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Variability and Trend of Heat Index in Thailand during 1975-2017 and Their Relationships with Some Demographic-Health Variables

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Abstract

Variability and trend of Heat Index (HI) in Thailand during 1975-2017 and their relationships with some demographic-health variables were analyzed. Results revealed the spatially coherent and widespread significant increase in Thailand's HI, consistent with significant country-wide warming. Thailand's HI as a whole significantly increased by 0.53°C per decade, and it was in the caution level but will gradually rise to the extreme caution level in the near future. Accompanying this trend, the HI distribution and characteristic have significantly shifted towards a higher health impact level in the recent decades. In addition, year-to-year HI variability significantly correlated with the El Niño–Southern Oscillation (ENSO) index, providing additional evidence that ENSO events are an important source of Thailand's climate variability including extremely hot weather. Further analysis showed that Thailand's HI had good positive associations with some demographic-health variables. These results provide some clues that increasing HI may contribute to elevated cases of heat-sensitive illness and pose an additional health risk to Thai people especially the elder persons which have rapidly grown under the aging society era. To better understand how heat and health in Thailand are linked, however, further detection and attribution studies based on newly available long-term health data are needed.

Keywords: Heat index; Trend; Demographic; Health

1. Introduction

A multiple-day heat or hot weather often referred to as 'heat wave' has recognized as a pervasive natural hazard (e.g., Coates *et al*., 2014; Perkins *et al*., 2016; Morabito *et al*., 2017). Heat waves have therefore attracted much scientific attention and are of great public concern due to their high impacts on society and environment, including a rise in mortality and morbidity (e.g., Gong *et al*., 2012; Sun *et al*., 2014; Rohini *et al*., 2016). When humidity is high, extremely hot weather events and heat waves can severely cause in humans' exacerbated illness and death (e.g., Koppe *et al*., 2004; Meehl and Tebaldi, 2004; Guo *et al*., 2012). Recent studies have shown with strong confidence that the increased frequency, severity and duration of heat waves, among other types of weather extreme events, are closely connected to human-caused climate change associated with an increased greenhouse effect (e.g., Field *et al*., 2012; Adina, 2014).

Accumulated evidence has revealed that heat waves occurred more often and lasted longer during the last decades. Kunkel *et al*. (2008) reported a strong increase in heat waves in the United State since 1960. Increasing numbers of heat waves during the beginning

1960s-the mid-2000s in the eastern Mediterranean (Kuglitsch *et al*., 2009) and over most parts of China (Ding *et al*., 2010) were observed. A record-breaking heat wave occurred in Europe in the summer of 2003 which caused around 70,000 heat-related deaths (Robine *et al*., 2008). During the 2003 European heat wave, monthly temperature in central Europe was beyond the historical distribution range (Schär *et al*., 2004). Other well-known examples of recent heat waves include the 2010 heat wave in Russia (Barriopedro *et al*., 2011), the 2015 heat waves in Pakistan (Qamar., 2015) and the 2016 heat waves in South Korea (Sang *et al*., 2018). In each case, severely hot temperatures contributed to human mortality and caused widespread economic impacts, inconvenience and discomfort. A global climate model further shows that heat waves would become more intense, longer lasting, and/or more frequent in a future warmer climate (IPCC, 2013). Moreover, regional multi-model experiments disclose that the probability of a summer experiencing mega-heat waves such as the 2003 European heat wave will increase by a factor of 5 to 10 within the next 40 years (Barriopedro *et al*., 2011).

Given the potentially significant social-economic impacts of heat waves, an up-to-date scientific knowledge at national, sub-national and local scales is tremendously essential for supporting decision-making processes and area-based implementation of effective adaptation actions especially for public health sector. In this study, HI derived from temperature and relative humidity data was calculated and its variability and trend for the period 1975 to 2017 were statistically analyzed for Thailand, a country for which the number of studies related to heat waves and extremely hot weathers are still limited. Associations between variability and trend in HI and ENSO index and some demographic-health variables were further examined.

2. Materials and Methods

2.1 Data Sources

In this study, daily records of mean surface air temperature (AT) and relative humidity (RH) obtained from Thai Meteorological Department (TMD) during 1975-2017 were used. The data are routinely measured at TMD's near-surface stations distributed across Thailand. To select the data with completeness and minimal missing values, the criteria used by Limsakul and Singhruck (2016) and Limsakul *et al*. (2017) were applied. Based on these criteria, 74 stations were initially chosen for the following quality control and homogeneity checks.

Demographic (annual number of total and elderly populations, labor forces and international tourists) and health (annual cases of hypertension, rheumatic heart disease, diabetes mellitus, pneumonitis, stroke, mood disorder and posttraumatic stress disorder) data were also used to correlate with annual Thailand's HI series. These variables were selected based on the heat-sensitive associations reported in the previous studies (e.g., Glen *et al*., 2010; Renjie *et al*., 2013; Xiang *et al*., 2014). The data were extracted from the available sources of long-term digitized demographic-health archives of Provincial Administration, National Statistical Office, World Bank and Office of the National Economic and Social Development Board. Note that periods of the data are shorter than HI series ranging from 16 to 25 years.

