-3 months was selected in this study because it is considered a good indicator for some monsoon regions (Svoboda et al., 2012). The identification of a drought event involves the determination of its onset and termination. Drought characterization should be able to quantify the severity, duration, and peaks of droughts. A drought event was defined using a truncation value, and quantification of drought characteristics involved calculations using the truncation value as a reference (Fig. 1b). The truncation level for the droughts was selected as −1; this enabled capturing droughts that create more than moderately severe dry conditions. Drought duration was defined as the number of consecutive months in which the SPI remained below the selected truncation level. Drought severity was defined as a cumulative SPI value during the relevant period below the chosen truncation level. Drought peak was

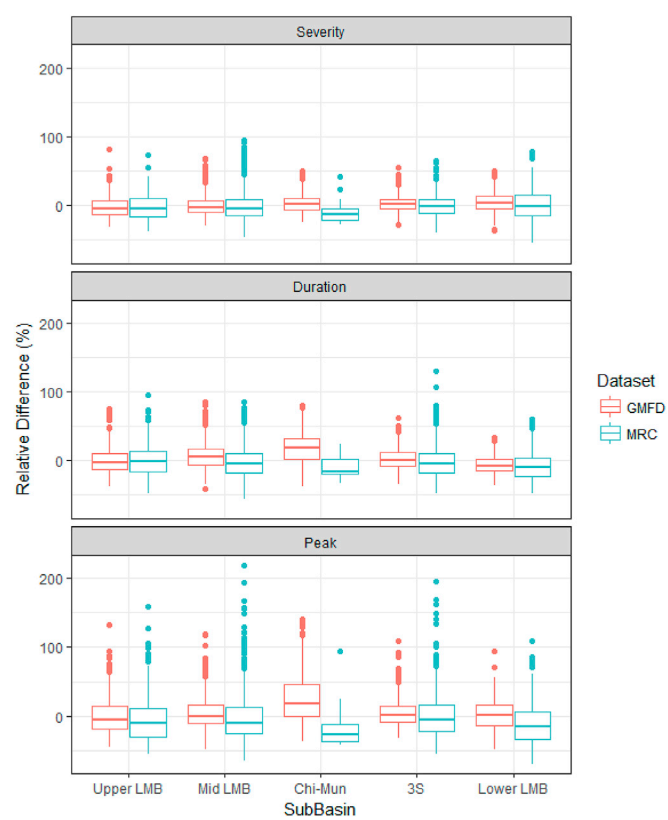

Fig. 4. Comparison of observed and GCM-simulated historical mean drought: (a) severity, (b) duration, (c) peak. Relative differences are normalized with the observed values.

