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Wetting tendency in the Central Mekong Basin consistent with climate change-induced atmospheric disturbances already observed in East Asia

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Abstract Regional and local trends in rainfall intensity, frequency, seasonality, and extremes were analyzed in the central Mekong Basin in continental Southeast Asia over the period 1953–2004 using the modified Mann–Kendall test, accounting for long-term persistence and the regional average of the Kendall's statistic. Regionally significant and insignificant wetting tendencies of the dry and wet seasons, respectively, were found to be consistent with rainfall alterations in the neighboring southeastern part of China and attributed by previous studies to the weakening of the East Asia Summer and Winter Monsoons. These observations suggest the existence of causal links between global warming and rainfall changes observed in continental Southeast Asia. Although these changes most likely did not alter agricultural production, they confirm the need to account for climate change impacts when assessing water resources availability in this region under rapid economic development.

1 Introduction

Detection of trends in rainfall time series attracts growing attention due to widespread concerns that the humaninduced increase in emission of greenhouse gases (GHG) is altering the Earth's climate and ecosystems (Walther et al. [2002;](#page-11-0) Letcher [2009\)](#page-11-0). Although the contribution of GHG to

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global warming has been demonstrated (Lashof and Ahuja [1990;](#page-11-0) IPCC [2007](#page-11-0)), their impact on precipitation remains uncertain, particularly at local scales. In general, higher temperature over lands induces higher evapotranspiration rates, thus increasing air humidity and precipitation (Trenberth [2005\)](#page-11-0). However, actual observations indicate that rainfall changes are more complex and spatially variable than temperature changes as attested by Frich et al. [\(2002](#page-11-0)) at the global level and by Manton et al. [\(2001](#page-11-0)) for Southeast Asia. This comparatively higher heterogeneity of rainfall changes is caused by the higher variability of precipitation, occurring at multiple temporal scales and possibly offsetting impacts of man-made climate change. Beyond this natural variability, rainfall changes over longer periods are expected to have major implications for water and food availability in Southeast Asia where livelihoods are intimately linked to rainfed agriculture (Barker and Molle [2004](#page-11-0)). Therefore, characterizing rainfall changes in the longest available records is required to improve the management of water resources over the long term.

Few analyses of historical rainfall changes have focused on Southeast Asia, while many studies have investigated past climate alterations in South and East Asia, i.e., India, China, Korea, and Japan. Manton et al. [\(2001](#page-11-0)) analyzed trends in extreme daily rainfall from 1961 to 1998 from 91 stations in 15 countries of Southeast Asia and South Pacific, using the Kendall tau test. They found that, in Southeast Asia, the annual number of rainy days decreased, while the proportion of extreme rainfall to the total annual depth increased. The frequency of extreme rainfall events declined at most stations. Kripalani and Kulkarni [\(1997](#page-11-0)) used records from 135 rain gauges with lengths ranging from 25 to 125 years within the period 1872–1989 to produce seasonal and annual areal rainfall time series for seven Southeast Asian countries. The Mann–Kendall test found no systematic change in any of the series. Kwanyuen ([2000\)](#page-11-0) analyzed

changes in rainfall in six river catchments of Northern Thailand over the period 1951–1997 using records from 20 rain gauges. The author detected decreasing trends in three catchments using hypothesis testing and T test. Boochabun et al. [\(2004\)](#page-11-0) applied a dynamic harmonic regression model to rainfall and flow time series extending from 1980 to 1999 over Thailand. They did not identify any significant changes in the time series. Sharma et al. [\(2006\)](#page-11-0) analyzed trends in extreme daily rainfall from 1961 to 2002 in Northern Thailand, applying the Kendall tau test to time series from 15 stations. They observed an insignificant decrease in annual rainfall and a significant decrease in annual cumulative depths produced by rainy days above 10 or 20 mm while the duration of rainless periods increased. In Lao People's Democratic Republic, Suzuki et al. [\(2007\)](#page-11-0) analyzed 50 years of daily rainfall recorded in Vientiane over the period 1951–2000 by averaging several variables capturing rainfall patterns over two successive 25-year periods. Droughts were found to be more frequent during the second period. Most of heavy rainfall (>100 mm/day) was observed in August and September during the first period and more widely spread from May to September during the second one. An additional analysis was carried out by Suzuki et al. [\(2008\)](#page-11-0) at four other rainfall stations in Laos over the same 25-year periods. Rain events were found to be heavier at the end of the rainy season during the second period at the four stations. Overall, the above studies reveal a general trend of increasing dryness over the second half of the twentieth century, with a more contrasted distribution of rainfall throughout the year. However, this trend becomes insignificant as the period of analysis extents to the full century (Kripalani and Kulkarni [1997](#page-11-0)). Most authors warn about the difficulties in identifying the precise causes of such trends.

