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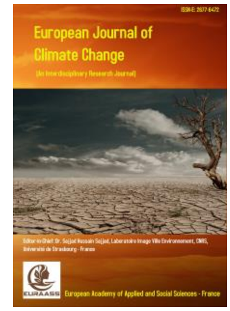

Research Article

Long–term spatio–temporal warming tendency in the Vietnamese Mekong Delta based on observed and high–resolution gridded datasets

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Abstract

The Vietnamese Mekong Delta is among the most vulnerable deltas to climate–related hazards across the globe. In this study, the annual mean and extreme temperatures from 11 meteorological stations over the Vietnamese Mekong Delta were subjected to normality, homogeneity and trend analysis by employing a number of powerful statistical tests (i.e. Shapiro–Wilk, Buishand Range test, classical/modified Mann–Kendall test and Sen's slope estimator). As for spatio–temporal assessment, the well–known (0.5° × 0.5°) high–resolution gridded dataset (i.e. CRU TS4.02) was also utilized to examine trend possibilities for three different time periods (i.e. 1901–2017, 1951–2017 and 1981–2017) by integrating spatial interpolation algorithms (i.e. IDW and Ordinary Kriging) with statistical trend tests. Comparing the calculated test–statistics to their critical values (α = 0.05), it is evident that most of the temperature records can be considered to be normal and non–homogeneous with respect to normality and homogeneity test respectively. As for temporal trend detection, the outcomes show high domination of significantly increasing trends. Additionally, the results of trend estimation indicate that the magnitude of increase in minimum temperature was mostly greater than mean and maximum ones and the recent period (1981–2017) also revealed greater increasing rates compared to the entire analyzed period and second half of the 20th century. In general, these findings yield various evident indications of warming tendency in the Vietnamese Mekong Delta over the last three decades.

Keywords:

CRU TS dataset, spatio–temporal variability, Vietnamese Mekong Delta, warming trend.

1. Introduction

Detecting and estimating statistical characteristics of a given time series are one of the most essential tasks in hydrology and climatology. Machiwal and Jha (2006) highlighted the prime importance of time series analysis techniques for analyzing hydro–

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meteorological datasets based on a comprehensive review, which will be conducive to a wide range of integrated water resources management in the context of climate change and variability. Additionally, Kundzewicz and Robson (2004) expounded a detailed instruction on the methodology for change detection in hydrological records, including several key stages such as preparing well–founded datasets, implementing exploratory data analysis, employing adequate statistical tests and interpreting test results.

In general, parametric slope–based and non–parametric rank–based approaches are available for hydro–meteorological trend detection and estimation. The latter (i.e. Mann–Kendall or Spearman's rho test) performs better than the former (i.e. linear regression) in case of non–normal or skewed data and the presence of outlier or extreme values (Jaagus, 2006; Partal & Kahya, 2006). However, these two approaches still necessitate the critical assumption of independence of hydro–meteorological observations. Previous studies have proposed a number of remedies against the effect of serial correlation on the performance of the Mann–Kendall (MK) test, embracing pre–whitening procedure (Kulkarni & von Storch, 1995), trend–free pre–whitening procedure (Yue et al., 2002), variance correction approach (Hamed & Rao, 1998; Yue & Wang, 2004) and block bootstrap (Kundzewicz & Robson, 2000). The fundamental theory and step–by–step procedure for implementing these modified MK tests were elucidated by Khaliq et al. (2009); Sonali and Nagesh Kumar (2013).

During the last few decades, there have been various salient case studies in the field of hydro–meteorological time series analysis across the globe. X. Zhang et al. (2000) evaluated spatial and temporal trends in maximum, minimum and mean temperatures, diurnal temperature ranges, precipitation totals and ratio of snowfall over total precipitation for southern Canada during 20th century and for the whole Canada during the second half of this century. Additionally, various abnormal and extreme indices were taken into account, indicating the occurrence of drought–like conjuncture of warm and dry conditions. Jaagus (2006) also clarified temporal trends in temperature, precipitation, snow cover duration and onset date of climatic seasons in Estonia over the second half of 20th century by employing linear regression and the MK test. Moreover, characteristics of large–scale atmospheric circulation were involved to compare with these climatic trend possibilities by applying the conditional MK test. Partal and Kahya (2006) applied both intra–block procedure (i.e. MK test) and aligned rank procedure (Sen's *T* test) to examine trend existence in precipitation data of each individual station as well as regional averages over Turkey for the period 1929–1993. Additionally, the contribution of each month to the annual trends was discussed clearly and the beginning years of detected trends were also determined by using the sequential MK test.

