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Les agricultures face au changement climatique.
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RESEARCH ARTICLE / ARTICLE DE RECHERCHE — OPEN ACCESS

Long-term change in rainfall distribution in Northeast Thailand: will cropping systems be able to adapt?

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Abstract – Climate vagaries and the lack of irrigation, frequently combined with coarse-textured sandy and unevenly distributed saline soils, explain low crop yields and the endemic relative poverty of the rural population in Northeast Thailand (NET). Local and regional trends in agriculturally-relevant rainfall variables were investigated using the Mann-Kendall test, modified to account for serial correlation, and applied to 17 stations across NET, and the regional average Kendall's statistic. Limited changes in rainfall frequency, intensity and seasonality are observed at individual stations over the study period (1953–2004). But we found a significant regional trend toward a wetter dry season. Based on an intimate knowledge of the local farming systems, we discuss the cropping systems adaptation to these rainfall changes. If the wetting of the dry season extends in the future, as expected according to most climate projections, households would not find it difficult to adapt, except for the problems caused by temperature rise, mainly due to their renowned adaptive capacity and high mobility that historically produced diverse and resilient rural livelihood systems.

Keywords: climate change adaptation / cropping systems / rainfall patterns / Thailand / trend

Résumé – Évolution de la pluviométrie au Nord-Est de la Thaïlande : les systèmes de culture pourront-ils s'adapter ? Les irrégularités climatiques combinées à des conditions édaphiques défavorables expliquent les faibles rendements agricoles du Nord-Est de la Thaïlande, la région la plus pauvre du pays où l'agriculture est majoritairement non irriguée. Des tendances locales et régionales sont recherchées dans des variables pluviométriques contrôlant la production agricole. Une version modifiée du test de Mann-Kendall prenant en compte l'autocorrélation est appliquée aux chroniques de 17 stations dans cette région. La statistique régionale moyenne de Kendall est utilisée pour les tests régionaux. Quasiment aucune tendance locale n'est observée dans la fréquence, l'intensité et la saisonnalité des pluies sur la période d'étude (1953–2004). En revanche, la saison sèche est devenue significativement plus pluvieuse à l'échelle régionale. La capacité des systèmes de culture locaux à s'adapter à ce changement climatique est discutée. Si, comme la plupart des modèles climatiques le prévoient, l'augmentation des pluies de saison sèche se confirme dans le futur, les agriculteurs n'éprouveront probablement pas de difficultés pour s'y adapter, à l'exception des problèmes liés à l'augmentation des températures. Leur capacité d'adaptation, forgée par des siècles de pratiques agricoles en régime pluvial incertain, et le recours aux migrations saisonnières ont permis l'établissement de systèmes agraires diversifiés et résilients.

Mots clés : adaptation aux changements climatiques / système de culture / régime de précipitation / Thaïlande / tendance

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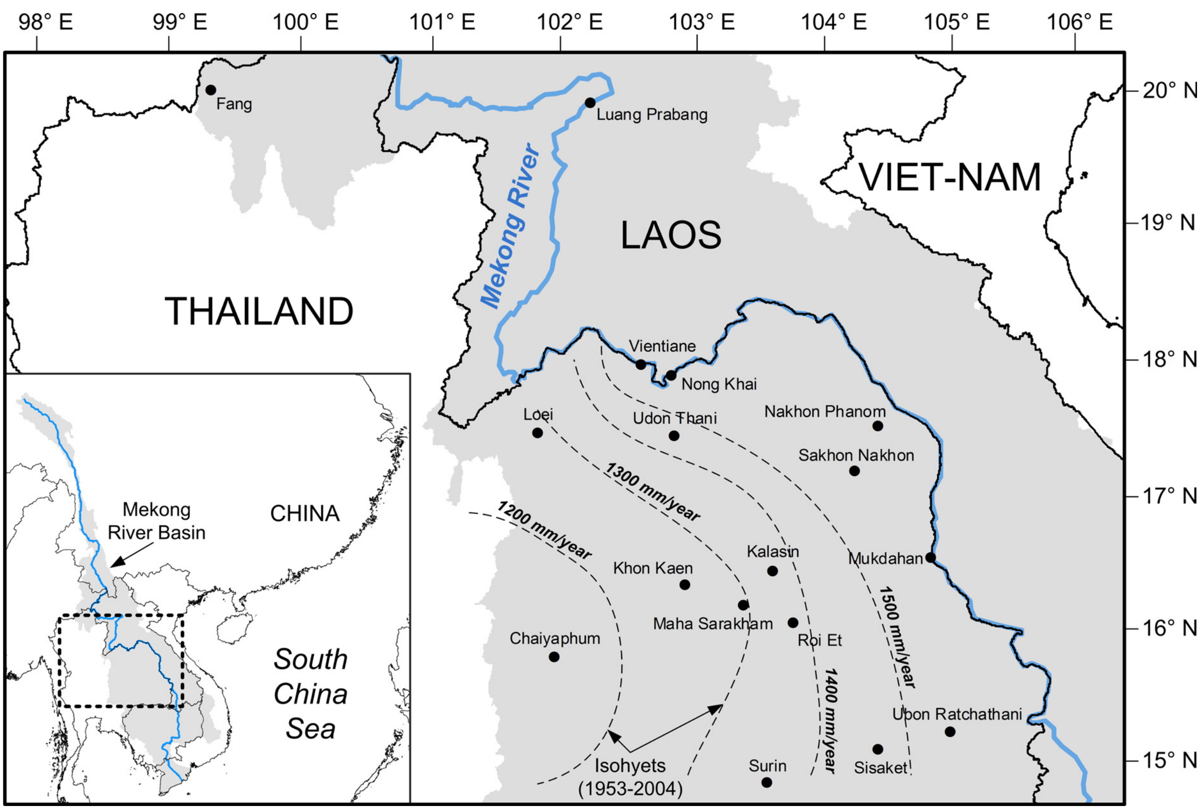