The nonparametric Mann–Kendall trend detection test (Mann [1945](#page-11-0); Kendall [1975](#page-11-0)) is one of the most extensively used tests to detect trends in hydroclimatic time series. This test does not require the tested sample to follow any particular distribution and it has a low sensitivity to outliers. The main requirement of this and other trend detection tests is that the data are independent since autocorrelation leads to an overestimation of trend significances (Cox and Stuart [1955](#page-11-0)). Generally, climate time series do not satisfy this requirement and exhibit long-term persistence resulting in the successions of natural multidecadal wet and dry periods (Hurst [1951\)](#page-11-0). Two techniques have been proposed to account for this effect: (1) "Pre-whitening" consists of de-correlating the time series before performing the trend detection test (von Storch [1995](#page-11-0)). As de-correlation alters trends and thus reduces the power of the test, Yue et al. ([2002](#page-12-0)) introduced the "trend-free prewhitening" methodology accounting for the effect of decorrelation on the trend statistical significance. Although this method produces better results, Hamed ([2009](#page-11-0)) showed that it only partially eliminate the original problem of higher rejection rate of the test. This author demonstrated that simultaneous estimations of the trend slope and of the autocorrelation coefficient enhances the effectiveness of prewhitening at the condition that the time series follow a first-order autocorrelation and not exceed 30 years. (2) The second technique leaves intact the time series and rather modifies the test so that it accounts for the effect of autocorrelation. Lettenmaier ([1976](#page-11-0)) used that technique, assuming that the climate time series follow a first-order autoregressive process. Recently, Hamed [\(2008\)](#page-11-0) used the scaling model (Koutsoyiannis [2003\)](#page-11-0) which accurately captures the correlation structure of climate time series to modify the Mann–Kendall test so that it becomes suitable for time series exhibiting long-term persistence. The phenomenon of long-term persistence can be explained by the multiscale variability of hydrometeorological time series also called scaling effect (Koutsoyiannis [2002](#page-11-0)). The scaling effect, which denotes the invariance properties of a time series aggregated on different time scales, can be formulated as follow: $\sigma_k = k^H \sigma$ where σ is the standard deviation of the original annual time series X_i (i=1, 2…), σ_k is the standard deviation of $Z_i^{(k)}$, $Z_i^{(k)}$ being an aggregated time series of X_i at the *k*-year time step $(k=1, 2,...): Z_1^{(k)} = X_1 + ... + X_k$, $Z_i^{(k)} =$ $X_{(i-1)k+1} + \ldots + X_{ik}$. *H* is the scaling coefficient, generally varying between 0.5 (no scaling effect) and 1.

When contrasted trends are detected within a same region, the field significance (Vogel and Kroll [1989](#page-11-0)) indicates whether one significant regional trend emerges from all stations. The field significance is the collective significance of a group of hypothesis tests. If each test is independent, the local significance levels of the individual tests will follow a uniform distribution which may be used to assess the overall field significance. But in most of the cases, neighboring stations repeatedly record the same phenomena, resulting in spatially correlated time series and overlaps in the information contained in each data point. Similar to the existence of autocorrelation, the presence of spatial correlations in a network, if not properly accounted, will inflate the field significance. Douglas et al. [\(2000](#page-11-0)) compared two methods to calculate the field significance in the presence of spatial correlations. The first one, analytical, assumes that the data are identically distributed and that the test statistic is normally distributed. This second hypothesis may not be satisfied when the number of stations does not exceed 20. The second method does not require the tested sample to follow any particular statistical distribution. An empirical cumulative distribution function of the regional test statistic is generated by a resampling technique (permutations or bootstrap). This resampling process preserves the crosscorrelation structure of the original dataset.

This paper investigates changes in rainfall pattern in the central part of the Mekong Basin over the period 1953– 2004. The study area is presented in Section [2.](#page-2-0) In Section [3,](#page-2-0)

31 annual variables derived from daily rainfall measured at 17 rain gauges are defined and submitted to the modified Mann–Kendall trend detection test accounting for long-term persistence (Hamed [2008](#page-11-0)). The field significance of trends for each of the 31 annual variables is evaluated through a resampling technique (Douglas et al. [2000\)](#page-11-0) based on permutations. Results are presented in Section [4](#page-7-0). In Section [5,](#page-9-0) observed changes in rainfall are compared with the results from previous studies and trend attribution is discussed.

2 Study area

This study focuses on the central part of the Mekong Basin where the longest rainfall time series of continental Southeast Asia can be found (Fig. 1). This region mostly corresponds to the undulating Plateau of Khorat in Northeast Thailand with elevations ranging from 100 to 500 m. Distances to the sea in this land-locked area vary between 200 and 400 km. About 80 % of the 21 million inhabitants live in rural areas. Agriculture is the main economic activity, dominated by rainfed lowland rice, particularly vulnerable to droughts and floods. Climate vagaries combined with coarse textured sandy and unevenly distributed saline soils explain low agriculture yields and the endemic population poverty (Panichapong [1985](#page-11-0)). The conversion of forest to subsistence cultivation of rainfed rice began centuries ago in lowland areas. About 35 years ago, deforestation extended to uplands areas where the cultivation of cash crops stimulated the emerging market economy (Walsh et al. [2001](#page-11-0)).