Machiwal and Jha (2008) carried out a well–conducted study that made use of multiple statistical tests to analyze rainfall time series characteristics (i.e. normality, homogeneity, stationarity, trend, periodicity and stochastic component) at Kharagpur (India) for the period 1957–2002. Particularly, the performance of selected methods was evaluated in detail to emphasize the importance of adequate choice and number of statistical tests for hydrological time series analysis. In the Far–West China, Q. Zhang et al. (2009) found a profound warming tendency during the period 1960–2004, mostly dominated by significantly increasing trends in minimum temperatures. Mohsin and Gough (2010) used long–term temperature time series from urban, suburban and rural meteorological stations to assess significance of detected trends and identify possible abrupt changes in relationship with ongoing urbanization in the Greater Toronto Area. Oguntunde et al. (2011) investigated spatial and temporal rainfall trends and variability in Nigeria for the whole 20th century by using global high–resolution gridded dataset (i.e. CRU TS2.1).

Viola et al. (2014) revealed numerous evident indications of warming trends in terms of space and time over Sicily for the period 1924–2006 and delved into a very long series (1793–2003) to substantiate greater magnitude of warming process as for recent decades (100, 50 and 25 years) compared to the whole 200–year period. Mir et al. (2015) also employed the MK test and Sen's slope estimator to quantify annual, seasonal and monthly trends in a number of climatic variables over the Satluj River basin, western Himalaya. Generally, it is found that the significantly increasing trends in temperatures (especially minimum temperature) were likely to control trend behaviors of the remaining climatic variables and eventually river discharge. Moreover, the results of trend detection in rainfall and snowfall indicated possible shifting of precipitation from solid to liquid in the study area. Sonali and Nagesh Kumar (2016) applied various modified MK test to the well–known high–resolution gridded dataset (i.e. CRU TS3.21) in order to analyze spatio–temporal trends of extreme temperatures along with potential evapotranspiration over India for the second half of 20th century. Moreover, the correlation between potential evapotranspiration and extreme temperatures was also discussed in detail.

As for analyzing spatial and temporal trend patterns in hydro–meteorological records over Vietnam, there have also been a number of prominent investigations during the last few decades. Nguyen-Thi et al. (2012) examined long–term rainfall trends in relation to tropical cyclone occurrences for the whole Vietnam and four sub–regions during the period from 1961 to 2008. Vu-Thanh et al. (2014) found a significant increase in drought conditions over seven climate sub–regions of Vietnam for the period 1961–2007 by employing PED index, while there were opposite trend directions between the northern and southern sub–regions as indicated by applying the de Martonne (*J*) index and standardized precipitation index (SPI). Moreover, an increasing trend in the drought–affected area was also documented by analyzing the number of stations affected by drought deriving from the *J* and SPI time series.

Nguyen et al. (2014) found a significant increase of 0.26 ± 0.10 °C/decade as for annual average temperature over the whole of Vietnam for the period 1971–2010, while rainfall trend behaviors were mostly dominated by insignificantly declining trends. Moreover, the linkage between ENSO and climate variability was interpreted explicitly and the reclassification of Vietnam's climate sub–regions was also proposed by applying cluster analysis. Recently, Ngo-Thanh et al. (2018) showed that the onset dates of rainy season and summer monsoon season over the Central Highlands of Vietnam tended to be earlier by 1.79 and 2.5 days/decade, while the retreat dates of these seasons did not vary considerably during the period 1981–2014, although there was no any statistically significant trend detected by utilizing the MK test. Kien et al. (2019) yielded numerous evident indications of climatic changes in conjunction with spatial distribution of agricultural land over Vietnam in order to emphasize some potential impacts of climate change on the Vietnam's agricultural sector, especially rice production in the Red River and Mekong River deltas.

The Vietnamese Mekong Delta (VMD) occupies the majority of agriculture and aquaculture area of Vietnam, contributing to approximately 55.2% and 69.6% of total rice and aquaculture production for the whole country in 2016 respectively (General Statistics Office, 2018). Generally, the VMD plays a crucial role in achieving national target of food security (Smajgl et al., 2015). However, the VMD was recognized as one of the most vulnerable regions in Southeast Asia to a number of climate–related hazards, mostly dominated by sea level rise (Yusuf & Francisco, 2009). In fact, there have been numerous hands–on solutions implemented in order to respond to possible impacts of sea level rise and salinity intrusion. Smajgl et al. (2015) emphasized that a reliable and effective adaptation strategy should integrate soft options (i.e. crop and land–use change) with hard options (i.e. investments of water infrastructure). However, such combined remedy still remains potential uncertainties, embracing temperature and rainfall changes. Nhan et al. (2011) stated that temperature and rainfall are among the most dominant weather/climate variables that greatly affect rice and aquaculture (especially shrimp) production in the VMD with the affected degree depending on different factors (i.e. cultivated plants and their growth stages, dry or wet seasons, irrigated or coastal regions). Hence, detailed information concerning long–term variability of mean and extreme temperatures will yield various scientific merits in proposing effective and efficient adaptation strategies for sustainable agriculture as well as integrated water resources management in the VMD.