Fig. 1. Study area and location of the rainfall stations.
Fig. 1. *Région d'étude et emplacement des stations pluviométriques.*

1 Introduction

Globally, climate change is expected to have tremendous effects on agriculture through changes in temperature, rainfall patterns, and the frequency and intensity of extreme weather events (IPCC, 2014). While temperature projections exhibit consistencies between climate models, rainfall projections are still contradicting in many instances, despite significant improvements in climate sciences and computational capacity (Knutti and Sedlacek, 2013). Although the Mekong is one of the few large basins where climate models perform best in reproducing the monsoon, there is an overall uncertainty in projections of the Southeast Asian summer monsoon (Hasson *et al.*, 2016). Against this background, insights into historical rainfall are necessary for both agricultural and water development planning. Detection of trends in rainfall time series is not straightforward, particularly in the Mekong where historic records are scarce, and rainfall generating mechanisms are complex (Hasson *et al.*, 2013). The objectives of this study were thus to assess local and regional trends in agriculturally-relevant rainfall variables over the last half century in Northeast Thailand (NET), which is the Mekong sub-region where the longest rainfall records are available, and infer future challenges for cropping systems adaptation.

2 Study area

NET covers one third of the kingdom and is home to about 21 million inhabitants (Fig. 1). It is a sandstone plateau undulating between 100 and 500 m above sea level, characterized by erratic rainfall and poor coarse-textured sandy and unevenly distributed saline soils leading to low crop yields and endemic rural population poverty. About 80% of the population live in rural areas, mainly from agriculture and remittances received from millions of seasonal and permanent migrants.

2.1 Climate

Due to the Southeast Asian summer monsoon blowing humid air masses from the Indian Ocean, the rainy season concentrates about 80–90% of annual rainfall between May and October. The dry season caused by the East Asian winter monsoon brings dry and cold northeasterlies wind from November to April. The occurrence of the rainy season onset mainly relates to the surface temperature of the Pacific and Indian Oceans (Singhrattna *et al.*, 2005). The multi-decadal variability of rainfall is partly due to the El Niño–Southern Oscillation (Räsänen and Kummu, 2013) and the North Pacific Oscillation (Wang *et al.*, 2007).

2.2 Cropping systems

The staple food crop in NET is aromatic rainfed lowland rice (RLR) making 75% of the paddy area in the country, 95% of it being located in NET where only 7% of the farm land has access to irrigation (OAE, 2011). A single RLR cycle is performed annually with rice seedlings prepared in May and transplanted when there is sufficient amount of ponded water in the fields (Fig. 2). Typical problems possibly occurring during the same