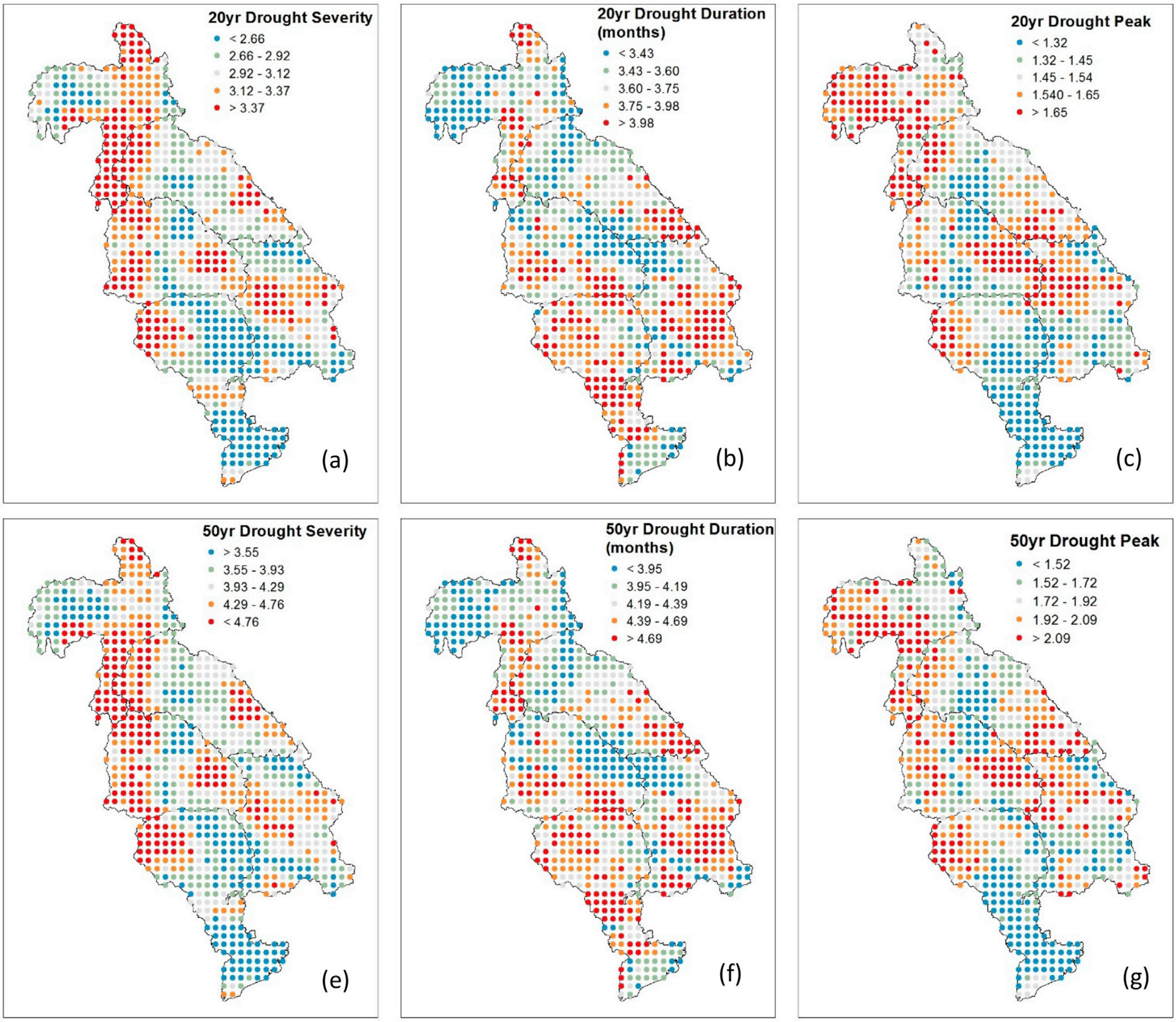

Fig. 5. Spatial distribution of historical drought characteristics: (a) 20-year drought severity, (b) 20-year drought duration, (c) 20-year drought peak, (d) 50-year drought severity, (e) 50-year drought duration, (g) 50-year drought peak (the color distribution of symbols is intended to emphasize the spatially distinguishable representation of drought severity). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

defined as the minimum SPI value below the truncation value in a recognized drought event.

4.2. Marginal and multivariate distributions

Six commonly used marginal distributions were selected as candidate distributions. The candidate distributions were exponential, gamma, lognormal, Weibull, generalized Pareto and logistic. Parameters for the distributions were estimated using the maximum likelihood estimation (MLE) method. The best-fitted distribution was selected using the Kolmogorov–Smirnov (K–S) test (Stephens, 1974; Ge et al., 2016). In this study, the commonly used Gumbel–Hougaard copula function was employed because it delivers multivariate extreme distributions that exhibit tail dependence (Masud et al., 2016). The Cramér-von Mises test (Berg, 2009) was employed to assess the goodness of fit for the copula functions. For trivariate distributions, a nested Gumbel–Hougaard copula function was used. The copula parameters were estimated using the Inference Functions for Margins (IFM) method (Bouyé et al., 2000).

4.3. Univariate and multivariate analyses

The calculation of return period or frequency analysis is a common practice in studying extreme events to meet the design objectives of hydrological and hydraulic designs. The return period of a drought is defined as the average interval time between occurrences of an event with a particular magnitude or greater (Shiau and Shen, 2001). Shiau (2006) calculated return period in a univariate setting using the following equations:

$$T = \frac{E(L)}{1 - F(s)} \tag{3}$$

$$T = \frac{E(L)}{1 - F(d)} \tag{4}$$

$$T = \frac{E(L)}{1 - F(pk)} \tag{5}$$

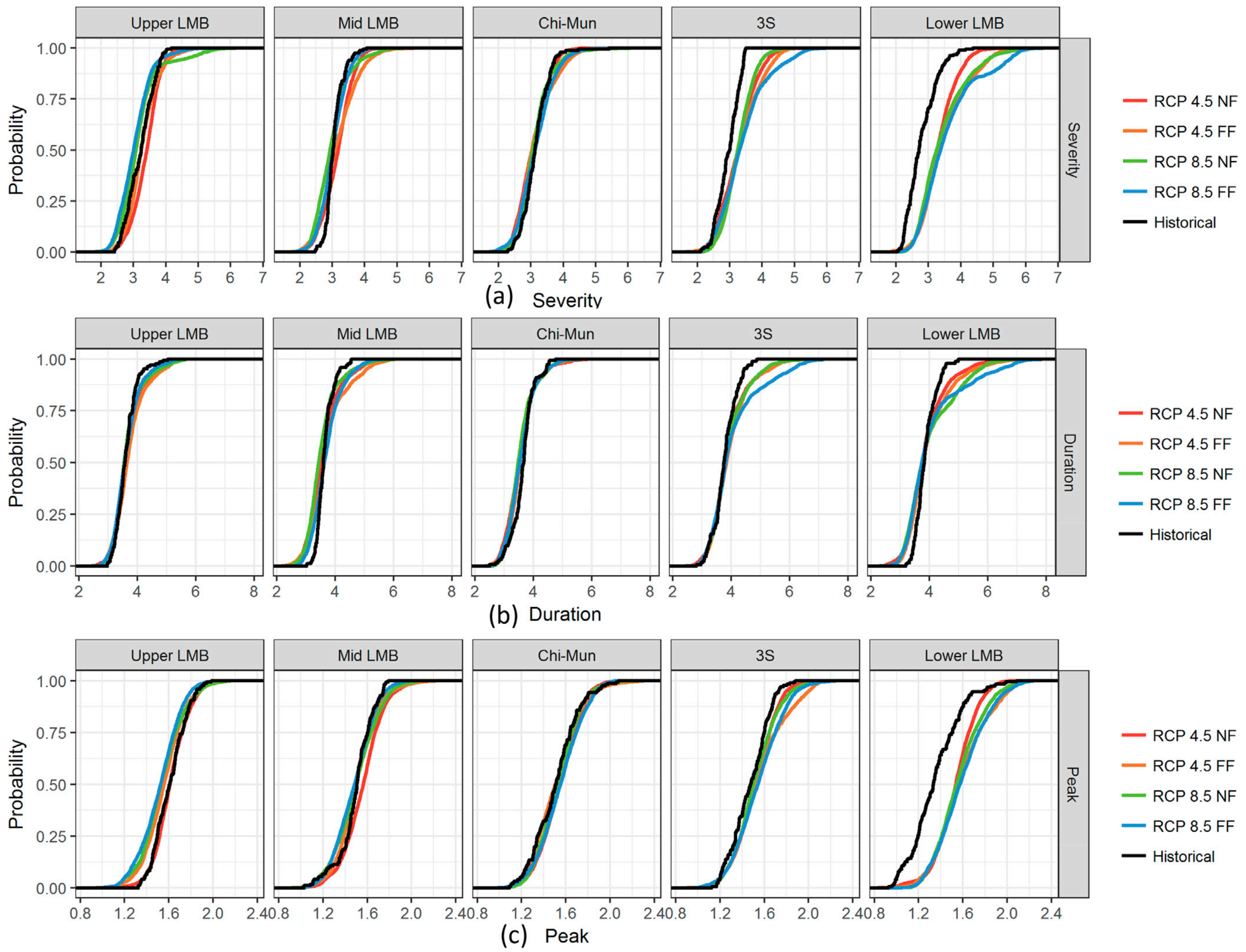

Fig. 6. Non-exceedance probability of observed and future drought characteristics in each subbasin (names of subbasins are printed above the panel): (a) 20-year drought severity, (b) 20-year drought severity, (c) 20-year drought peak (Historical indicates the period of 1963–2005, NF indicates near future (2016–2057), FF indicates far future [2058–2099]).

where T indicates return period (years) for the relevant drought characteristic and s, d and pk represent the drought characteristics severity, duration and peak, respectively. $E(L)$ is the expected drought interval time. Based on Shiau (2006), the trivariate joint occurrence probability was calculated using the equation shown below.