To best of authors' knowledge, there is no study that takes spatial and temporal trend possibilities of both observed and gridded temperature datasets in the VMD into consideration. In an attempt to cover this lacuna, the present study was conducted to (i) test the normality and homogeneity of observed records, (ii) detect and estimate the temporal trends over three recent decades, and (iii) examine the spatial and temporal trends of high–resolution gridded dataset (CRU TS4.02) for three different time periods (i.e. 1901–2017, 1951–2017 and 1981–2017).

2. Study area and data

The selected study area is the Vietnamese Mekong Delta, which is located in the southwestern part of Vietnam and also in the most downstream area of the transboundary Mekong river basin (Figure 1). The total area of the VMD is approximately 40,816 km^2, with the proportion of agricultural land being nearly 64.3%. By 2017, the number of inhabitants was around 17.7 billion and the proportion of population living in the rural area was nearly 74.5% (General Statistics Office, 2018).

According to the well–known world map of the Köppen–Geiger climate classification proposed by Peel et al. (2007), the general climate of the VMD is categorized as tropical monsoon (Am) or tropical savannah (Aw) climate. Additionally, the VMD is located in the western part of Southern Delta, which is one of seven climate sub–regions of Vietnam (Nguyen et al., 2014; Vu-Thanh et al., 2014; Kien et al., 2019). In general, the annual mean temperature in the VMD is around 27.1°C with monthly variations being from approximately 25.5°C in January to 28.6°C in April, whereas the total amount of annual rainfall varies from around 1300 mm to 2400 mm, mostly contributed by rainfall in the rainy season. It is evident that the occurrence of salinity intrusion in the dry season and of flooding in the rainy season are likely to be more exacerbated due to the combined impacts of sea level rise and hydropower operation in the upstream area of the Mekong river, which could lead to water scarcity or water–related hazards in the VMD.

This study delved into both types of data to explore warming tendency in the VMD. The observed dataset consists of monthly mean, minimum and maximum temperature time series obtained from 11 local meteorological stations for the period 1978/1985–2015. It is worth mentioning that the spatial distribution of these selected station is fairly proportional to the whole extent of the VMD (Figure 1). In addition, the well–known high–resolution gridded dataset (CRU TS4.02) of monthly mean, maximum and minimum temperatures, which was generated by the Climatic Research Unit – University of East Anglia (UK), was also subjected to spatial and temporal trend analysis. Briefly, the CRU TS dataset comprises of 10 climatic variables and covers global land surface at a 0.5° × 0.5° resolution (excluding Antarctica). This study utilized the contemporary version (CRU TS4.02) that covers the period 1901–2017. Harris et al. (2014) presented a detailed description of the CRU TS dataset. Previous versions (CRU TS2.1 or 3.21) were also used successfully by Oguntunde et al. (2011); Sonali and Nagesh Kumar (2016) for the purpose of hydro–meteorological trend analysis.