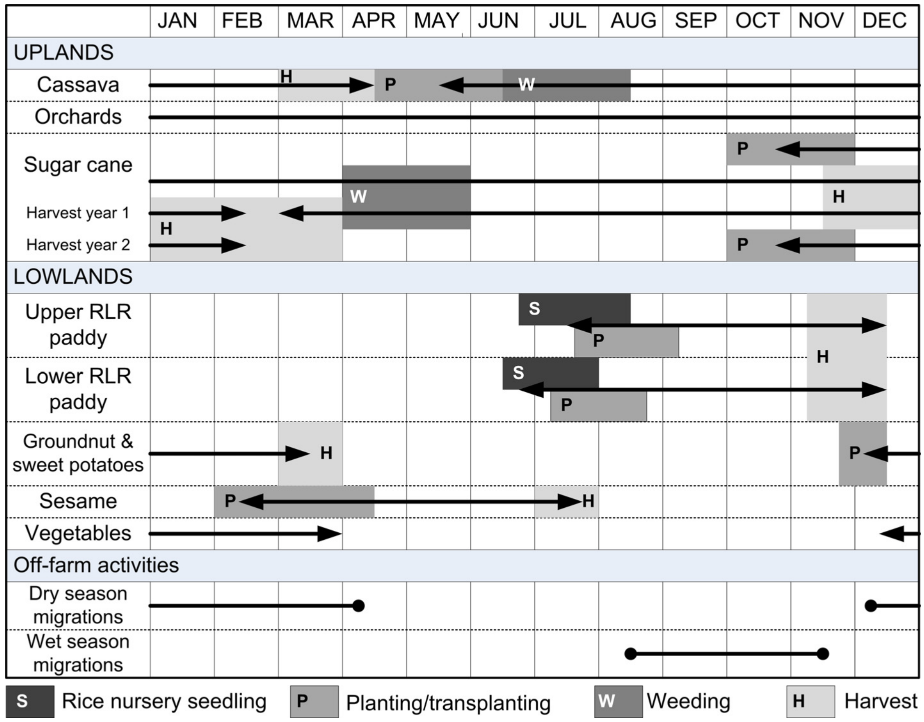

Fig. 2. Calendars of major crops in Northeast Thailand, adapted from Barnaud (2002) and Devillers and Cousinou (2003).
Fig. 2. *Calendriers des principaux cycles culturaux dans le Nord-Est de la Thaïlande, adapté de Barnaud (2002), et Devillers et Cousinou (2003).*

crop year include dry spells in the early rainy season and deep flooding at the peak of the wet monsoon in September. Farmers usually sow several rice seedling nurseries at different dates and elevations to minimize risks of total crop failure. If the rainy season is delayed or too weak, farmers do not transplant rice but practice direct-seeding, which produces lower yields mainly due to weed infestation (Sanusan *et al.*, 2010). Double cropping systems are limited to groundnut and sweet potato after RLR, and sesame before RLR (Polthanee and Marten, 1986). While the initial stage of the cycle (December–January) relies on residual soil moisture, light rainfall during the second part (February–March) provides yields up to 2 and 6 t.ha^{-1} for groundnuts and sweet potatoes, respectively (Polthanee, 1991). Sesame, planted between February and April, and harvested in late July, relies on a mix of residual moisture from the previous rainy season and pre-rainy season light rainfall (Fig. 2). These double-cropping systems tend to be abandoned because of unfavourable climatic constraints including erratic rainfall, especially during the earliest stages of the rainy season, and rising temperature depleting soil moisture through increased evapotranspiration (Polthanee and Marten, 1986; Polthanee and Promkhambut, 2014).

The main industrial crops are sugarcane and cassava. Sugarcane is usually located above the paddies where the soil productivity is too low for RLR. It is planted at the end of the rainy season when the soil moisture decreases but still allows ploughing with reduced efforts. The development then stops at the peak of the dry season. Harvest extends from December to March. Ratooning starts as soon as there is enough water after harvest (mostly in April) and can last two years allowing two additional harvests. Cassava is usually preferred to sugarcane in water deficient areas on sandy soils because of its higher drought-tolerance (Polthanee *et al.*, 2014). A diverse range of mainly vegetable and horticultural crops are traditionally planted on the bank of rivers after water recedes at the end of the rainy season. This small-scale dry season production is for home-consumption and local markets (Fig. 2).

The conversion of forest to RLR began centuries ago in lowland areas. In 1950, forests covered more than half of NET (Sutthipibul, 1987). Thereafter, deforestation extended to upland areas where cash crops stimulated the emerging market economy. In 2009, 36% of NET was covered by RLR, 16% by forest, 10% by annual crops, 4% by tree plantations, most of the remaining land being non-agricultural surface (MOA, 2010). Despite the lack of scientific evidence, the rapid deforestation that occurred over the last half century is often blamed as a major cause for the recurrent droughts that have been faced by farmers in the region.

3 Material and methods

3.1 Rainfall variables

Quality-controlled daily rainfall time series were provided by the Mekong River Commission for 17 stations in NET covering the period January 1953–December 2004 (Tab. 1). Thirty annual variables were derived from the daily data to capture the main climate features that control rainfed agricultural production. They are grouped into five categories.

3.1.1 Timing of the rainy season (variables 1 to 3)

These variables correspond to the ordinal dates (number of days since January 1st) of the onset and retreat of the