2.2 Quality Control and Homogeneity Checks

The quality and homogeneity of the selected data were statistically tested using the commonly used methods (Tank *et al*., 2009). The outliers were first identified for each data series by comparing their values to adjacent days and to the same day at nearby stations before they were edited or removed. The second step was to assess homogeneity of data based on the penalized t-test and the penalized maximal F-test. These methods are able to identify multiple step changes in time series by comparing the goodness of fit of a two-phase regression model with that of a linear trend for the entire base series (Wang *et al*., 2007; Wang, 2008). Based on homogeneity test, 62 inhomogeneity records of AT were detected. It was observed that the significant shifts presented in the AT records systematically occurred around 2005-2006. Further inquiry with TMD found that the method for calculating daily mean AT have been changed around that time. The recent period from the 2006 onwards was then used as the reference base to adjust the previous period of the inhomogeneity data records. For RH, there were 37 records identified as inhomogeneity. Unlike AT records, significant shifts of RH records occurred randomly in time. A relative inhomogeneity adjustment which the candidate series is examined with the nearby homogeneity stations were applied (Aguilar *et al*., 2003). The homogeneous nearby stations well correlated with the inhomogeneous records were selected as the reference series. Following the quality control procedure and homogeneity checks, the data set of 74 high-quality records (Figure 1) were prepared for calculation of HI and further analysis.

2.3 Heat Index used

Many heat indices have been used to estimate heat exposure and to capture the combined adverse effects of several weather factors (e.g. Parson, 2014; WMO-WHO, 2015). It is recognized that AT alone is not a good indicator of human thermal environment or heat. Most of thermal indices are then a combination of at least two variables in order to well describe the complex condition of heat exchange between the human body and its environment. One of the commonly used thermal indices for environmental health research is Steadman's apparent temperature (Steadman 1979a, 1984b). It relies only on temperature and moisture, often also called "Heat Index". One of its advantages is that it is a simple index suitable for variability and long-term change study based on observed weather data. In this study, we used the Steadman's apparent equation derived from a multiple regression analysis (Rothfusz, 1990) which the formula is as follows;

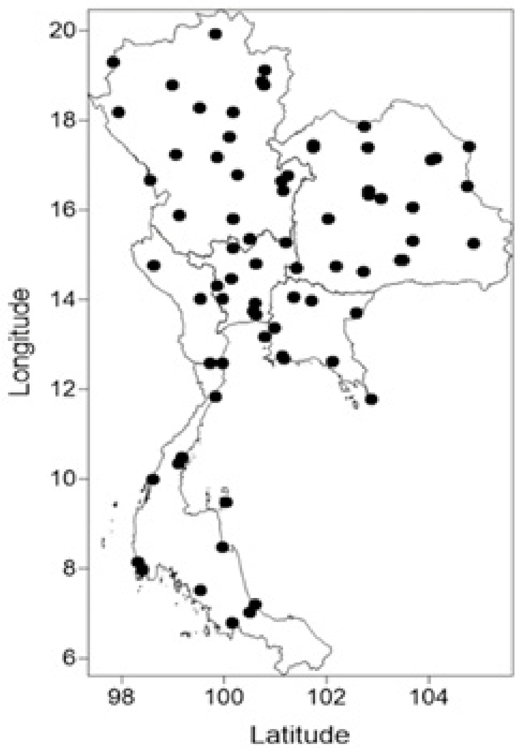

Figure 1. Geographic locations of 74 weather stations with high-quality daily AT and RH for the period 1975-2017

$$HI = -42.379 + 2.04901523T + 10.14333127R - 0.22475541TR - 6.83783 \times 10^{-3} T^2 \;\; 5.481717 \times 10^{-2} R^2 + 1.22874 \times 10^{-3} T^2 R \;\; 8.5282 \times 10^{-4} TR^2$$

$$°C = (°F - 32) \times 5/9$$

Where HI is the heat index (°C), T represents the air temperature (°C) and RH denotes the relative humidity (%). The HI values calculated based on this formula has an error of ±0.08°C (Zahid and Rasul, 2010; Rajib *et al*., 2011).

2.4 Analysis Methods

At each station, HI was calculated from daily records of AT and RH. Monthly and yearly series of AT, RH and HI were then computed from daily data. A non-parametric Kendall's tau-based slope was applied to estimate linear trends from yearly series of AT, RH and HI (Sen, 1968; Chu *et al*., 2010). This method is more appropriate to address non-normal distributions of data and to account for the outliers and autocorrelation (Klein Tank *et al*., 2009). In this paper, a trend is statistically significant if its p-value equals or less than 0.05.

A station-by-station trend was estimated to illustrate the spatial patterns of AT, RH and HI. To provide overall trends of three variables in Thailand as a whole, time series for 1975-2017 were created by averaging anomalies of all stations to a base period of 1975-2017 by giving all the stations equal weight.