$$P(S \geq s \text{ or } \mathrm{D} \geq d \text{ or } \mathrm{PK} \geq pk) = 1 - F(s) - F(d) - F(pk) + C[F(s), F(d)] + C[F(s), F(pk)] + C[F(d), F(pk)] - C[F(s), F(d), F(pk)] \tag{6}$$

The time series data of precipitation for RCP 4.5 and RCP 8.5 scenarios during 2016–2099 were divided into two equal parts as the 2016–2057 and 2058–2099 periods. Future projections of drought analysis were grouped into four categories: RCP 4.5 2016–2057, RCP 4.5 2058–2099, RCP 8.5 2016–2057 and RCP 8.5 2058–2099. Univariate analyses were employed to calculate drought associated with 20- and 50-year return periods. Finally, drought risk was assessed with the multivariate analysis using copula functions for the selected thresholds of drought characteristics obtained from the historical data. The selected thresholds were characterized using the 95th percentile of historical drought severity, duration and peak values for all of the grids in the LMB.

5. Results and discussion

5.1. Precipitation projections of future scenarios

Because drought is a dynamic event directly connected with precipitation patterns, insights into the shift of the average precipitation pattern were considered important to understand the future drought conditions in the region. Fig. 2 illustrates the mean monthly precipitation in the LMB with error bars indicating one standard deviation of uncertainty. The results of the RCP 4.5 scenario showed an increase in mean precipitation in the majority of the months. Notably the results of the RCP 8.5 scenario indicated a decrease in mean precipitation from September to December. Fig. 3 illustrates the mean monthly precipitation at the subbasin level with error bars indicating one standard deviation of uncertainty. Notably, in the 3S and Lower LMB subbasins, all future scenarios indicated a decrease in mean monthly precipitation from September to December. Although the mean monthly precipitation was expected to increase in the period from June to August, typically the wet season (MRC, 2005), the decrease in precipitation in dry months (November and December) may hinder the adaptation to droughts in the 3S and Lower LMB regions. Eastham et al. (2008) analyzed changes in wet season (May–October) and dry season (November–April) precipitation levels by 2030 using 11 GCMs (obtained from CMIP3) in the A1B scenario.