Table 1. Rainfall stations.
Tableau 1. *Stations pluviométriques.*

Stations	Latitude North	Longitude East	Elevation m	Mean annual Rainfall (mm)
Chaiyaphum	15°48′	101°51′	250	1,133
Fang	19°58′	99°14′	470	1,312
Kalasin	16°26′	103°31′	142	1,344
Khon Kaen	16°20′	102°51′	157	1,220
Loei	17°27′	101°44′	251	1,238
Luang Prabang	19°53′	102°08′	301	1,297
Maha Sarakham	16°11′	103°18′	150	1,219
Mukdahan	16°32′	104°44′	138	1,500
Nakhon Phanom	17°30′	104°20′	140	2,289
Nong Khai	17°52′	102°45′	173	1,597
Roi Et	16°03′	103°41′	140	1,375
Sakhon Nakhon	17°10′	104°09′	160	1,563
Sisaket	15°07′	104°20′	124	1,478
Surin	14°53′	103°29′	145	1,347
Ubon Ratchathani	15°15′	104°53′	127	1,596
Udon Thani	17°26′	102°46′	178	1,434
Vientiane	17°57′	102°31′	170	1,625

rainy season (variables 1 and 2, respectively), and of the first day of the rainiest 5-day period (variable 3), which coincides, with the rainfall peak of the rainy season. The onset of the rainy season was defined as the first day of the first 10-day period that meets two conditions: the 10-day rainfall depth is higher than the mean 10-day rainfall depth averaged over the period 1953–2004, and at least two of the next three 10-day periods satisfy the first condition. Because of the high rainfall variability, the variations between consecutive 10-day rainfall depths were first smoothed by a 3-time-step moving average. The retreat of the rainy season was defined by symmetrical conditions, starting from the end of the calendar year and moving backward through the 10-day periods. Figure 3 in Lacombe *et al.* (2012) illustrates how variables 1 and 2 are defined. Farming practices and crop yields are closely related to the occurrence of the rainy season, particularly its onset. A delayed rainy season onset may result in delayed transplanting of RLR seedlings or poor emergence and early vegetative growth of crops. A delayed retreat of the rainy season may result in excess soil moisture before and during rice harvest with risks of yield and grain quality losses.

3.1.2 Extreme events (variables 4 and 5)

Variable 4 is the total rainfall depth of the rainiest 5-day period. Variable 5 corresponds to the greatest number of consecutive rainy season days with less than 1 mm of rainfall per day. It reflects farmers' drought definition, which associates drought to extended dry spells during the wet season (Amir Faisal *et al.*, 2014). These extreme events create anoxic conditions through prolonged flood submersion, or drought stress, reducing crop yields.

3.1.3 Intensity index (variable 6)

The intensity index is the number of rainiest days that cumulate 67% of annual rainfall depth (Sun *et al.*, 2006). A low index is associated to a rainfall pattern with few but heavy rainy days while a large index reflects a more regular distribution of rain events in the year.

3.1.4 Seasonal rainfall depths (variables 7 to 18)

These 12 variables correspond to the cumulative rainfall depth for different pairwise associations of three periods (whole year, rainy season and dry season) and four ranges of daily rainfall depths (whole range, low, medium and high rainfall). The low, medium and high ranges of daily rainfall were determined so that the cumulative daily rainfall depths within each of these three ranges are the same over the study period.

3.1.5 Seasonal numbers of rainy days (variables 19 to 30)

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 7–18.

3.2 Local and regional trend tests

Each of the 510 annual time series (30 variables at 17 stations) were tested for the presence of trends with the Mann-Kendall test (Mann, 1945; Kendall, 1975), one of the most frequently used trend detection tests applied to hydro-meteorological time series. This non-parametric test is robust as it does not require the data to follow any particular statistical