Empirical Orthogonal Function (EOF) technique was used to identify the dominant spatio-temporal patterns of HI. The EOF is multivariate statistics widely applied to analyze spatio-temporal variability and physical behaviors in climate studies (e.g., Preisendorfer, 1988; Hannachi *et al*., 2007). EOF analysis aims to linearly transform a space-time field into orthogonal functions (eigenvalue/eigenvector) of physically interpretable patterns of variability, while retaining as much as possible of the variance presented in the original data sets. In practice, EOF analysis produces three outputs: coefficients time series, spatial loadings (eigenvectors) and eigenvalues which are the fraction of total variance explained by each EOF mode.

To statistically compare the differences in characteristics of HI over the last four decades, the annual series were arbitrarily separated into two 21-year periods: 1976-1996 and 1997-2017. The probability distribution functions (PDFs) were then generated by binning annual values across their range for the 1976-1996 and 1997-2017 intervals. PDF calculation was done by fitting the data before and after 1997 intervals with gamma distribution function which shape (α) and scale (γ) parameters had been estimated by Maximum Likelihood method (Borrow and Hulme, 1996; Lloyd-Hughes and Saunders, 2002). A 2-tailed Kolmogorov-Smimov test was employed to evaluate whether the probability of two periods was significantly different. This test compares two sets of data under the null hypothesis that two PDFs for two time periods are identical but with unspecified distribution (Griffiths and Bradley, 2007; Chu *et al*., 2010).

Spearman's rank order correlation was employed to examine the degree of associations between annual Thailand's HI series and some demographic-health variable series. The lengths of annual Thailand's HI and demographic-health variable series used for correlation analysis ranged from 16 to 25 years. A correlation was taken to be significant when the no-correlation null hypothesis was exceeded with a probability of 95%.

3. Results and Discussions

3.1 Histogram and Seasonal Variations of HI

Histograms of daily HI calculated based on all AT and RH data were illustrated in Figure 2. Analysis revealed that HI in Thailand during 1975-2017 exhibited a normal distribution with most of the values (63.4%) in range of 27-35°C (Figure 2a). HI derived from this study is comparable with the values calculated in South Korea (Ho *et al*., 2006), Pakistan (Zahid and Rasul, 2010) and Bangladesh (Rajib *et al*., 2011). When looking at sub-region pictures, the distribution of HI was relatively similar (Figure 2).

However, the HI in the central and eastern parts showed a large proportion of higher values than other sub-regions (Figure 2b and 2c). Limjirakan and Limsakul (2012) also showed that AT in the central and eastern Thailand was higher than other sub-regions. Rapid urbanization and industrialization and change in land use taken place in these sub-regions (Limjirakan and Limsakul, 2012) may attribute to such observation.

When considering in the context of the health impact levels classified by National Weather Service, it was found that more than 80% of HI in Thailand during 1975-2017 in the caution and higher health-impact classes (Table 1). Whereas, the HI with extreme caution, danger and extreme danger levels was greater than 40%. A larger proportion of HI in these classes implies a higher exposure to hot weather for Thai people especially the vulnerable groups such as elderly persons, outdoor workers and poor people.