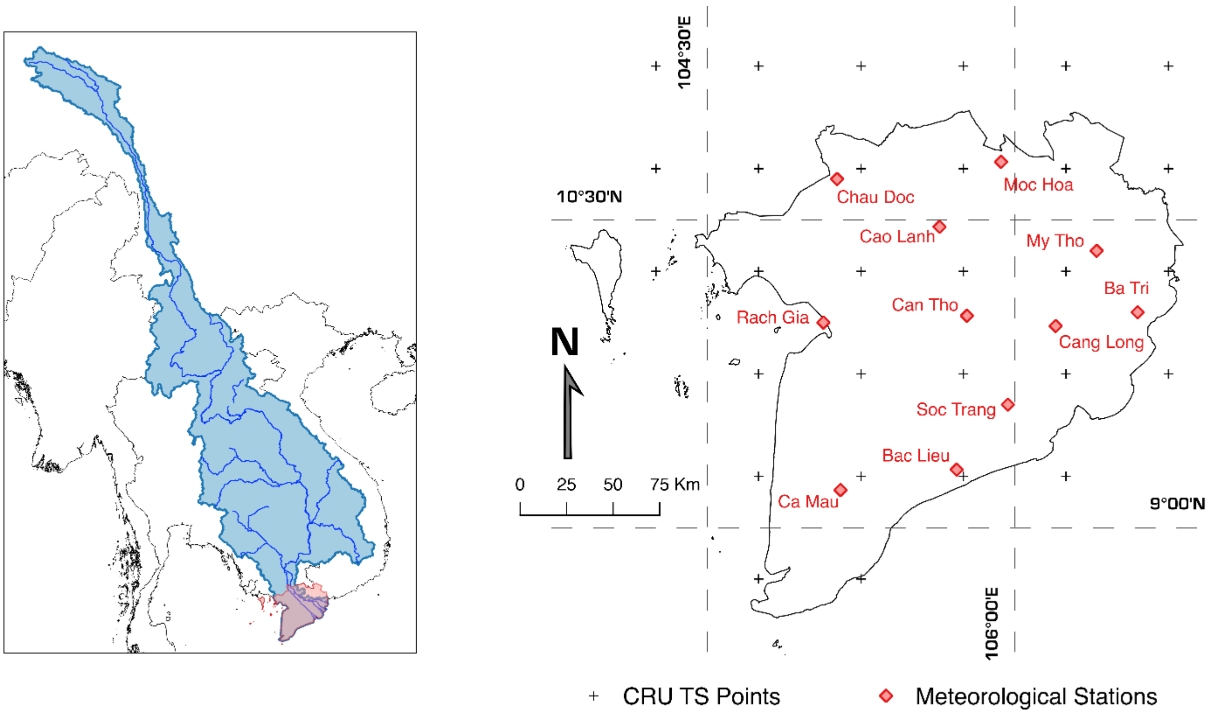


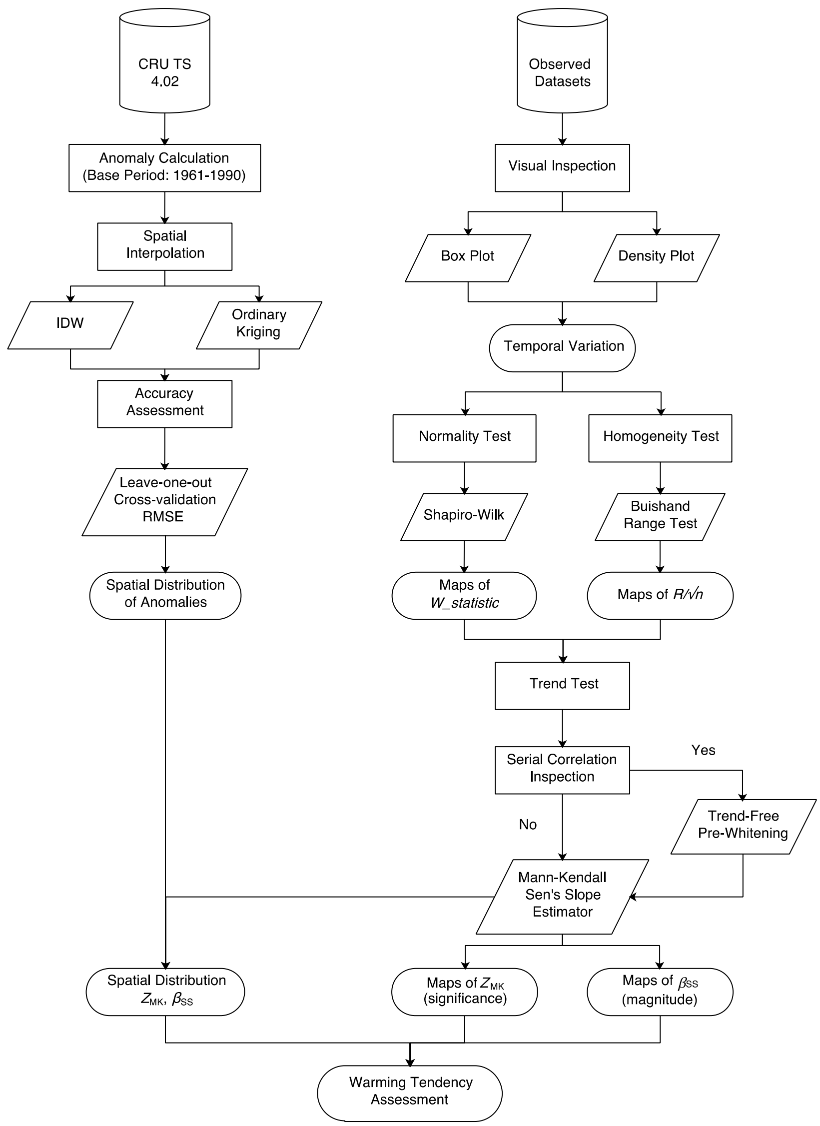
Figure 1: Geographical location of the Vietnamese Mekong Delta.

3. Methodology

Figure 2 shows a brief description of the methodological framework employed in this study. As for the observed dataset, the first step is to visually inspect raw temperature data by utilizing box plot and density plot, which are of the most powerful tools for exploratory data analysis (EDA). In practice, a well–conducted EDA forms a crucial role of evaluating hydro–meteorological changes (Kundzewicz & Robson, 2004). Then, all of observed temperature records are subjected to normality and homogeneity test by applying the Shapiro–Wilk (SW) and Buishand range (BR) test respectively. The SW test was introduced by Shaphiro and Wilk (1965) and also substantiated that performing better than other counterparts such as Kolmogorov–Smirnov, Lilliefors and Anderson–Darling (Mendes & Pala, 2003; Steinskog et al., 2007; Razali & Wah, 2011). The BR test, which is a cumulative deviation approach for identifying possible departures from homogeneity of hydro–meteorological records, was proposed by Buishand (1982). It is found that the BR test is superior to the commonly used von Neumann ratio test as indicated by Buishand (1982) based on data generation method and by Machiwal and Jha (2008) based on observed rainfall data.