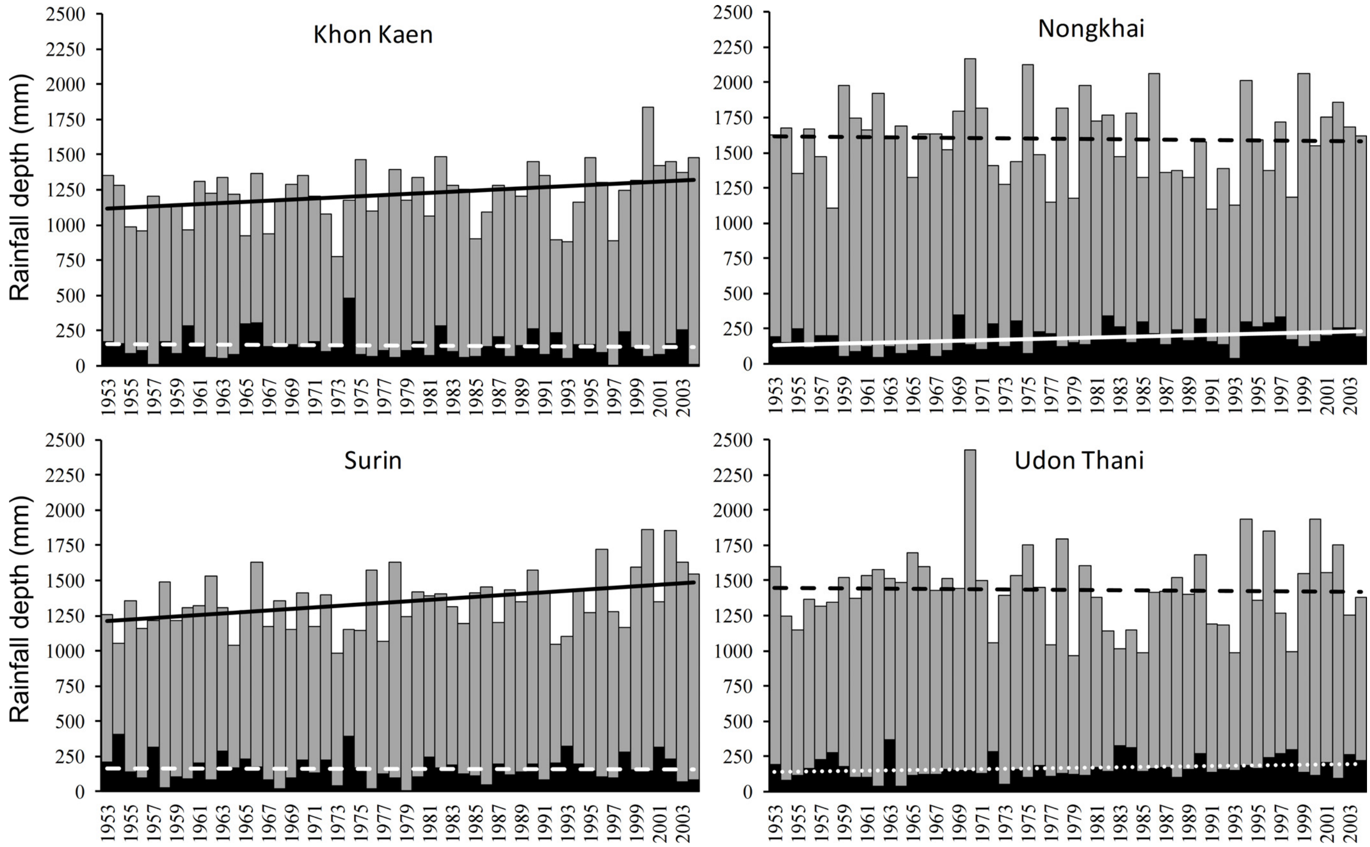

Fig. 3. Time series for annual (grey) and dry season rainfall (black). Solid trend line is significant at 95% confidence level. Dotted trend line is significant at 90% confidence level. Dashed trend line is statistically insignificant.

Fig. 3. *Chroniques des pluies annuelles (gris) et de saison sèche (noir). Ligne continue : tendance significative au seuil de 95 %. Ligne pointillée : tendance significative au seuil de 90 %. Ligne en tirets : tendance non significative.*

distribution and it has low sensitivity to outliers. A modified version of this test (Hamed, 2008) was used to account for possible auto-correlations and to minimize the related overestimation of trend significance. Trend slopes were calculated with the Sen's slope estimator (Sen, 1968).

This modified Mann-Kendall test determines whether a trend exists locally but does not confirm if a trend is evident throughout an entire region. The field significance (Vogel and Kroll, 1989), equivalent to the statistical significance of a regional trend, indicates whether a trend emerges from a group of stations in the same region. It was calculated as follows. Possible auto-correlation was first removed by pre-whitening the rainfall time series, *i.e.* by assuming a first-order auto-correlation structure and removing it from the time series (Hamed, 2009). A regional average Kendall's statistic (Douglas *et al.*, 2000) was calculated for each one of the 30 rainfall variables using a re-sampling technique (Kundzewicz and Robson, 2004). The field significance associated with the regional Kendall's statistic was finally derived from the re-sampled time series using the Weibull plotting position formula. Two confidence levels of trend significance (90% and 95%) were considered at both local and regional scales.

It should be noted that different auto-correlation structures are considered in this analysis: long-term persistence at local level and first-order auto-correlation at regional level. Assuming a first-order auto-correlation at both local and regional levels would enable an accurate comparison of local and regional significances of trends, as performed in Lacombe *et al.* (2012). However, this alternative approach, although more consistent, might be less accurate. Indeed, the long-term persistence, not easily accountable in the regional trend test, better reflects the natural behaviour of meteorological time series at the local level, hence our proposed approach.

4 Results

Out of the 510 tested time series, only 44 and 63 exhibit a trend significant at the 95% and 90% confidence levels, respectively (Tabs. 2, 3 and 4). Significant trends in the timing of the rainy season (variables 1–3), in the intensity of extreme events (variable 4), and in the intensity index (variable 6) are almost inexistent. Only four stations exhibit significant trends in the duration of dry spells (variable 5) (Tab. 2). Among the 24 significant trends in cumulative rainfall depths, 20 are positive. Among the 26 significant trends in the number of rainy days, 21 are positive. The few negative trends are observed during the rainy season only, indicating that rainy season trends are more heterogeneous in direction than those, uniformly positive, observed during the dry season (Tabs. 3 and 4).