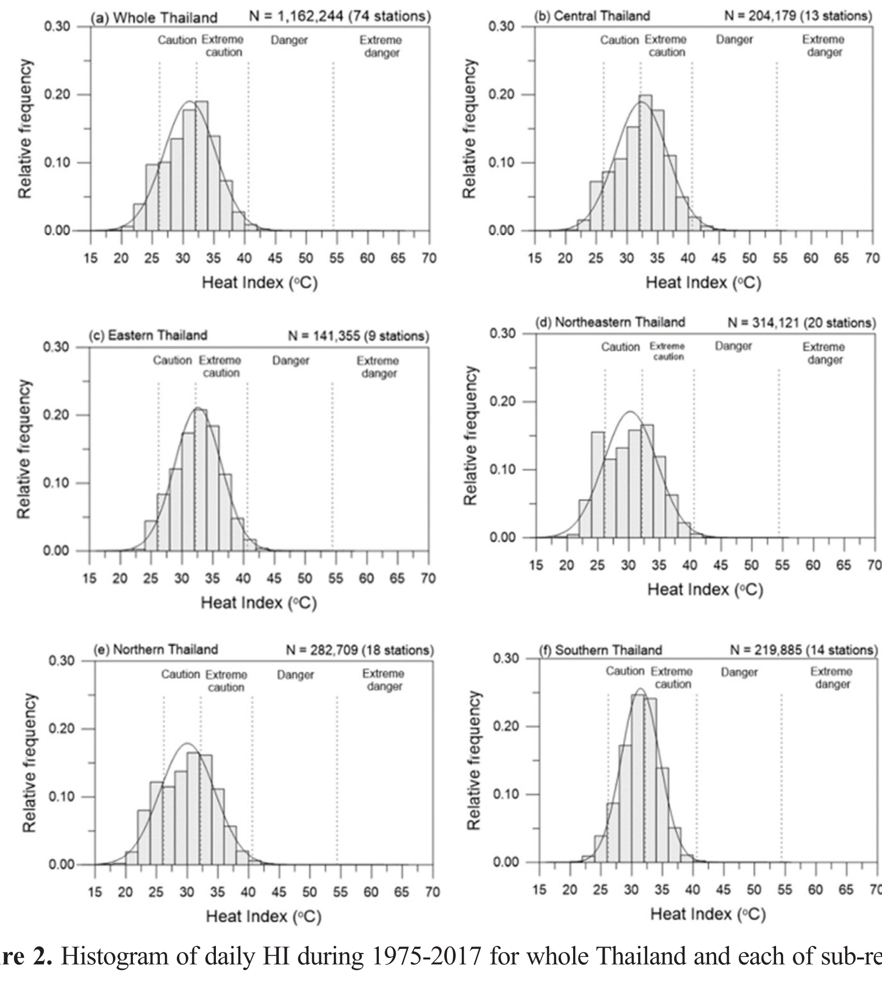

Figure 2. Histogram of daily HI during 1975-2017 for whole Thailand and each of sub-regions

Table 1. Percentages of HI in Thailand during 1975-2017 for each level of the health impacts

HI (°C)	Category	%
< 26.7	Normal	18
26.7 – 32.2	Caution	40
32.2 – 40.6	Extreme caution	41
40.6– 54.4	Danger	1
> 54.4	Extreme danger	-

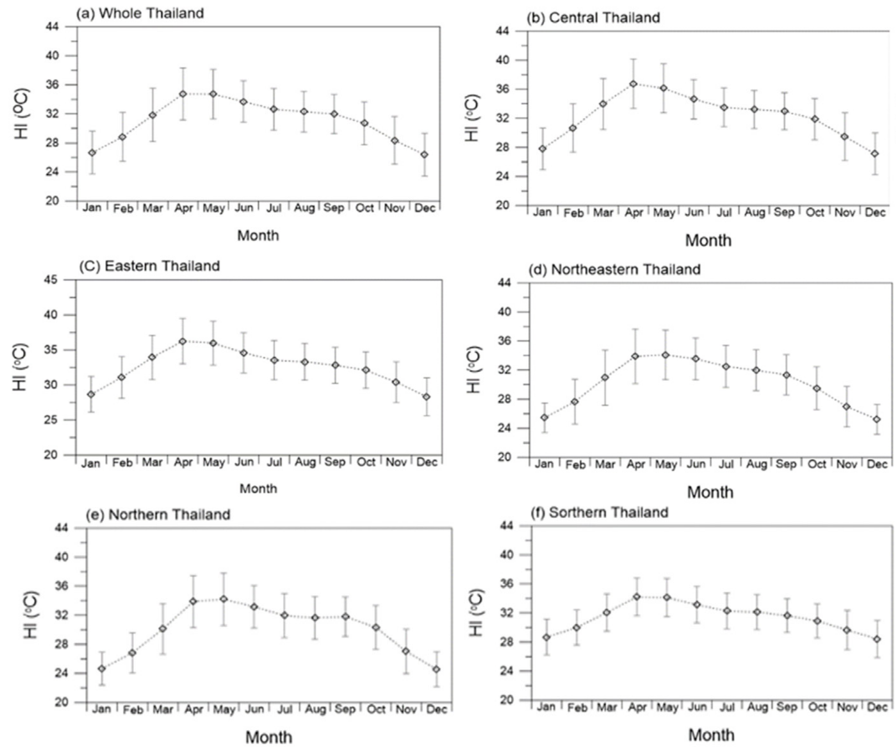

Figure 3. Monthly climatology of HI during 1975-2017 for whole Thailand and each of sub-regions

The results also showed that HI exhibited similar seasonal patterns (Figure 3). That is, maximum values of HI occurred during the period of March-July corresponding to higher levels of AT and RH. HI exhibited substantial variability during April-June as indicated by large standard deviations (Figure 3). Interestingly, the peak of HI in northern Thailand corresponds well to the period when highest haze pollution from open burning takes place (Suwanprasit *et al*., 2018). The occurrence of these climate and air pollution-related hazards in the same time is believed to have strong synergy to exert substantial effect on local people health. Seasonal patterns of HI observed in this study are similar to those reported in the East Malaysia (Suparta and Yatim, 2017) and Pakistan (Zahid and Rasul, 2010).