With regard to temporal trend analysis over three recent decades in the VMD, the non–parametric Mann–Kendall test (Mann, 1945; Kendall, 1975) and Sen's slope estimator (Sen, 1968) are applied to all of observed mean and extreme temperature time series in order to explore long–term trend possibilities. Furthermore, the trend–free pre–whitening (TFPW) procedure, which was proposed by Yue et al. (2002), is also incorporated in the examination to eliminate the effect of serial correlation on the performance of the MK test. Theoretically, there are a large number of formal statistical tests for normality, homogeneity and trend. Previous studies (Kundzewicz & Robson, 2004; Machiwal & Jha, 2008; Khaliq et al., 2009) recommended applying more than one test to avoid misinterpretation. For the sake of simplicity, this study only employs one test to assess each property (i.e. normality, homogeneity and trend) of all observed temperature records. The method selection is primarily based on the power of each statistical test as pointed out above. The Appendix section provides the descriptions of the SW test, BR test, MK test, Sen's slope estimator and the TFPW procedure in detail. It is worth noting that the outcomes found by these methods are shown in maps for more convenient assessment.

In the meantime, the CRU TS4.02 dataset of mean and extreme temperatures is also taken into account to yield more evident indications of spatial distribution of warming trends for three different time periods (i.e. 1901–2017, 1951–2017 and 1981–2017). The first step is to calculate temperature anomalies relative to the base period (1961–1990). Then, all of temperature anomaly time series are subjected to spatial interpolation by two common algorithms (i.e. IDW and Ordinary Kriging, which are representative of deterministic and statistical models respectively). The next step is to determine better interpolation technique by comparing the root mean square error (*RMSE*) values derived from the process of leave–one–out cross–validation. Subsequently, the interpolated maps of all temperature anomalies for three time periods are also incorporated in the examination of trend possibilities by applying the



classical/modified MK test and Sen's slope estimator. Finally, warming tendency over the VMD is discussed based on these outcomes.

Figure 2: Schematic framework of research methodology.

4. Results and discussion

Figure 3 represents a preliminary interpretation of temporal variations in the observed mean and extreme temperatures at 11 local meteorological stations in the VMD, while a general comparison between the observed and gridded datasets based on regional averages is shown in Figure 4. Particularly, the largest year–to–year variation was found in Ca Mau and Bac Lieu stations as for annual mean temperature, with the interquartile range (*IQR*) values reaching approximately 0.69°C and 0.64°C respectively. The *IQR* values of the remaining annual mean temperature time series varied from 0.29°C at Rach Gia station to 0.46°C at Can Tho station. With regard to extreme temperatures, Chau Doc and Ba Tri stations were responsible for the greatest temporal variation, with the *IQR* values around 0.78°C and 1.08°C respectively. The remaining stations also varied significantly, with the *IQR* values ranging from 0.42–0.70°C and 0.43–0.88°C as for annual minimum and maximum temperature records respectively. Generally, it is apparent that most of annual extreme temperature time series showed greater temporal variation compared to the annual mean ones.

It is also discernible that all of box plots (Figure 3) are arranged in ascending order based on the long–term median values depicted by the middle horizontal lines, which makes it more convenient to compare the magnitude of annual temperature records in the VMD. Particularly, the highest values as for annual mean and minimum temperature records were found in Rach Gia station (at 27.6°C and 22.7°C respectively), while the figure as for annual maximum temperature at this station was significantly lower than most of other stations. Meanwhile, Moc Hoa and Chau Doc stations were responsible for the highest values of annual maximum temperature records, at approximately 34.1°C.

Concerning temporal variations on monthly basis, all of density plots (Figure 3) show that temperature in the VMD is highest during April and May, while the coldest period usually occurs during December and January. The intra–annual variation takes place significantly from the coldest to hottest months. It is also apparent that the regional averages of monthly mean and maximum temperatures show the same pattern, which decreases gradually from the hottest to coldest months. Meanwhile, the regional averages of monthly minimum temperature vary slightly between April and October. Generally, these self–explanatory plots yield a number of statistical characteristics of all observed temperature records graphically.

As shown in Figure 4, there is a high agreement between the observed and gridded dataset based on regional averages. It is discernible that the line plots of both datasets exhibit the same pattern throughout the considered period, although mean and minimum temperature time series as for CRU TS dataset are consistently higher compared to the observed dataset, while maximum temperature time series show opposite pattern. Additionally, correlation test shows strong and positive correlation between both types of temperature data, with the non–parametric Spearman’s rank correlation coefficient values around 0.846, 0.767 and 0.867 as for mean, minimum and maximum temperatures respectively. These initial findings provide a reliable foundation for further spatio–temporal trend analysis by utilizing CRU TS dataset in combination with the observed dataset on station–wise basis.