Table 2. Sen's slopes and significance of trends in variables 1–6.
Tableau 2. *Pentes et significativités des tendances pour les variables 1–6.*

		Timing of the rainy season			Extreme events		Intensity index
Variable number		1	2	3	4	5	6
Rainfall stations	Chaiyaphum					−0.08[b]	
	Fang	−0.27[a]					0.16[b]
	Kalasin						
	Khon Kaen						
	Loei						
	Luang Prabang		0.27[a]		0.61[a]		
	Maha Sarakham						
	Mukdahan					0.04[b]	
	Nakhon Phanom					0.02[a]	
	Nong Khai					−0.05[a]	0.14[b]
	Roi Et						
	Sakhon Nakhon						
	Sisaket						
	Surin	−0.26[a]		−1.00[b]			
	Ubon Ratchathani				1.22[b]		
	Udon Thani						
	Vientiane			−0.80[a]			
Field significance							

[a] 90% significance.
[b] 95% significance.

Table 3. Sen's slopes and significance of trends in variables 7–18.
Tableau 3. *Pentes et significativités des tendances pour les variables 7–18.*

		Rainfall depth											
		Whole year				Rainy season				Dry season			
		All	Low	Medium	High	All	Low	Medium	High	All	Low	Medium	High
Variable number		7	8	9	10	11	12	13	14	15	16	17	18
Rainfall stations	Chaiyaphum				−3.49[b]								
	Fang				−3.82[b]								
	Kalasin										0.63[b]		
	Khon Kaen	4.19[b]			3.36[b]	3.51[b]			2.74[a]				
	Loei				2.60[a]								
	Luang Prabang	6.05[b]				5.98[a]		3.32[b]					
	Maha Sarakham												
	Mukdahan												
	Nakhon Phanom												
	Nong Khai				−4.01[a]				−4.18[a]	2.00[b]	1.00[b]	1.05[b]	
	Roi Et												
	Sakhon Nakhon	5.01[a]			5.55[b]				5.00[b]				
	Sisaket												
	Surin	5.12[b]			5.45[b]	5.64[b]			5.46[b]				
	Ubon Ratchathani												
	Udon Thani									1.33[a]			
	Vientiane												
Field significance										>0[a]		>0[a]	>0[a]

[a] 90% significance.
[b] 95% significance.

Table 4. Sen's slopes and significance of trends in variables 19–30.
Tableau 4. *Pentes et significativités des tendances pour les variables 19–30.*

		Number of rainy days											
		Whole year				Rainy season				Dry season			
		All	Low	Medium	High	All	Low	Medium	High	All	Low	Medium	High
Variable number		19	20	21	22	23	24	25	26	27	28	29	30
Rainfall stations	Chaiyaphum								−0.04[a]			0.01[a]	
	Fang				−0.06[b]						0.09[b]		
	Kalasin	0.31[b]	0.30[b]							0.14[b]	0.14[b]		
	Khon Kaen				0.05[b]				0.05[b]				
	Loei				0.06[b]								
	Luang Prabang	0.23[b]				0.30[b]		0.13[b]					
	Maha Sarakham											0.02[a]	
	Mukdahan												
	Nakhon Phanom												
	Nong Khai									0.26[b]	0.20[b]	0.06[b]	
	Roi Et			−0.04[a]									
	Sakhon Nakhon												
	Sisaket	0.82[b]				0.75[b]					0.08[b]		
	Surin				0.08[b]				0.08[b]				
	Ubon Ratchathani												
	Udon Thani						−0.14[b]						
	Vientiane								−0.03[a]				
Field significance		>0[a]								>0[a]	>0[a]	>0[a]	>0[a]

[a] 90% significance.
[b] 95% significance.

Figure 3 displays annual and dry season rainfall time series at four stations where contrasting trends are observed. In Nongkhai and Udon Thani, dry season rainfall has significantly increased while annual rainfall does not exhibit any significant trend. In contrast, in Surin and Khon Kaen, annual rainfall has significantly increased while dry season rainfall does not exhibit any significant trend. This comparison illustrates two types of heterogeneities:
- the complex behaviour of climate trends which can reveal contrasting trend significances across seasons, though at the same location;
- the high spatial variability of rainfall trends directions between stations distant by less than 200 km.

Despite insignificant trends at most stations in the onset and retreat of the rainy season (Tab. 2), Figure 4 shows that high inter-annual variability exists. The variability of the onset (standard deviation = 17 and 22 days in Nakhon Phanom and Surin, respectively) is greater than that of the retreat (standard deviation = 11 and 13 days, respectively). This difference illustrates the difficulty for farmers to determine the appropriate sowing time while harvesting time is mainly determined by the photoperiodicity of their RLR cultivars.