Seasonal rainfall pattern is controlled by the East Asian and Indian Monsoons, with two contrasted seasons: the wet season starts in late April–early May and ends in October. The dry season starts in November and ends in April. The wet season is characterized by humid winds coming from the Southwest, induced by the development of circulation features and convective activity in the tropical East Indian Ocean and the Bay of Bengal (Yihui and Chan [2005\)](#page-12-0). The dry season is due to the East Asian Winter Monsoon bringing dry and cold winds (northeasterlies) along the east flank of the Siberian high and the coast of East Asia (Zhou [2011\)](#page-12-0). Lasting about 6 months, the wet season accounts for nearly 90 % of total annual rainfall. Rainfall distribution within the wet season is bimodal with a first peak in late May and a second one (the highest) in late August–early September. The inter-annual rainfall variability over the central part of the Mekong Basin involves large-scale air convection over the Indo-China and South China Seas and the Southern Bay of Bengal. The occurrence of the onset of the monsoon may be related to the basin-wide sea surface temperature of the Pacific and Indian Oceans (Lau and Yang [1997](#page-11-0); Singhrattna et al. [2005](#page-11-0)) and to the snow cover in the Eurasia and the Tibetan Plateau (Yihui and Chan [2005\)](#page-12-0). The multidecadal variability of rainfall is partly due to the El Niño Southern Oscillation (Kripalani and Kulkarni [1997](#page-11-0); Xu et al. [2004](#page-12-0)) and the North Pacific Oscillation (Wang et al. [2007\)](#page-12-0).

3 Material and methods

3.1 Rainfall variables

Among the 20 daily rain gauges with more than 50 years of records provided by the Mekong River Commission, 17

were selected as providing consistent data (Table 1 and Figure [1\)](#page-2-0), based on an analysis with the regional vector (Brunet-Moret [1979](#page-11-0)). This method aims at detecting anomalies and error measurements in rainfall records by comparing time series from neighboring stations. Over the studied period (January 1953–December 2004), original rainfall time series of each station include between 0 and 4.2 % of missing data (Table 1), equivalent to 1.2 % of missing data in the whole dataset. Gaps were filled in through multiple linear regressions using best correlated stations (R^2 >0.6 and significance level >99 % according to the F test). Multiple linear regression is a simple method commonly used to estimate missing values in rainfall datasets (Makhuvha et al. [1997](#page-11-0)). Regression models were fitted with monthly cumulative rainfall and used to interpolate daily time series where observed data are missing. This method could distort the intramonthly distribution of daily rainfall in patched rainfall time series. However, correlations between 1-year time series of daily rainfall averaged over the period 1953–2004 $(R^2>0.6$ and significance level $>99\%$ according to the F test) suggest that the distribution of rainy days is uniform among times series used in the regression models. Thirty one annual variables (Tables [2](#page-4-0) and [3\)](#page-4-0) were derived from daily rainfall so as to capture the main climate features that control rainfed agriculture and have an impact on human livelihoods. Variables 1–19 were previously defined by

Lacombe et al. ([2012](#page-11-0)). These variables are assembled into five categories:

 \bullet Occurrence of the wet season (variables 1–3). These three variables include the ordinal dates (number of days since January 1) of the beginning of the wet season (variable 1), of the end of the wet season (variable 2) and of the first day of the wettest 5-day period (variable 3). The beginning of the wet season was defined as the first day of the first 10-day period of the year that satisfies two conditions: (1) the cumulative rainfall depth of this 10-day period exceeds the mean 10-day rainfall depth of the station, averaged over the period 1953–2004 and (2) at least two of the next three 10-day periods satisfy the first condition. Due to the extreme temporal variability of rainfall, the 10-day rainfall depths were first smoothed by a three time-step moving average. The end of the wet season was defined by symmetrical conditions, starting from the end of the calendar year and moving backward through the 10 day periods (Fig. [2a](#page-8-0)). Agricultural practices and yields are intrinsically linked to these variables as cropping calendars closely depends on rainfall seasonal patterns. A shift in the wet season onset, peak, and/or retreat may result in crop yield reduction through drought stress at the earlier stages of plant development and/or excess water at harvesting time.

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Table 2 List of the 31 rainfall variables, variables 1–7

- Extreme events (variables 4–6). Variable 4 corresponds to the cumulative rainfall depth of the wettest 5-day period. Variable 5 represents the number of rainy days whose rainfall depth exceeds the 156th heaviest daily rainfall depth of the period 1953–2004, i.e., there are three extreme events per year in average. Variable 6 corresponds to the duration of the longest rainless period recorded during the wet season, i.e., consecutive days with less than 1 mm of rainfall per day. These extreme events, which generally induce drastic reductions of crop yields, are particularly harmful for farmers. Typically, droughts induce water stress, high rainfall intensity has destructive impacts on seedlings, and floods create anoxic conditions through prolonged submersion.
- Rainfall intensity index (variable 7). This variable captures the combined effect of rainfall frequency and intensity, calculated as the number of heaviest rainy days that constitutes two thirds of the total annual rainfall as suggested by Sun et al. ([2006](#page-11-0)). This variable was calculated as follows: daily rainfall depths were sorted from the heaviest to the lightest and the number of heaviest rainfall days that are required to accumulate two thirds of the annual rainfall amount was calculated. This variable typically indicates how many daily rainfall events dominate

the local precipitation budget. A low value reflects a rainfall regime made of few but intense rainfall events while a large value corresponds to a more homogenous distribution of daily rainfall events throughout the year.