Proceeding with implementing formal statistical tests (i.e. normality, homogeneity and trend) for all observed temperature records in the VMD, Figure 5 portrays the results of normality test by the SW test. It is clear that most of calculated W statistic values are greater than their critical percentage points (α = 0.05), so the null hypothesis of normal distribution cannot be rejected. Thus, it is inferred that most of annual temperature records in the VMD can be considered to be normal except the annual mean temperature at Soc Trang station, minimum temperature at Cang Long station and maximum temperature at Ba Tri station. These outcomes are fairly consistent with those found by box plots as shown in Figure 3, in which the box plots of these non–normal time series exhibit a large discrepancy between arithmetic mean and median values, or adjacency of middle lines (median) to either bottom or top horizontal lines representing the first or third quartiles.

Concerning homogeneity test for all observed temperature records, it is worth mentioning that this study performed both absolute and relative homogeneity tests as shown in Figure 6 and Figure 7 respectively. Absolute test is that uses only single station time series, while relative test is that uses the reference time series derived from taking difference between actual values of considered station and respective regional means of the remaining stations in a certain year (Buishand, 1982). Theoretically, relative test is more powerful in case there is presence of sufficient correlation between the test and reference series, otherwise absolute test is more preferable (Wijngaard et al., 2003; Kang & Yusof, 2012).

It is apparent that the majority of calculated $R\sqrt{n}$ statistic values are greater than their critical values at the 5% significance level indicating departures from homogeneity, though absolute and relative tests yielded different results at a number of stations. In general, 6 and 5 out of 11 records were non–homogeneous consistently as for annual mean and extreme temperatures respectively. Additionally, there were 4 and 2 out of 11 stations that exhibited inhomogeneity as for all temperature variables detected by absolute and relative tests respectively. It is commonly acknowledged that non–homogeneous time series should be excluded or adjusted reasonably for further trend analysis (X. Zhang et al., 2000; Viola et al., 2014; Kien et al., 2019). However, this study still involved all temperature records in order to provide more outcomes regarding temporal trend examination.

It is documented that these inhomogeneities could be caused by natural effects and/or artificial factors such as measurement techniques, observational procedure and instruments, surrounding environment characteristics and structures, relocation of stations

(Buishand, 1982; X. Zhang et al., 2000; Wijngaard et al., 2003; Viola et al., 2014). However, this study did not have any opportunity to assess these historical metadata. Therefore, it will be more valuable to involve historical metadata for further investigations (e.g. detect breaking points or correct non–homogeneous records).