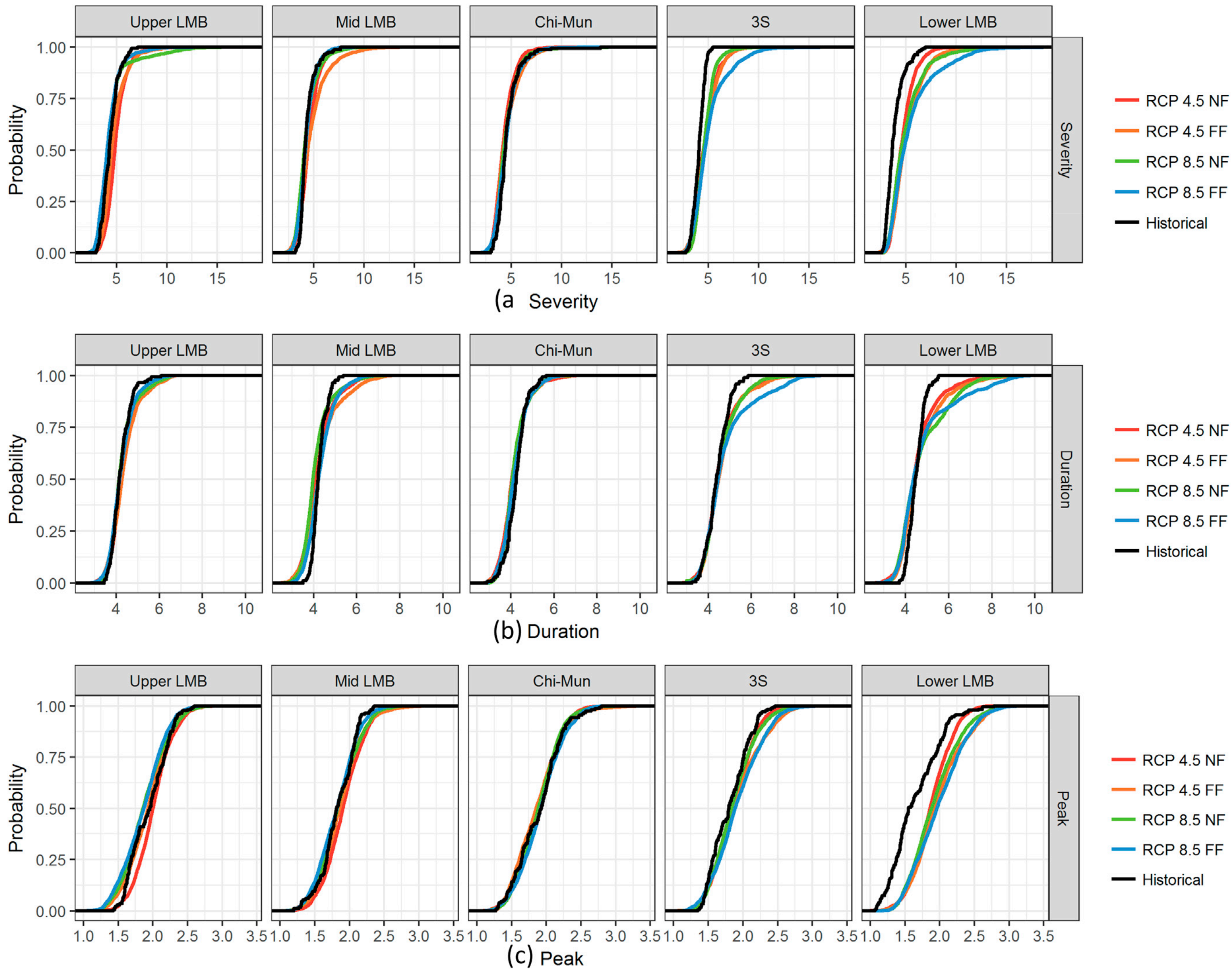

Fig. 7. Non-exceedance probability of observed and future drought characteristics in each subbasin (names of subbasins are printed above the panel): (a) 50-year drought severity, (b) 50-year drought severity, (c) 50-year drought peak (Historical indicates the period of 1963–2005, NF indicates near future (2016–2057), FF indicates far future [2058–2099]).

Eastham et al. (2008) concluded that all of the subbasins show a decrease in dry season precipitation whereas an increase in wet season precipitation was observed in all subbasins. Our results also indicate the same tendency in the majority of subbasins in the RCP 8.5 scenario.

5.2. *Validation of GCM-Simulated drought characteristics*

GCM-simulated historical mean drought characteristics were compared with corresponding values from GMFD historical records. In addition to the GMFD historical dataset, we compared the mean drought characteristics computed using precipitation data (1980–2005) from 143 gauge stations obtained from the Mekong River Commission (MRC). The precipitation dataset obtained was shorter than the historical time period used in our study (1964–2005). However, precipitation data from the MRC (26 years) did not cover a sufficiently long period to compute the SPI because it is recommended that at least 30 years of monthly precipitation data be available to compute the SPI (Svoboda et al., 2012). Nevertheless, we conducted a comparison analysis of mean drought characteristics computed from the observed and GCM historical data. The percentages of relative differences in drought characteristics from all 15 GCMs with the corresponding historical values are illustrated in Fig. 4. Considering the comparison using the GMFD dataset, the median percentage differences of mean drought severity were between +10% and −10%. The median percentage differences of mean drought durations indicated similar results to changes in drought severity. However, in the Lower LMB, GCM-simulated drought durations showed a higher median percentage difference of +20%. Although the median percentage differences of mean drought peaks were analogous to differences in changes in mean severity and duration, the relative differences indicated a wide range of change in the Lower LMB. It should be noted that a higher number of occurrences of overestimation of GCM-simulated mean drought severity and duration were observed in the Lower LMB. As illustrated in Fig. 4, the median relative percentage change computed using the MRC dataset is similar to that of GMFD-based analysis. However, the outliers indicate that some gauge locations indicate greater deviations from GCM historical mean drought characteristics, particularly for drought peak values.