- Cumulative rainfall depths per season and per range of daily rainfall (variables 8–19). These 12 variables correspond to the sums of daily rainfall depth for specific pairwise combinations of three periods (whole year, wet season and dry season) and four ranges of daily rainfall depths (whole range, low, medium, and high rainfall). Low, medium, and high rainfall were defined at each station by two thresholds determined as follows: for each of the three periods, the sorted cumulative distribution of daily rainfall from 1953 to 2004 was split into three identical depths, thus defining two values corresponding to one third and two thirds of the total depth of this distribution. The daily rainfall thresholds were defined as the antecedents of these two values using the sorted cumulative distribution function (Fig. [2b](#page-8-0)).
- Number of rainy days per season and per range of daily rainfall (variables 20–31). These 12 variables correspond to the number of rainy days (rain>1 mm/ day) for the similar pairwise combinations of periods and daily rainfall ranges as those defined for variables 8–19. The computation of rainfall depths and numbers of rainy days (variables 8–31) for different ranges of daily rainfall (low, medium, and high) enables contrasting changes that may occur in different rainfall ranges to be observed: trends in variables involving small values are not offset by the presence or absence of trends in the variables involving larger values. In addition, it is worth noting that agricultural yields on the one hand and runoff production (floods) on the other hand, react nonlinearly to rainfall input, making similar total annual depth producing a large range of runoff depths and agricultural yields, thus justifying the detection of trends in different ranges of daily rainfall.

		Cumulative rainfall depth			Number of rainy days						
		Range of daily rainfall			Range of daily rainfall						
		Whole range	Low	Medium	High	Whole range	Low	Medium	High		
Period	Year	8	9	10	11	20	21	22	23		
	Wet season	12	13	14	15	24	25	26	27		
	Dry season	16	17	18	19	28	29	30	31		

Table 3 List of the 31 rainfall variables, variables 8–31

Table 4 Trends in rainfall variables over period 1953–2004, variables 1–7

Bold values Sen's slopes of significant trends according to the modified Mann–Kendall test. Zero values: absence of significant trend. Small italic values Sen's slope of significant trends according to original Mann–Kendall test, found to be nonsignificant by the modified Mann–Kendall test. Values without and with brackets are statistically significant at the 95 and 90 % confidence levels, respectively. Underlined values are significant at 90 and 95 % confidence levels according to modified and original Mann–Kendall tests, respectively. Refer to method for definition of units

3.2 The Mann–Kendall test under the scaling hypothesis

For each of the 17 rainfall stations and 31 rainfall variables (i.e., 527 time series altogether), the significance of trends were assessed by the Mann–Kendall test modified by Hamed [\(2008\)](#page-11-0) to account for long-term persistence. The main steps of calculations are summarized below. Further details about the modified test procedure can be found in Hamed ([2008\)](#page-11-0). Given a time series X_i ($i=1, \ldots, n$), the test statistic S of the original Mann–Kendall test is given by:

$$
S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sgn}(X_j - X_i) \quad \text{where} \quad \text{sgn}(\theta) = \begin{cases} 1 & \text{if } \theta > 0 \\ 0 & \text{if } \theta = 0 \\ -1 & \text{if } \theta < 0 \end{cases} \tag{1}
$$

The variance $V_0(S)$ of the statistic S is calculated as follow:

$$
V_O(S) = n(n-1)(2n+5)/18
$$

$$
-\sum_{i=1}^{m} t_i(t_i-1)(2t_i+5)/18
$$
 (2)

where *m* is the number of groups of tied ranks, each with t_i tied observations. The significance of trends can be tested by comparing the standardized variable Z in Eq. 3 with the standard normal variate at the desired significance level, where the subtraction or addition of unity in Eq. 3 is a continuity correction (Kendall [1975\)](#page-11-0).

$$
Z = \begin{cases} \frac{S-1}{\sqrt{V_O(S)}} & \text{if } S > 0\\ 0 & \text{if } S = 0\\ \frac{S+1}{\sqrt{V_O(S)}} & \text{if } S < 0 \end{cases}
$$
 (3)

If the original Mann–Kendall test concludes to the significance of a trend, the effect of scaling (Koutsoyiannis [2003](#page-11-0)) will be checked, following Hamed's recommendations (Hamed [2008](#page-11-0)): the original time series is first de-trended with the Sen's slope estimator (Sen [1968\)](#page-11-0) S_0 given by

$$
S_0 = \text{median}\left(\frac{X_j - X_i}{j - i}\right) \forall i < j \tag{4}
$$