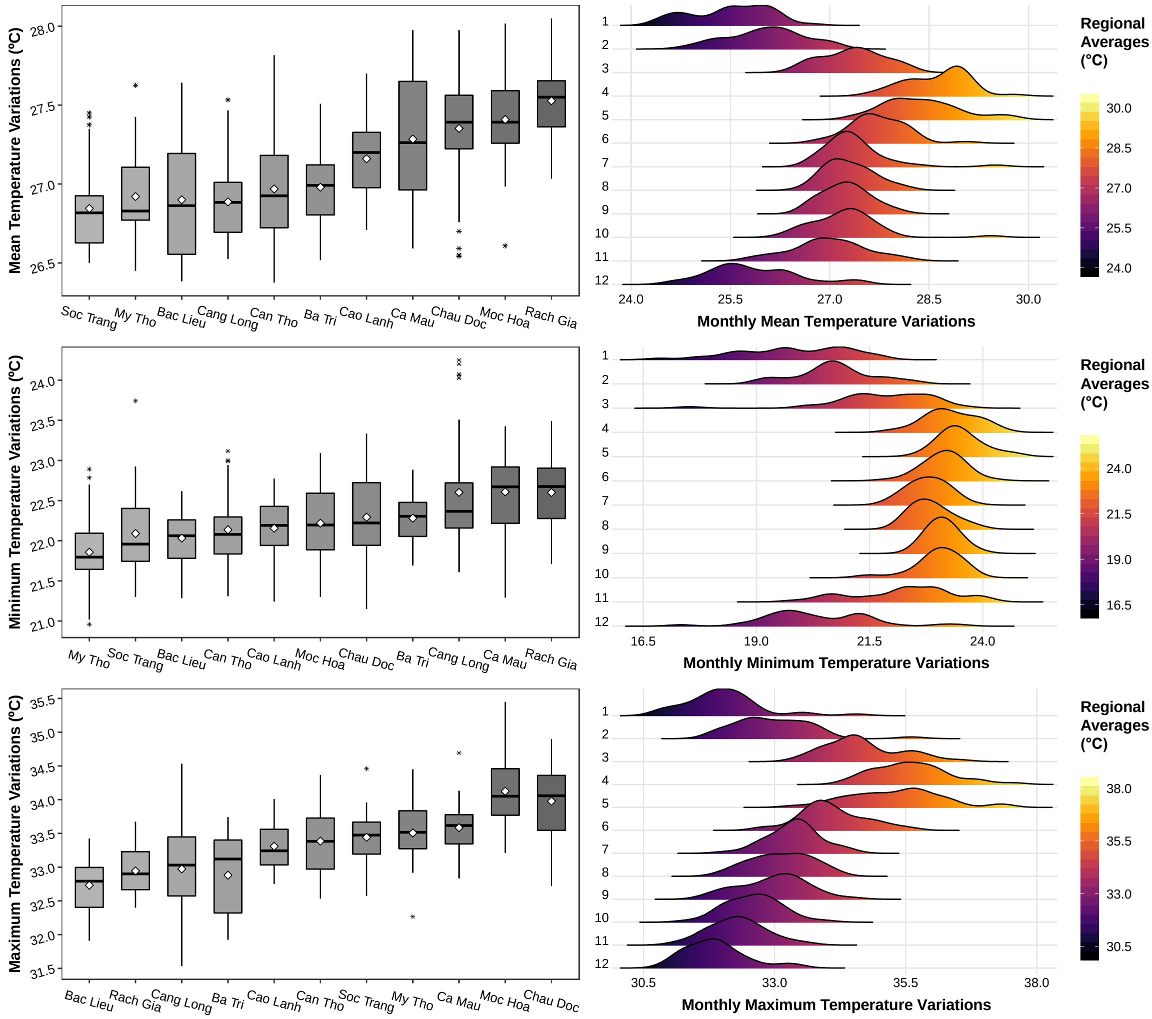


Figure 3: Temporal variations of all observed temperature records. The inside diamond symbols stand for arithmetic means.

Turning to the evaluation of temporal trend possibilities during three recent decades over the VMD, Figure 8 and Figure 9 represent the results of temperature trend detection and estimation respectively, with statistically significant trends denoted by solid symbols. It is discernible that all of annual mean and minimum temperature records were characterized by significantly increasing trends, with the estimated slopes ranging from 0.012–0.032°C/year and 0.016–0.039°C/year respectively. Similarly, trend behaviors of annual maximum temperature were mainly dominated by positive trend with the estimated slopes varying from 0.014–0.048°C/year, except Moc Hoa and Rach Gia stations, in which experienced decreasing trends. However, these declining ones were detected insignificantly. It is also apparent that Can Tho city, which is the largest city in the VMD, exhibited the greatest increase of 0.048°C/year as for annual maximum temperature. The magnitude of increase in annual mean and minimum temperatures at Can Tho station was also greater than most of other stations. These outcomes are fairly compatible with the critical issue of overwhelming urbanization analogous to the Greater Toronto Area (Mohsin & Gough, 2010) and the western half of Iran (Tabari & Talaee, 2011).

According to the Sen's slope estimator, the rates of increase in annual minimum temperature are greater than the annual mean and maximum ones at most considered stations, accounting for 8 and 6 out of 11 stations respectively. These outcomes are in line with various parts of the world (X. Zhang et al., 2000; Q. Zhang et al., 2009; Tabari & Talaee, 2011; Sonali & Nagesh Kumar, 2013; Mir et al., 2015; Sonali & Nagesh Kumar, 2016). Generally, these findings yield an evident indication of warming tendency in the VMD over three recent decades, which is in accordance with previous studies on national scale (Nguyen et al., 2014; Kien et al., 2019).

In addition to station–wise analysis based on the observed dataset, this study also utilized the high–resolution gridded dataset (CRU TS4.02) in order to examine spatio–temporal trend behaviors in the VMD for three time periods. Figure 10 represents spatial distribution of interpolated Sen's slope estimator values by employing Ordinary Kriging according to a relative comparison between *RMSE* values of Ordinary Kriging and IDW algorithms (at around 0.0181 and 0.0303 respectively). It is expected that these outcomes show consistently increasing trends as for mean and extreme temperature anomalies for all time periods. With regard to spatial patterns, both mean and minimum temperatures exhibited greater increase in the western part of the VMD compared to the eastern region. Meanwhile, maximum temperature experienced lower increase in the southwestern part as for the whole considered period and over three recent decades as opposed to the remaining period.

In comparison with mean and maximum temperatures, the magnitude of increasing trends in minimum temperature is consistently stronger as for three time periods, which is fairly compatible with the aforementioned results based on the observed dataset. Additionally, all temperature variables showed greater rates of increase over three recent decades (1981–2017) compared to the whole analyzed period (1901–2017) as well as the period since the second half of 20th century (1951–2017), which is also in line with previous studies (Sonali & Nagesh Kumar, 2013; Viola et al., 2014). In general, these findings demonstrate high applicability of the CRU TS dataset for the purpose of spatio–temporal trend analysis, which will be conducive to further investigations in the VMD (e.g. crop simulation modeling, hydrologic and hydraulic modeling, vulnerability assessment to climate change and variability).