Figure 5 shows that the few 90%-field significant regional trends correspond to increases in rainfall depths and numbers of rainy days during the dry season mainly (Tabs. 3 and 4). Except for the timing of the rainy season onset and of the 5-day rainiest period (variables 1 and 3) exhibiting insignificant declining regional trends, all other variables exhibit rising regional trends, revealing an overall increase of rainfall depths and number of rainy days during both seasons. This highlights the importance of evaluating regional trends, which not only indicate the spatial extent of a changing pattern but also enable the detection of long-term changes that remain insignificant at individual stations due to the high variability of small-scale rainfall events and related sampling issues.

5 Discussion

The ability of the Mann-Kendall test to detect true trend in climate time series might be reduced when the tested variable is discrete and includes several ties as in the case of variable 5 (duration of longest dry spells). We plotted the statistical significance of the local trends in this variable against their slope and found that the lower detection threshold (90%) corresponds to a slope equivalent to an additional 1.6 day of mean longest dry spell over the 52-year study period. This result confirms the ability of the test to detect slight changes in the studied rainfall variables.

Increased dry season rainfall in NET was found to be consistent with wider on-going climate dynamics observed in East Asia and explained by the weakening of the East Asian winter monsoon (Zhou, 2011). These changes were attributed to global warming (Zhang *et al.*, 2011), indicating that rainfall is likely to continue increasing in the future. This wetting tendency may appear counterintuitive. 2015 has been the driest

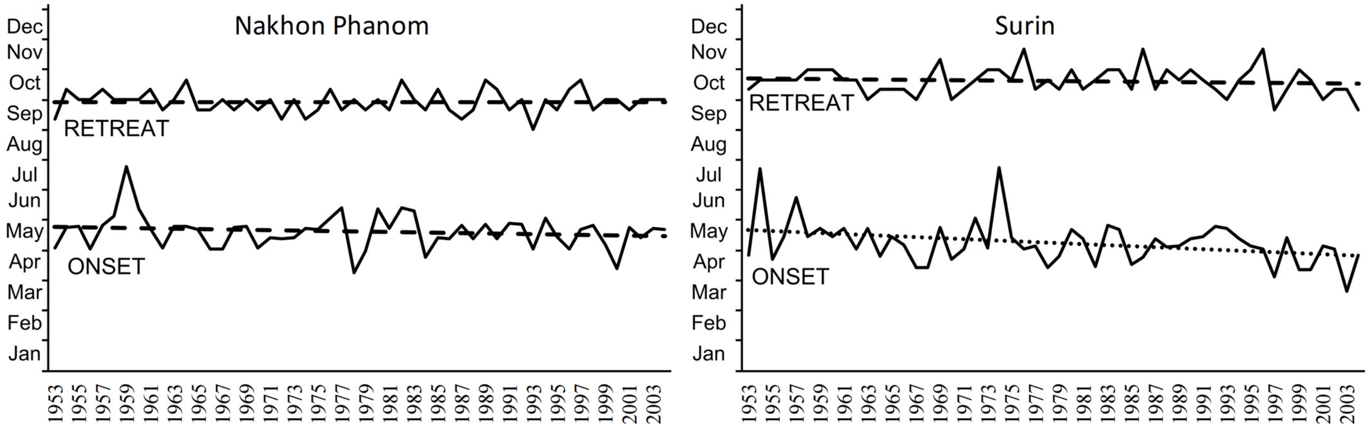

Fig. 4. Occurrence of the onset and retreat of the rainy season. Dotted trend line is significant at 90% confidence level. Dashed trend lines are statistically insignificant.

Fig. 4. *Évolution de la date de début et de fin de la saison des pluies. Ligne pointillée : tendance significative au seuil de 90 %. Ligne en tirets : tendance non significative.*

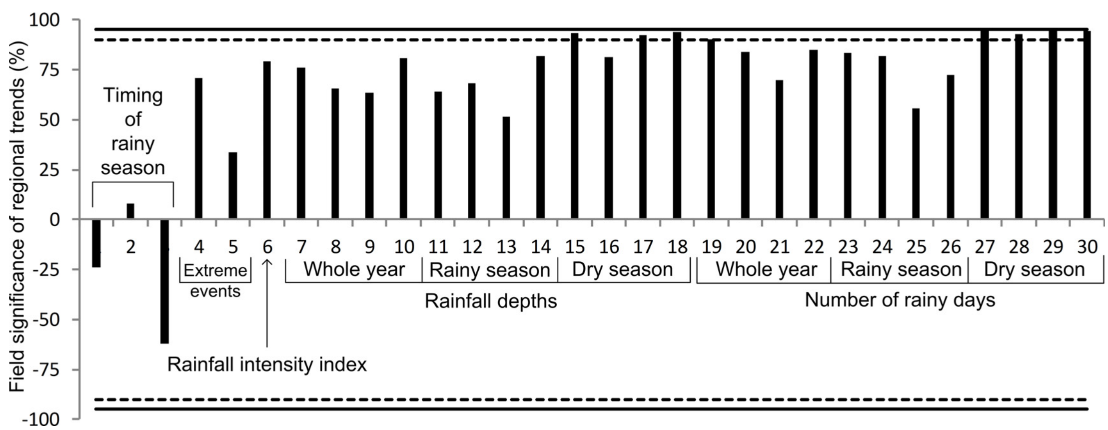

Fig. 5. Field significances of regional trends. Positive and negative values correspond to positive and negative trends, respectively. Solid horizontal line: 95% significance level. Dotted horizontal line: 90% significance level. NB: field significance = statistical significance of regional trend.