3.2 Variability and Trend of HI

The coherent and widespread significant increases stood out from spatial pattern of station-by-station trends of annual Thailand's HI during 1975-2017 (Figure 4a). 89.2% of the stations showed positive trends at the significant rates ranging from 0.3 and 1.7°C per decade. Zahid and Rasul (2010) found similar trends of HI in different regions of Pakistan, showing significant increase during the summer season from 1961 to 2007. In addition, the increasing trends of HI during 1961-2010 were evident in almost all the regions of Bangladesh (Rajib *et al*., 2011). By comparison, station-by-station HI trends were spatially consistent with significant country-wide warming observed in Thailand which 73% of AT series showed significant increases at the rates ranging from 0.21-0.76°C per decade (Figure 4b). Such a great spatial association between HI and AT was supported well by a highly significant correlation ($r = 0.90$, $p < 0.01$; $n = 74$) between the two. This was particularly true for the HI with the increasing rate greater than 1°C per decade occurred at the same sub-regions concentrated in the central and east parts of Thailand where remarkable increases in AT were marked (Figs. 4a and 4b). It should be noted, however, that trends in HI have a very low association with those in RH (Figure 4a and 4c). Based on these results, it is reasonable to say that, in Thailand, AT rather than RH is the major contribution of variability and change in HI.

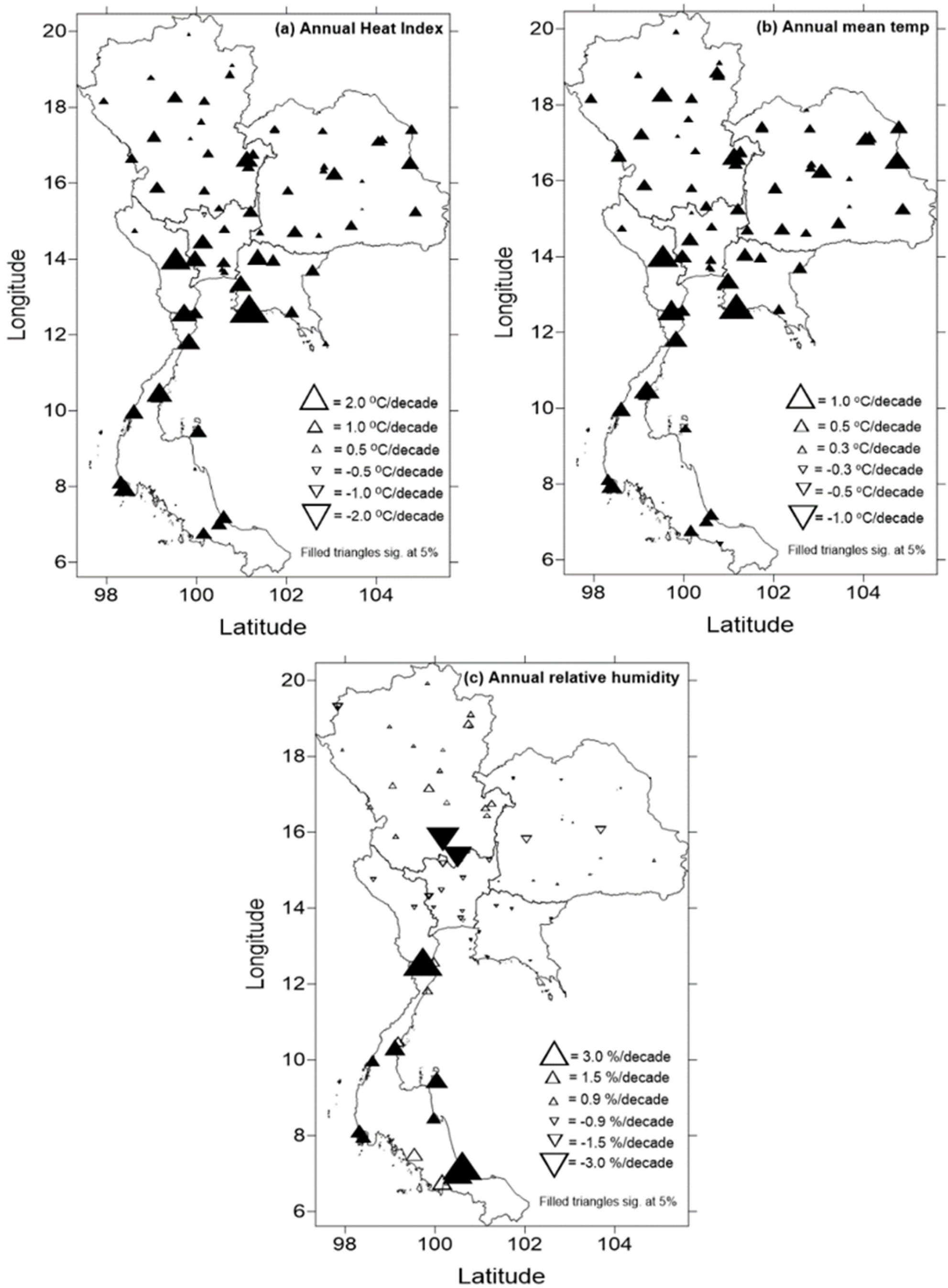

Figure 4. Trend per decade for annual HI(a), AT(b) and RH(c) in Thailand for the period 1975-2017

Averaging annual values of all stations for the period 1975-2017, HI in Thailand as a whole increased significantly by 0.53°C per decade (2.3°C for 43 years) (Figure 5a). Compared with the previous studies, this increasing rate is higher than the trend detected in the Mesoamerica and Caribbean Region (0.5°C per decade) (Ramirez-Beltran *et al*., 2017), is comparable with the trend reported in Pakistan (0.63°C per decade) (Zahid and Rasul, 2010), but is lower than the trend observed in Bangladesh (1.5°C per decade) (Rajib *et al*., 2011). For the past 43 years (1975-2017), HI in Thailand was in the caution level but will gradually rise to the extreme caution level in the near future. Similar significant increase was also observed in AT but the rate averaged all stations was lower nearly twofold (Figure 5b). These results indicate that HI increases almost two times compared with the warming level occurred in Thailand.