The de-trended time series is transformed into equivalent normal variates Z_t using the inverse standard normal distribution function (Hogg and Tanis [1988](#page-11-0)):

$$
Z_t = \Phi^{-1}\left(\frac{R_t}{n+1}\right) \tag{5}
$$

where R_t is the rank of the de-trended observation X_t , n is the number of observations, and $\Phi^{-1}()$ is the inverse standard normal distribution function. The scaling coefficient H of the equivalent normal variate is estimated by maximizing the log-likelihood function (Eq. 6) proposed by Mac Leod and Hipel [\(1978\)](#page-11-0):

$$
\log L(H) = -\frac{1}{2} \log |C_n(H)| - \frac{Z^T [C_n(H)]^{-1} Z}{2\gamma_0} \tag{6}
$$

where log $L($) is the log-likelihood function, γ_0 is the variance of Z, Z is the matrix of the equivalent normal variates Z_t , Z^T is the transposed matrix of Z, and $C_n(H)$ is the matrix of autocorrelation estimators for a given scaling coefficient H (Koutsoyiannis [2003](#page-11-0)). The existence of the scaling effect $(H\neq 0.5)$ is tested using the mean and standard deviation of H for the uncorrelated case, estimated by Hamed [\(2008](#page-11-0)). If there is no scaling effect, the time series will have a significant trend whose slope is estimated using the Sen's slope estimator (Eq. [4\)](#page-5-0). If there is a scaling effect, the variance $V(S)$ of the modified Mann–Kendall test statistic will be estimated using the autocorrelation coefficient introduced by Kendall and Stuart ([1976](#page-11-0)):

$$
V(S) = \sum_{i < j} \sum_{k < l} \sin^{-1} \left(\frac{\rho_{jl} - \rho_{il} - \rho_{jk} + \rho_{ik}}{\sqrt{\left(2 - 2\rho_{ij}\right)\left(2 - 2\rho_{kl}\right)}} \right) \tag{7}
$$

where ρ_{ij} is the autocorrelation coefficient at lag *i–j*. The modified variance is finally corrected for bias with the factor B established by Hamed ([2008](#page-11-0)) as a function of n and H and the modified test statistic Z^* is standardized (Eq. [8](#page-7-0)). Z^* is compared with the standard normal variate like in the original test. If the modified test indicates that the times series has a significant trend at the desired significance level, its slope will

Table 5 Trends in rainfall variables over period 1953–2004, variables 8–19

	Rainfall depth												
	Variable number	Year				Wet season				Dry season			
		All 8	Low 9	Med 10	High 11	All 12	Low 13	Med 14	High 15	All 16	Low 17	Med 18	High 19
Rainfall stations	Chaiyaphum	$\mathbf{0}$	$\mathbf{0}$	$\mathbf{0}$	-3.49	$\mathbf{0}$	$\mathbf{0}$	$\mathbf{0}$	$\mathbf{0}$	$\overline{0}$	$\mathbf{0}$	$\overline{0}$	$\mathbf{0}$
	Fang	Ω	3.39	$\mathbf{0}$	-3.82	$\mathbf{0}$	2.70	θ	Ω	θ	$\mathbf{0}$	$\mathbf{0}$	$\boldsymbol{0}$
	Kalasin	Ω	$\mathbf{0}$	$\mathbf{0}$	$\mathbf{0}$	$\mathbf{0}$	$\overline{0}$	$\mathbf{0}$	Ω	θ	0.63	$\mathbf{0}$	$\mathbf{0}$
	Khon Kaen	4.19	$\mathbf{0}$	$\mathbf{0}$	3.36	3.51	θ	$\mathbf{0}$	(2.74)	Ω	$\mathbf{0}$	$\mathbf{0}$	$\boldsymbol{0}$
	Loei	θ	$\boldsymbol{0}$	$\boldsymbol{0}$	(2.60)	$\mathbf{0}$	θ	θ	θ	θ	θ	$\mathbf{0}$	$\boldsymbol{0}$
	Luang Prabang	6.05	$\mathbf{0}$	3.64	$\boldsymbol{0}$	(5.98)	θ	3.32	Ω	Ω	$\mathbf{0}$	$\mathbf{0}$	$\boldsymbol{0}$
	Maha Sarakham	$\mathbf{0}$	$\mathbf{0}$	$\overline{0}$	$\overline{0}$	$\mathbf{0}$	$\overline{0}$	$\mathbf{0}$	$\mathbf{0}$	θ	$\mathbf{0}$	$\overline{0}$	$\mathbf{0}$
	Mukdahan	θ	$\boldsymbol{0}$	Ω	$\mathbf{0}$	$\mathbf{0}$	θ	θ	Ω	θ	$\mathbf{0}$	$\mathbf{0}$	$\boldsymbol{0}$
	Nakhon Phanom	θ	$\overline{0}$	Ω	$\mathbf{0}$	$\mathbf{0}$	θ	θ	Ω	θ	θ	$\overline{0}$	$\mathbf{0}$
	Nong Khai	$\mathbf{0}$	3.02	$\overline{0}$	(-4.01)	$\mathbf{0}$	$\overline{0}$	$\mathbf{0}$	(-4.18)	2.00	1.00	1.05	$\mathbf{0}$
	Roi Et	Ω	$\mathbf{0}$	$\mathbf{0}$	$\overline{0}$	$\boldsymbol{0}$	θ	θ	θ	Ω	$\mathbf{0}$	$\mathbf{0}$	$\boldsymbol{0}$
	Sakhon Nakhon	(5.01)	$\boldsymbol{0}$	$\mathbf{0}$	5.55	$\mathbf{0}$	$\overline{0}$	θ	5.00	Ω	$\mathbf{0}$	$\mathbf{0}$	$\mathbf{0}$
	Sisaket	Ω	4.94	$\mathbf{0}$	Ω	$\mathbf{0}$	4.97	θ	θ	θ	θ	$\mathbf{0}$	$\mathbf{0}$
	Surin	5.12	$\mathbf{0}$	$\mathbf{0}$	5.45	5.64	θ	$\mathbf{0}$	5.46	Ω	$\mathbf{0}$	$\mathbf{0}$	$\mathbf{0}$
	Ubon Ratchathani	θ	$\mathbf{0}$	$\mathbf{0}$	$\mathbf{0}$	$\mathbf{0}$	θ	θ	Ω	Ω	θ	$\mathbf{0}$	$\mathbf{0}$
	Udon Thani	Ω	$\mathbf{0}$	$\mathbf{0}$	$\mathbf{0}$	$\mathbf{0}$	θ	θ	Ω	(1.33)	$\mathbf{0}$	$\mathbf{0}$	$\boldsymbol{0}$
	Vientiane	θ	$\mathbf{0}$	$\mathbf{0}$	$\mathbf{0}$	$\mathbf{0}$	θ	θ	θ	θ	$\mathbf{0}$	$\overline{0}$	$\mathbf{0}$
	Field significance	$\mathbf{0}$	$\mathbf{0}$	$\mathbf{0}$	$\mathbf{0}$	$\mathbf{0}$	$\overline{0}$	θ	$\mathbf{0}$	$(>=0)$	$\mathbf{0}$	$(>=0)$	(>0)