5.3. *Historical drought characteristics*

The spatially averaged (subbasin-wise) SPI-3 calculated for the historical period of 1964–2005 was plotted, and drought events were identified using the truncation value −1. Additionally, the results were compared with the similarly spatially averaged Palmer Drought Severity

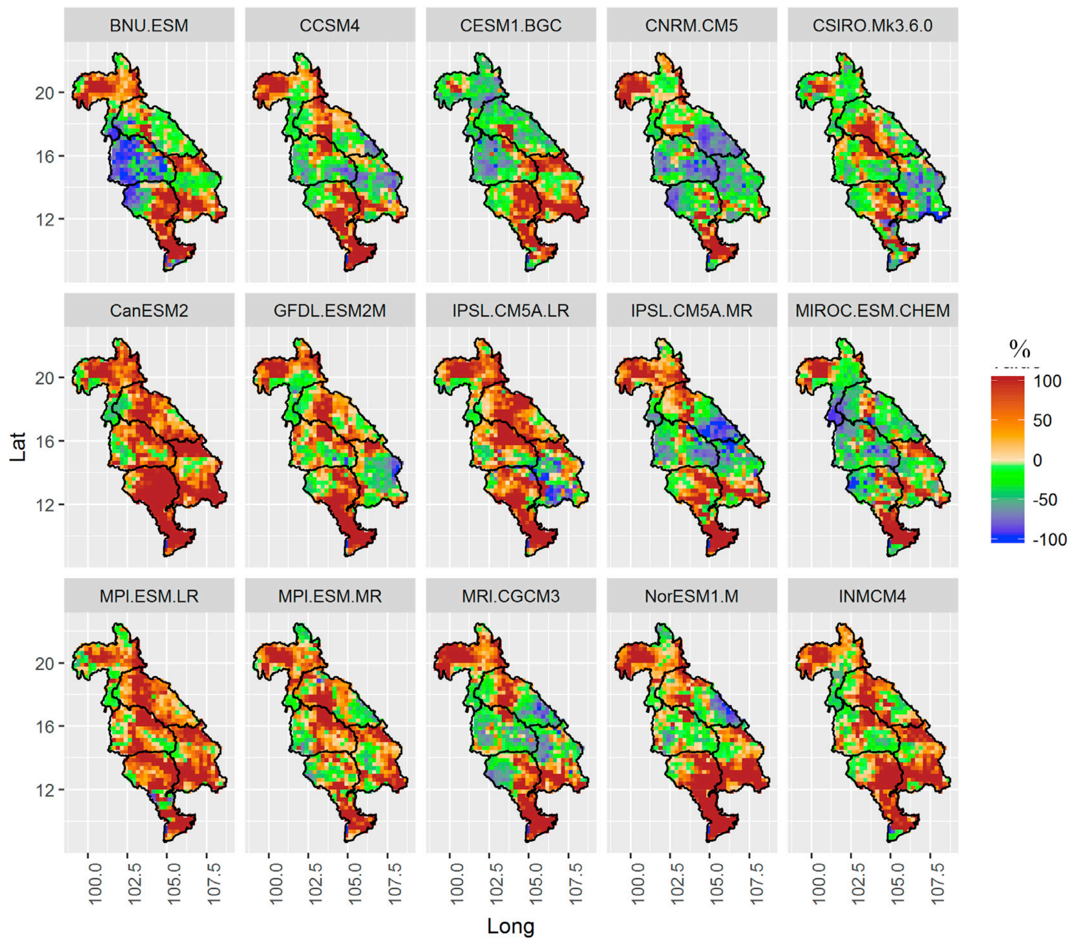

Fig. 8. Distribution of percentage differences in trivariate joint occurrence probabilities of the selected significant drought thresholds (severity ≥ 3.13 and duration ≥ 4 months and peak ≥ 1.47) in RCP 4.5 near future (NF) (2016–2057) compared with historical period (1964–2005). (Relative differences are normalized with the corresponding trivariate joint occurrence probabilities obtained using observed data.)