To further examine year-to-year variability in HI and its relation to ENSO phenomenon, correlation analysis between detrended HI anomalies and the Multi-ENSO Index (MEI) series was performed. The MEI was used to represent the state of ENSO, as it integrates more meteorological and oceanographic information than other indices (Wolter and Timlin, 1998). It was evident that year-to-year variability in HI significantly correlated positively with the MEI ($r = 0.53$, $p = 0.01$; $n = 43$) (Figure 6). HI in Thailand appeared to be higher than normal in the El Niño (positive MEI) years such as 1987, 2015 and 2016 whereas it tended to be lower than usual for the La Niña (negative MEI) years (1999, 2008 and 2011). Our analysis provides additional evidence to support the findings of Limsakul and Goes (2008) which showed that ENSO events are an important source of interannual variability in Thailand's surface air temperatures including its extreme events and heat.

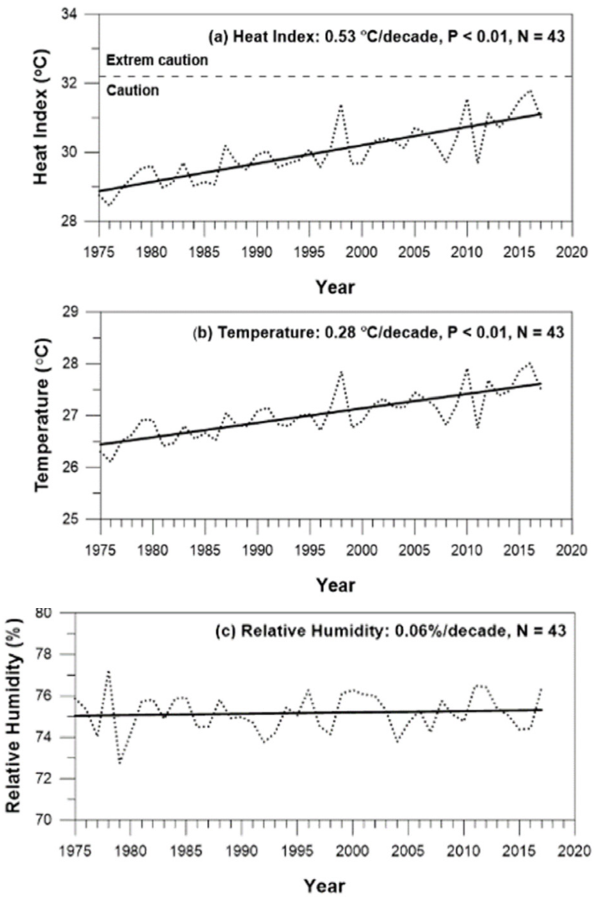

Figure 5. Anomaly series and trends of annual HI(a), AT(b) and RH(c) in Thailand for the period 1975-2017

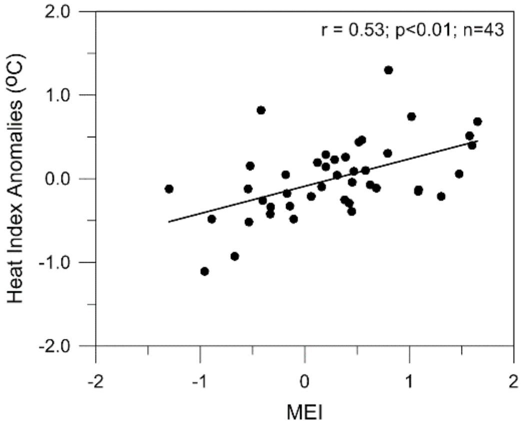

Figure 6. Correlation between HI anomalies and MEI series

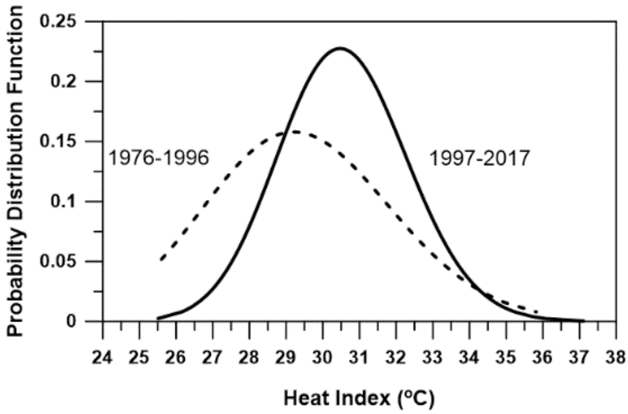

Figure 7. Normalized annual PDFs of HI estimated by gamma distribution. Dash and solid lines are the fitted gamma functions to the data before and after 1997