Bold values Sen's slopes of significant trends according to the modified Mann-Kendall test. Zero values: absence of significant trend. Small italic values Sen's slope of significant trends according to original Mann-Kendall test, found to be nonsignificant by the modified Mann-Kendall test. Values without and with brackets are statistically significant at the 95 and 90 % confidence levels, respectively. Underlined values are significant at 90 and 95 % confidence levels according to modified and original Mann–Kendall tests, respectively. Refer to method for definition of units

Table 6 Trends in rainfall variables over period 1953–2004, variables 20–31

Bold values Sen's slopes of significant trends according to the modified Mann–Kendall test. Zero values: absence of significant trend. Small italic values Sen's slope of significant trends according to original Mann–Kendall test, found to be nonsignificant by the modified Mann–Kendall test. Values without and with brackets are statistically significant at the 95 and 90 % confidence levels, respectively. Underlined values are significant at 90 and 95 % confidence levels according to modified and original Mann–Kendall tests, respectively. Refer to method for definition of units

be estimated using the Sen's slope estimator (Sen [1968\)](#page-11-0) in Eq. [4.](#page-5-0)

$$
Z^* = \begin{cases} \frac{S-1}{\sqrt{V(S)B}} & \text{if } S > 0\\ 0 & \text{if } S = 0\\ \frac{S+1}{\sqrt{V(S)B}} & \text{if } S < 0 \end{cases}
$$
 (8)

3.3 Field significance

For each one of the 31 rainfall variables, a regional average Kendall's statistic S_m was calculated as suggested by Douglas et al. ([2000](#page-11-0)):

$$
S_m = \frac{1}{m} \sum_{k=1}^{m} S_k \tag{9}
$$

where S_k is the statistic S of the Mann–Kendall test for the kth station among the *m* stations of the region $(m=17$ in our study case). An empirical cumulative distribution function of S_m was generated by permuting years 10,000 times in the original dataset, by calculating S_m for each resampled dataset, and by

ranking the 10,000 values of S_m in ascending order. This resampling process preserves the spatial correlation structure of the data. However, it does not allow accounting for the phenomenon of long-term persistence because the autocorrelation structure of the original dataset is not preserved by the permutation process. Consequently, original time series were initially prewhitened according to Hamed's methodology (Hamed [2009\)](#page-11-0), prior to being submitted to the regional test. The field significance associated with the regional Kendall's statistic S^h _m computed from the historical dataset was calculated using the Weibull plotting position formula:

$$
P(S_m < S^h_m) = \frac{r}{B+1} \tag{10}
$$

where r is the rank of S^h_m and $B=10,000$.

4 Results

Tables [4,](#page-5-0) [5](#page-6-0), and 6 display the results of the trend test applied to each variable at each station and at the regional level for the 90

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Fig. 2 Schematic representations of techniques used to determine beginning (variable 1) and end (variable 2) of wet season (a) and to generate threshold values used to define variables 8–31 (b). Rainfall at Vientiane (year 2004 in a) is used to illustrate both techniques

and 95 % significance levels. Among the 527 time series submitted to the test, 46 and 71 time series present a trend significant at the 95 and 90 % confidence levels, respectively. The original Mann–Kendall test would have concluded to the presence of 22 and two additional trends (materialized in Tables [4](#page-5-0), [5,](#page-6-0) and [6](#page-7-0) by small italic characters) significant at the 95 and 90 % confidence levels, respectively. Their insignificance, according to the modified Mann–Kendall test, is explained by the phenomenon of long-term persistence as illustrated in Fig. 3: the presence of 5- to 15-year trends with opposite slopes is accounted by the modified Mann–Kendall test as part of the natural variability. The slope of the long-term trend (which is significant according to the original Mann– Kendall test) thus becomes insignificant with regards to these multiyear periods exhibiting local trends.