Index (PDSI) using the truncation value of −2, which was obtained from an available global PDSI data set in 2.5° resolution (Dai, 2011; Dai et al., 2004) (See Supplementary Material Part A, Figs. A1–A15). To assess the efficacy of the SPI-3 in capturing the historical droughts in the LMB, the years 1992, 1997, 1998, 2002 and 2004 were selected using the spatially averaged SPI-3 and PDSI plots. For example, the northeastern Thailand region was under severe drought conditions in the years 1992, 1997, 1998 and 2004 (Prapertchob et al., 2007), and the mapped SPI-3 values indicated a significant extent of lower SPI-3 values in northeast Thailand, particularly during October and November. In Vietnam, the Mekong Delta region experienced drought conditions during the majority of 1992 (Shaw and Nguyen, 2011a); the SPI-3 was able to capture the drought conditions in the delta effectively. Moreover, in 2004, Cambodia was under a severe drought (Shaw and Nguyen, 2011b), which was successfully captured by historical drought results, as shown in the figures in Supplementary Material Part A. As a component of the validation, the SPI results were compared with the existing global dataset of the PDSI (Dai, 2011; Dai et al., 2004), demonstrating good agreement with the PDSI dataset. A graphical representation of these results is presented in Supplementary Material Part A as spatial maps of SPI-3 and PDSI values in 1992, 1997, 1998, 2002 and 2004. The spatial distributions of historical drought characteristics associated with two return periods (20-year and 50-year) are illustrated in Fig. 5. The range indicated by each color is associated with the quintiles of the values of each characteristic to provide a more spatially distinguishable illustration. The spatial distribution of the same characteristic is similar in both return periods. For example, severity was higher in the Upper Chi-Mun Basin area for both return periods compared with other regions. The Upper Chi-Mun Basin, the Upper Tonle Sap Basin and most portions of the Upper LMB showed higher drought severity and duration (in 20-year and 50-year return periods) relative to other portions of the Mekong basin. However, some sections of the Upper LMB, which showed relatively lower drought severity and duration values, indicated a higher drought peak. Relatively, lower values of drought severity and peaks were evident in the Mekong Delta area. However, relatively higher drought duration values can be observed in most parts of the Lower LMB and 3S. Considering the relative distribution of drought characteristics in these two return periods, it was noticeable that in some portions of the LMB, one or two drought characteristics were anomalous compared with others. The results of the univariate analyses were useful in identifying the local drought characteristics.

5.4. Drought characteristics of future scenarios

To better understand the differences in drought characteristics for each future scenario (RCP 4.5 2016–2057, RCP 4.5 2058–2099, RCP 8.5 2016–2057 and RCP 8.5 2058–2099), the probabilities of each drought characteristic obtained from all 15 downscaled GCMs were plotted against the historical drought characteristics. It should be noted that the characteristic values of all the grids in a subbasin were considered when estimating probabilities. The probabilities were estimated by empirically deriving CDF from the Kaplan-Meier method (Kaplan and Meier, 1958). Figs. 6 and 7 represent the probabilities of drought characteristics associated with 20-year and 50-year return periods, respectively. The shift to the right in CDF for a drought characteristic in future scenarios indicates an increased severity or duration or peak for the same non-exceedance probability. For example, in 3S and Lower LMB subbasins, median 20-year return period drought severity and peak were higher than historical magnitudes. Considering the upper LMB, median drought severity and peak in the RCP 8.5 scenario were lower than in the historical period. However, the 20-year return period drought duration did not demonstrate any drastic difference between historical and future droughts. The results of 50-year return period drought characteristics (Fig. 7) were analogous to the 20-year return period associated results. Spatial representation of the relative differences in drought characteristics for future scenarios in each GCM is provided in Supplementary Material Part B. The spatial maps of relative differences (%) show an increase of 20-year and 50-year return period drought severity in the Mekong Delta (See Supplementary Material Part B: Figs. B1–B24). Six of 15 GCMs projected a reduction in drought magnitudes in Chi-Mun in all future scenarios. Notably, CanESM-2 showed a significant increase in drought severity associated with 20-year and 50-year return periods in most parts of the LMB, particularly the Lower LMB. ICEM (2013) analyzed agricultural droughts on the basis that drought occurs when monthly precipitation is less than 50% of evapotranspiration. That report indicated that a significant increase in drought duration is expected in the southern portions of the LMB including southern Lao PDR by 2050, using downscaled datasets from six CMIP3 GCMs. Our study results indicate such an increase in drought duration in southern portions (particularly 3S). Furthermore, ICEM (2013) noted a decline in the drought duration in northern parts of the LMB; our results also indicate a reduction of drought duration in that region, particularly in the RCP 8.5 scenario. Moreover, we compared GCM control runs and GCM future scenarios; future drought assessment may indicate higher drought severity in some cases whereas drought duration (in most cases) and peaks (in some cases) may diminish. Those results are presented in Part C of the supplementary material. The differences in these estimates are partially because of the discrepancies in the resampling of the grid cells, which has led to overestimation or underestimation of median drought characteristics in the future.