3.3 PDFs of HI Distribution

The PDFs computed for the 1976–1996 and 1997–2017 intervals showed a positive shift in Thailand's HI in the recent decades, consistent with a significant shift in AT as identified by Limjirakan and Limsakul (2012) (Figure 7). Based on a two-tailed Kolmogorov-Smimov test, the PDFs of HI in the 1997–2017 intervals was significantly different from the previous period at the 1% level. The statistically significant differences in PDFs between two periods indicate a significant shift in Thailand's HI under ongoing anthropogenically-caused warming toward the higher health-impact level in the most recent decades.

3.4 Trends and Dominant Mode of HI Frequency

Analysis of station-by-station trends for each of the health impact levels showed overall decline in the frequency of HI in the caution and extreme caution levels which were observed in the southern, eastern and central parts of Thailand (Figure 8). On the other hand, there was an obvious increase in the frequency of HI in the danger level with significant rise noticed in the same areas (Figure 8). EOF analysis disclosed that the leading mode of HI frequency distribution explained 83% of the total fractional variance (Figure 9). This leading mode showed a shift from decreases in the caution and extreme caution levels to substantial increase in the danger level (Figure 9).

The pattern of loadings revealed that the majority of stations exhibited this shift was those located in the southern, eastern and central parts of Thailand similar to what was observed in the spatial trend maps. These results provide additional evidence of a shift in Thailand's HI frequency distribution over the past 43 years towards a higher health impact level, in concert with significant warming and concomitant increases in HI and upper-tail extreme temperature events.

3.5 Relationships between HI and Some Demographic-Health Variables

Correlation analysis revealed that annual Thailand's HI had good positive correlations with some demographic-health variables, highlighting possible causal associations between rising heat and health risk. Annual HI showed significant correlations with the number of total populations, elder populations and international tourists (Table 2). These results may suggest that a higher proportion of Thai people especially the elder persons which have grown rapidly under aging society era (Knodel, 2015) has increasingly exposed hotter weather, posing an additional health risk and causing a higher vulnerability to heat-related illness. Kuzuya (2013) showed that nearly half of Japanese patients taken to hospital due to heatstroke were aged 65 years or older. More recently, Cheng *et al*. (2018) found significant associations between heat waves and mortality in the elderly population of Australia. Significant associations between rising HI and increasing numbers of labor forces and international tourists may also provide additional evidence of an increasing health risk of these vulnerable groups who are physiologically and environmentally more susceptible to hot weather. Previous studies pointed out that outdoor workers particularly in agriculture, construction and other industries have increasingly exposed hot weather that leads to severe illness or death (Jackson *et al*., 2010; OHSA, 2013).