Fig. 3 Short trends versus long-term trend. Example of the rainfall intensity index (variable 7) at Sisaket. Solid line linear trend over the whole period (1953–2004), *dotted lines* linear trends over periods including 5–15 years

Changes in the occurrence of the wet season are virtually non-existent since two stations (Fang and Surin) and one station (Luang Prabang) only exhibit significant trends for variables 1 and 2 (beginning and end of the wet season, respectively) at the 90 % confidence level. Only two stations, Surin and Vientiane, present a significant trend for variable 3 (occurrence of the wettest 5-day period) at the 95 and 90 % confidence levels, respectively. Same conclusions can be drawn for the variables 4 (rainfall depth of the wettest 5-day period), 5 (number of extremely high daily rainfall depths), 6 (duration of the longest rainless period recorded during the wet season), and 7 (rainfall intensity index): changes with statistical significance greater or equal to 90 % in variable 4 involve two stations (Ubon Ratchathani and Luang Prabang), whereas four stations exhibit significant trends for variables 5 (Mukdahan, Nong Khai, Sakhon Nakhon, and Surin), and 6 (Chaiyaphum, Mukdahan, Nakhon Phanom, and Nong Khai). Variable 7 displays significant changes at two stations (Fang and Nong Khai; cf. Table [4\)](#page-5-0).

Among the 17 and 24 trends in cumulative rainfall depths, significant at the 95 and 90 % confidence levels, respectively (Table [5](#page-6-0)), 15 (resp. 20) are positive, meaning that significant changes mainly result in increases of rainfall amounts. Significant trends associated with the number of rainy days (Table [6](#page-7-0)) reflect the changes observed in rainfall depths with similar proportions of positive changes: 19 (resp. 21) upward trends among a total of 21 (resp. 26)

Fig. 4 Field significances of variables 1–31. Positive and negative values correspond to positive and negative regional trends, respectively. Solid line 95 % significance level, dotted line 90 % significance level

significant trends. The few negative trends are observed during the wet season only (variables 15, 25, and 27), indicating that wet season rainfall changes are more heterogeneous than those, uniformly positive, observed during the dry season. Figure 4 displays the field significance associated to each variable. At the regional level, none of the variables are field significant at the 95 % confidence level. Field significant trends at the 90 % confidence level mostly occur during the dry season and correspond to increases in rainfall depths for the "whole", "medium", and "high" ranges of daily rainfall (variables 16, 18, and 19) and to increases in the number of rainy days for all ranges of daily rainfall (variables 28–31). One other regional rising trend, significant at the 90 % confidence level, is observed for variable 20 (number of rainy days per year, considering the whole range of daily rainfall). Except for variables 1 and 3 (occurrence of beginning and peak of wet season, respectively) associated to insignificant declining regional trends, all other variables exhibit insignificant rising regional trends (Fig. 4).

5 Discussion

Previous investigations of rainfall trends undertaken in Southeast Asia concluded that rainfall either remained stable (Kripalani and Kulkarni [1997;](#page-11-0) Boochabun et al. [2004\)](#page-11-0) or decreased (Kwanyuen [2000;](#page-11-0) Manton et al. [2001](#page-11-0); Sharma et al. [2006](#page-11-0)) over the second half of the twentieth century. In contrast, the trends detected in the present study mainly exhibit positive slopes, corresponding to rainfall increases. Although it is not possible to precisely explain such discrepancies because likely causes are numerous (geographical discrepancies, differences of statistical tests, and confidence levels), the difference in lengths of the studies' periods is likely to explain part of the opposite results. The values of field significance for the current study area were recalculated over the period 1961–1998 in order to be comparable with the results from Manton et al. ([2001\)](#page-11-0) whose study area encompasses that of the current study. Negative regional trends, significant at the 95 % confidence level, were

observed for total annual rainfall (variable 8), high annual rainfall (variable 11), total and high wet season rainfall (variables 12 and 15), and the frequency of extreme rainy days (variable 5). These results reflect the consistency between the current study and that of Manton et al. ([2001\)](#page-11-0). Similarly, consensuses were observed over the period 1980– 1999 between this study and that of Boochabun et al. [\(2004](#page-11-0)) whose study area includes Northeast Thailand. The contrasting results obtained over different periods in the current study area reflect the phenomenon of long-term persistence as illustrated in Fig. [3](#page-8-0). Field significances could not be recalculated over the periods selected by Kripalani and Kulkarni [\(1997\)](#page-11-0) and Kwanyuen [\(2000\)](#page-11-0) which start in 1911 and 1951, respectively.

Although regional trends associated to variables 19 and 31 (rainfall depth and number of rainy days produced from "high" rainy days during the dry season, respectively) are field significant at the 90 % confidence level, none of the stations exhibit significant trends for these variables (Tables [5](#page-6-0) and [6\)](#page-7-0). However, 12, out of the 17 stations, were found to exhibit insignificant positive trends. The repetition of insignificant positive trends observed at different stations increases the likelihood that these trends are not the result of a random process and actually exist, thus explaining the presence of a significant positive trend at the regional level. This example illustrates the high importance of evaluating regional trends and not trends observed at individual stations only. Computing regional trends enables the detection of significant changing rainfall patterns that remain statistically insignificant at the local level.