Fig. 5. *Significativité des tendances régionales. Les valeurs positives et négatives correspondent aux tendances positives et négatives, respectivement. Les lignes horizontales continues et pointillées correspondent aux seuils de significativité de 95 % et 90 %, respectivement.*

year since 1995 in Southeast Asia, due to an extreme El Niño event (FAO, 2015). Such episodes remain in the memories while insignificant and gradual increases in rainfall go unnoticed, thus possibly giving the impression that rainfall has reduced over recent decades (Amir Faisal *et al*., 2014).

Mean dry season rainfall increased by 12 mm from 1953 to 2004. Although it is statistically significant at the regional level, this slight increase corresponds to about 7% of the mean total dry season rainfall, far lower than the typical crop water requirements in NET which vary from 500 mm to 1,500 mm per cropping cycle (Allen *et al*., 1998).

No effect of increased dry season rainfall is expected on RLR since rice quality is mainly controlled by the number of rainy days during the rainy season (Polthanee and Promkhambut, 2014), which did not vary significantly (Tab. 4). Due to the absence of regional trends in the rainy season retreat, the increase in dry season rainfall is unlikely to occur in its earliest phase, leading to no change in the risk of damaged quality of the paddy at harvest. Similarly, the absence of regional trend in the rainy season onset is unlikely to accelerate the switch from RLR transplanting to direct seeding. Increased rainfall in the early dry season is unfavourable for groundnut plantation because it creates a hard soil surface and soil crusting leading to poor germination, more weeds, and often the need to plough again and replant the crop. But additional rainfall in February–March is favourable after pegging and during pod filling stage. Additional rainfall at the end of the dry season could contribute to secure the establishment of sesame before RLR but this system remains risky due to the highly variable rainy season onset (Fig. 4).

The deep rooting system and fast crop establishment of sugarcane will be favoured by additional rain at the beginning of the dry season. The limited additional dry season rainfall combined with coarse textured soils in these uplands should not hamper the harvest and the transport of the cane by trucks. No significant impact of additional rainfall in the dry season on cassava is expected as most of the crop growth occurs during the wet season (Fig. 2). Recently, rubber plantations have been established in the more humid areas of the region and a wetter dry season will benefit this relatively new perennial crop.

Vegetables and horticultural crops planted on the bank of rivers will benefit from a wetter dry season, especially during its cooler first half. A moderate increase in dry season rainfall may sustain river base-flow at a higher level than currently observed, thus benefiting gardens grown on river banks. But at this stage, the detected increase in rainfall seems too limited to help recharge the shallow aquifers and small ponds on which these systems depend frequently to expand their planted areas.

6 Conclusions

While positive effects of the detected change in rainfall pattern on the existing cropping systems dominate, it is still far too limited to stimulate farmers' switch to new types of mono or double cropping systems, or to use more external inputs, in order to increase crop yields. Benefit from additional dry season rainfall remains marginal but more remarkable effects are expected in the future if these trends persist, as expected according to the most updated climate projections for the East Asian winter monsoon (Xu *et al*., 2016). The benefit of additional rainwater for crop production should also be considered in light of the expected warming trend. Above 35 °C, a temperature threshold that tends to be exceeded more frequently at rice flowering time in NET (Pornamnuaylap *et al*., 2014), pollen fertility decreases, inducing yield declines. Several naturally spontaneous adaptations include early anthesis time, panicle cooling through transpiration, and the selection of heat-tolerant varieties (Lafarge *et al*., 2016). Increased temperature also depletes soil water reserves through enhanced evapotranspiration. The benefit from additional rainfall is enhanced if drought risks are moderated by supplemental irrigation water resources, such as the expansion of thousands of small and multipurpose on-farm ponds installed across NET during the past two decades. They allow the practice of integrated farming systems combining rice, fish rearing, fruit and vegetable production and contribute to food security at the household level across this region. For centuries, the very adaptive and resilient Lao-Isan population in NET has been facing climate uncertainties with up to six-month dry season with scorching temperatures in March–April forcing them to practice internal seasonal migrations to wet spots and to secure part of their food from non-timber forest products. More recently migrations head to urban centres and foreign countries to generate off-farm incomes supporting the continuation of small-scale family farming. Gaining from this traditional flexibility, there is no doubt that NET farmers will find ways to adapt to the limited change in rainfall distribution reported here.

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