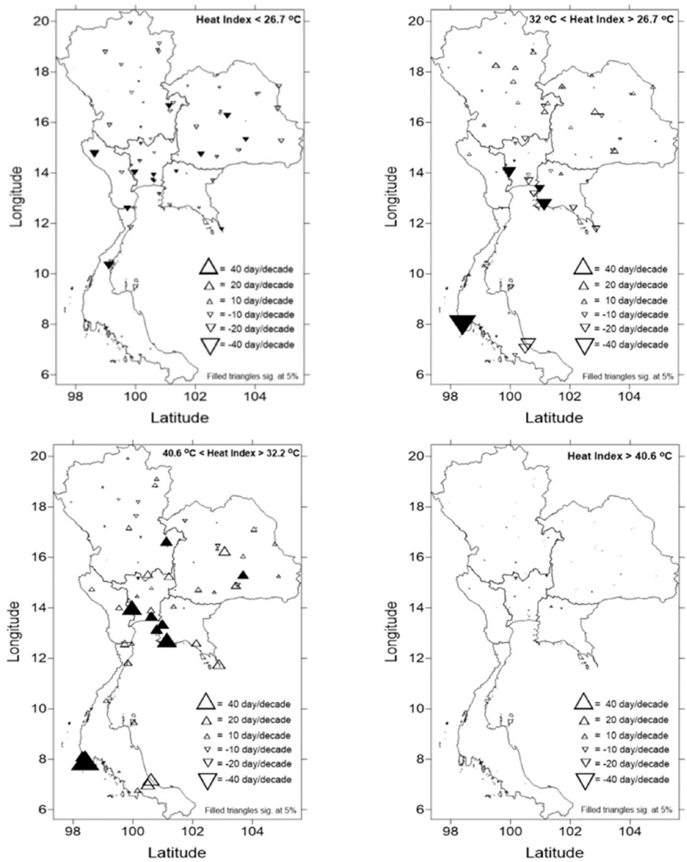

Figure 8. Trend per decade of HI frequency in each of health impact classes

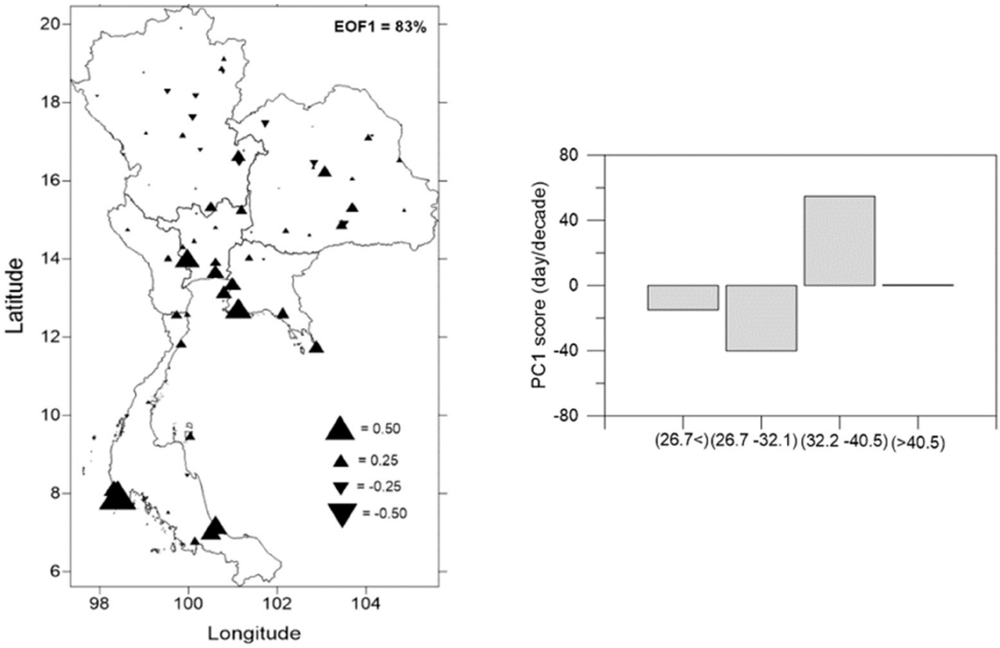

Figure 9. Loadings of EOF1 and its associated component scores analyzed based on HI frequency trends of all stations for each of the health impact classes (74 stations × 4 health-impact class trend matrix)

Table 2. Correlation between HI and some selected demographic-health variables

Demographic	*r*	n
Total population	0.65**	25
Elderly population ≥ 65	0.65**	25
Labor force	0.50*	24
International Tourist Arrivals	0.56*	16
International Tourist ages ≥ 65	0.50*	16
Health		
Hypertension	0.62*	23
Rheumatic heart disease	0.67*	23
Diabetes mellitus	0.58*	23
Pneumonitis	0.63**	22
Stroke	0.65**	23
Mood disorder	0.61*	22
Posttraumatic stress disorder	0.61*	22

*Significant at the 5% level. ** Significant at the 1% level.

n = periods of data series used for correlation analysis which are 25 years (1993-2017) , 24 years (1993-2016), 16 years (2000-2015), 23 years (1994-2016) and 22 years (1994-1999 and 2001-2016) respectively.

Significant relationships as observed in Table 2 may also indicate that larger number cases of heat-sensitive illness have increasingly exposed to rising HI which has become an additional predisposing factor making these illness conditions worse. This is due to fact that extreme heat and hot weather can exacerbate the physiological adaptive capacity of sick and vulnerable people (Somkid, 2017). Kenny *et al*. (2010) found individuals with diabetes have significantly higher rates of heat illness and death during heat waves than the general population. In addition, diabetes mellitus is associated with several metabolic, cardiovascular and neurologic dysfunctions, which may also play roles in impairing thermoregulatory mechanisms during heat exposure. Chen *et al*. (2013) showed that hot temperature was associated with increased risk of stroke mortality in China. It was also found that heat waves were associated with increased rates of admissions for mental disorders in conjunction with other disorders such as cardiovascular and renal illness in Australia (Nitschke, 2011). Wang *et al*. (2014) demonstrated that extreme temperature posed a risk to the health and well-being for individuals with mental and behavior illnesses. Moreover, Hansen *et al*. (2008) found a positive association between ambient temperature and hospital admissions for mental and behavioral disorders during heat waves.

4. Conclusions

Analysis of variability and trend of HI in Thailand during 1975-2017 and their possible relationships with some demographic-health variables can highlight the interesting findings as follows:

1. Thailand's HI exhibited both prominent year-to-year variability and significant long-term trend. Both of them are related to interannual climate variability especially that associated with ENSO and ongoing human-caused warming.

2. Thailand's HI had good positive associations with some demographic-health variables. These results provide some clues that the increasing HI may contribute to elevated cases of heat-sensitive illness and pose an additional health risk to Thai people especially the elder persons which have rapidly grown under the aging society era.

3. To better understand cause-effect links of heat and health in Thailand, further detection and attribution studies based on newly available long-term health data are needed.

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