The dry season rainfall increase observed over the last half century in the central part of the Mekong Basin is consistent with rainfall changes observed in Southeast China where the climate is controlled by the East Asian Monsoon (Qian et al. [2007](#page-11-0)). Zhang et al. ([2011a,](#page-12-0) [b](#page-12-0)) analyzed changes in Chinese daily precipitation and their links with the spatial and temporal variations of atmospheric circulation of water vapor flux over the period 1960–2005. They observed wet and dry tendencies in Southeast China during the winter (i.e., dry season) and in Northeast China

during the summer (i.e., wet season), respectively. The dry season wetting tendency in Southeast China was explained by the weakening of the East Asian Winter Monsoon enhancing the moisture supply from the wet southwesterlies toward Southeastern China (Zhou 2011). Since part of the southwesterlies crosses continental Southeast Asia before reaching Southeastern China, they most likely explain the dry season rainfall increase observed in the central part of the Mekong Basin. The rainfall decrease observed during the summer (wet season) in Northeast China was attributed to the weaker East Asian Summer Monsoon inducing decreased northward propagation of water vapor flux (Wang and Zhou [2005;](#page-12-0) Qian et al. [2007\)](#page-11-0). This climate alteration induced summer rainfall increase (wet season) in Southeast China because of a longer rainy season (Wang and Zhou [2005](#page-12-0)). Although not statistically significant, wet season rainfall has consistently increased in the central part of the Mekong Basin between 1953 and 2004, thus suggesting that the East Asian Summer Monsoon weakening is altering rainfall patterns in similar ways in the two neighboring regions of Southeast China and Continental Southeast Asia. The lower statistical significance of rainfall increase observed in the central part of the Mekong Basin could be attributed to the climatic influence of the Indian Summer Monsoon whose multi-annual variations are different from those of the East Asian Summer Monsoon, and whose influence noticeably reduces toward Southeast China (Yihui and Chan [2005](#page-12-0)). Consistencies of rainfall changes observed in Continental Southeast Asia and in Southeastern China suggest that these two neighboring regions have been subject to the same alterations of large-scale atmospheric circulations. Zhang et al. ([2011a](#page-12-0)) attributed the rainfall changes observed in Southeastern China to global warming, thus suggesting the existence of causal links between rainfall changes observed in the central part of the Mekong Basin and human-induced climate change.

Although the dry season has become statistically significantly wetter over recent decades in the central part of the Mekong Basin (cumulative dry season rainfall increased by about 12 mm from 1953 to 2004, in average), impact on agriculture is negligible: total rainfall depth from November to April, averaged over the period 1953–2004 (about 175 mm within 6 months) is far too low to allow rainfed crop production during the dry season. Typical crop water requirements in this region vary from 500 to 1,500 mm per cropping cycle (Allen et al. [1998](#page-11-0)). Moreover, this slight rainfall increase is not likely to have an impact on irrigation requirements of dry season crops. Although the annual number of rainy days and total annual cumulative rainfall depth have increased from 67 to 72 days/year (variable 20) and from 1,403 to 1,447 mm/year (variable 8) over the period 1953–2004, respectively, effects on agriculture production are not straightforward: the insignificant increases in the magnitude and frequency of extreme events (variables

4–6) may have offset the possible water-related yield increases through higher crop damages.

6 Conclusion

Characterizing the impacts of global warming on rainfall in Southeast Asia is very important because the economy of this region mostly relies on rainfed agriculture. However, changes in rainfall pattern and their possible associations to climate change have remained poorly understood in this subtropical area located south of China. Previous analyses which quantified changes in Southeast Asian rainfall over the last decades show contrasting results and the causes behind the observed changes were rarely investigated. This lack of consistency and consecutive incompleteness reflect the extreme difficulty in detecting and attributing trends in the context of multiyear variability of rainfall: the direction of a trend may change if the date of the start and/or end of the studied time series is modified by few years. In addition, the statistical significance of a trend may be overestimated if the presence of successive multiyear wet and dry periods is not properly accounted by the trend detection test. To address these issues, our analysis used a modified version of the Mann–Kendall test, accounting for the phenomenon of long-term persistence, thus better discriminating multiyear variability and long-term unidirectional trends. The computation of regional trends enabled the detection of significant synoptic disturbances that remain insignificant at the local level because of the high variability of small-scale rainfall events and related sampling issues. Our results indicate that dry season rainfall has significantly increased in frequency (more rainy days) and intensity (higher cumulative rainfall depths) in the central part of the Mekong Basin from 1953 to 2004. Same significant trend was observed in the annual number of rainy days. Although statistically insignificant, wet season rainfall followed the same patterns of changes. A comparison of these rainfall patterns with changes previously observed in East China reveals strong consistencies indicating that the wetting tendency of the dry and wet seasons in the central Mekong Basin most likely results from the global warming-induced weakening of the East Asia summer and winter monsoons and to the consecutive alterations of atmospheric water vapor circulation. Although the dry season rainfall increase observed from 1953 to 2004 is statistically significant, it remained minor in magnitude with negligible implications for agriculture. However, this study suggests the existence of causal links between global warming and rainfall changes observed in the central part of the Mekong Basin over the last half century, confirming the need to account for climate change impacts when assessing the water resource availability in this region under rapid economic development.

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