Because precipitation is the only requirement for the SPI analysis, it is considered a relatively simple method with which to assess drought conditions; hence, the scenarios of water demand were not considered. However, the review of the existing body of literature suggested that rain-fed lowland rice regions are more vulnerable to meteorological droughts; thus, understanding a precipitation-based assessment of drought for this region is more appropriate. Irrigated dry-season rice is also vulnerable to meteorological droughts although the vulnerability may be assessed effectively by investigating the variables that are pertinent to hydrological drought, including streamflow, groundwater level, and available storage. Additional details on the basin-wide water demand evaluation is provided in Part D of the supplementary material.

As a secondary analysis, changes in drought risk were assessed by calculating the trivariate joint occurrence probabilities of exceeding significant drought severity, duration and peak thresholds using Equation (6). The significant drought thresholds were identified using the 95th percentile of the historical drought characteristics. The identified thresholds were 3.13 for severity, 4 months for duration and 1.47 for the peak. Fig. 8 illustrates percentage changes to the trivariate joint occurrence probabilities of exceeding significant drought thresholds in RCP 4.5 for 2016–2057. Since the spatial patterns of change in trivariate probabilities were analogous, only the results from RCP 4.5 for 2016–2057 were presented. Results from 14 of the 15 GCMs indicated increased probabilities of drought in the Mekong Delta. Analysis of at least 11 of the 15 GCMs indicated increased probabilities in most parts of the Upper LMB. The results of the change in trivariate probabilities were similar to the results of the univariate analysis. For example, CanESM2 and MPI-ESM-LR projected a drastic increase in trivariate probabilities, which was consistent with the results from the univariate analysis of drought severity and peak values.

6. Conclusions

- This study identified and characterized drought characteristics using SPI-3 for the historical period (1964–2005) and four future scenarios (RCP 4.5 2016–2057, RCP 4.5 2058–2099, RCP 8.5 2016–2057, and RCP 8.5 2058–2099) using 15 GCMs. According to the results obtained from 15 GCMs, it was evident that drought severity and peak may be elevated significantly in the Lower LMB and 3S with climate change. Among 15 GCMs, CanESM2 model projections indicated a greater increase in drought severity in most areas of the LMB. Considering the consensus among the results obtained from 15 GCMs, the Mekong Delta is expected to experience a significant increase in drought. This could affect the rice farmers in the delta area, which contributes more than 50% of the total rice production in Vietnam (Ngoc Thuy et al., 2015). The results of multivariate probabilities of particular significant drought thresholds using copula functions were obtained for drought risk assessment. Most GCMs indicated increased probabilities of significant drought scenarios in the entire LMB region, and the Lower LMB region was specifically projected to experience an elevated drought risk.
- Because the SPI-3 series was calculated for the historical and future years 2016–2057 and 2058–2099, the three-month averages of accumulated precipitation that were used while standardizing the index could differ. To understand the shift in average conditions, the simulated average monthly precipitation for future scenarios was compared with historical values. GCM projections showed an increase in average monthly precipitation under the RCP 4.5 scenario. For the RCP 8.5 scenario, the average monthly precipitation from September to December indicated a significant decrease, which indicated that historically dry months were expected to become drier in the future.
- It should be noted that the SPI measures the deviation from the long-term mean, which changed in future scenarios. Hence, the historical and future drought characteristics were not based on the same long-term average baseline. Average monthly precipitation provided a general frame of reference for quantification and map drought scenarios over a range of spatiotemporal scales. However, the standardization of the SPI allowed comparing droughts between historical and future climatic conditions (Svoboda et al., 2012) although the average climate was subjected to change over different time periods. Because the SPI only uses precipitation for input, the effect of changes in evapotranspiration with temperature and soil moisture can play a vital role in predicting future drought characteristics. Hence, additional metrics such as the Standardized Precipitation-Evaporation Index (SPEI) (Vicente-Serrano et al., 2010) and the Reconnaissance Drought Index (RDI) (Tsakiris et al., 2007) can be explored.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.wace.2017.07.004.

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