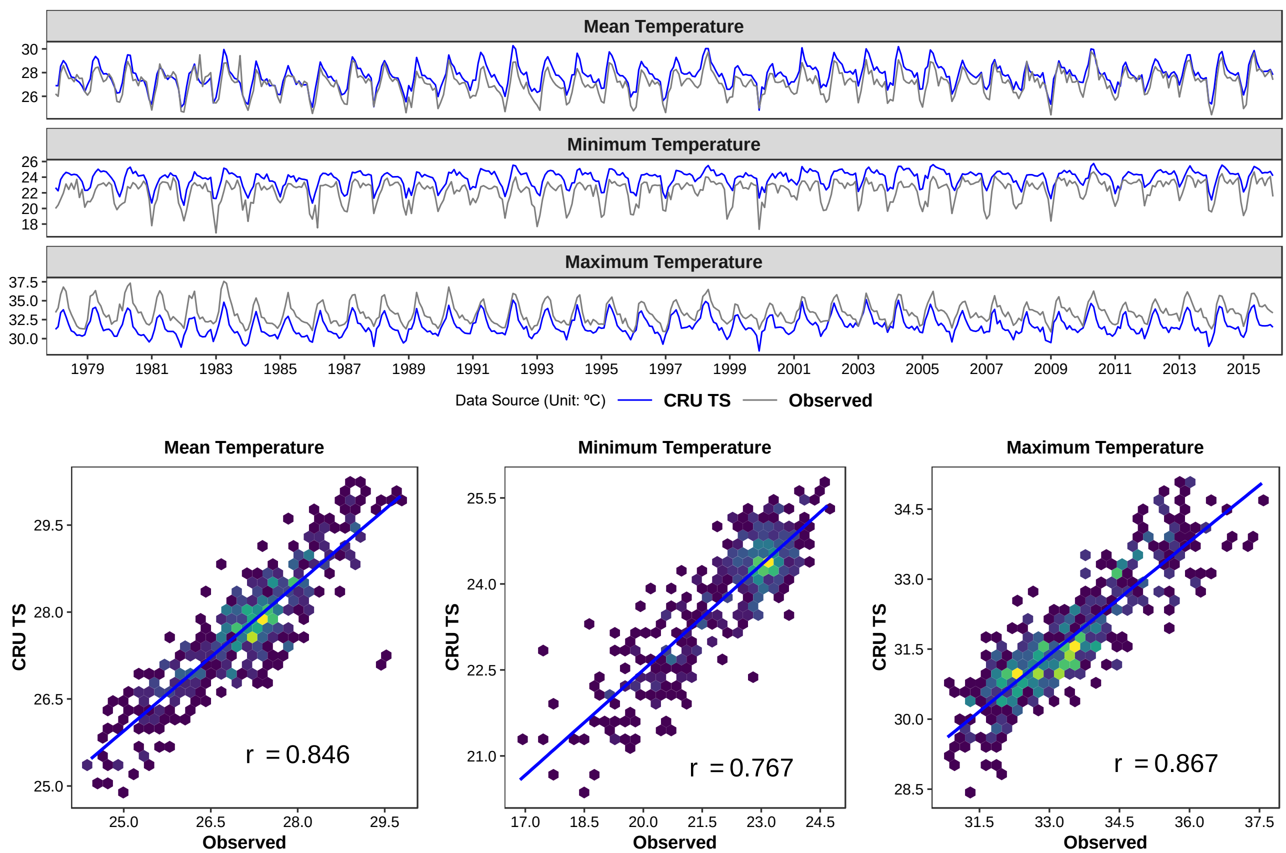


Figure 4: Comparison between observed and gridded datasets based on regional averages.

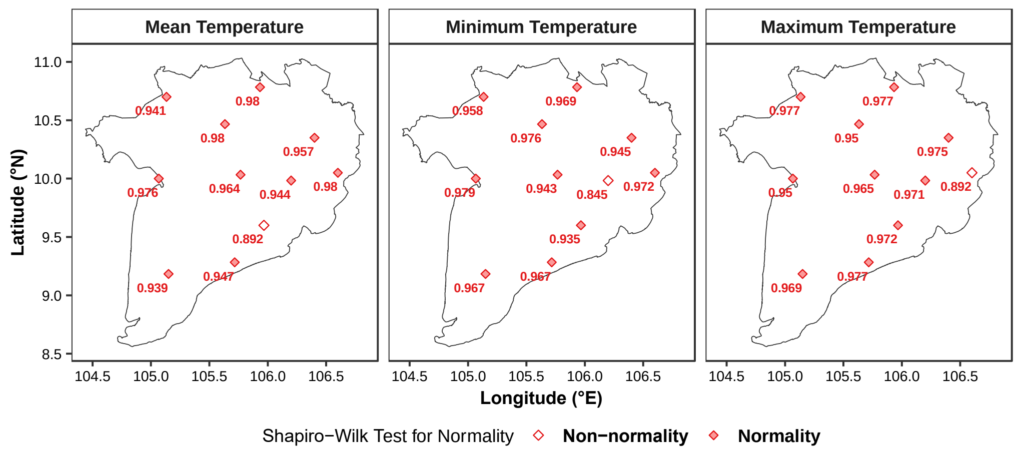


Figure 5: Normality test results for all observed temperature records.

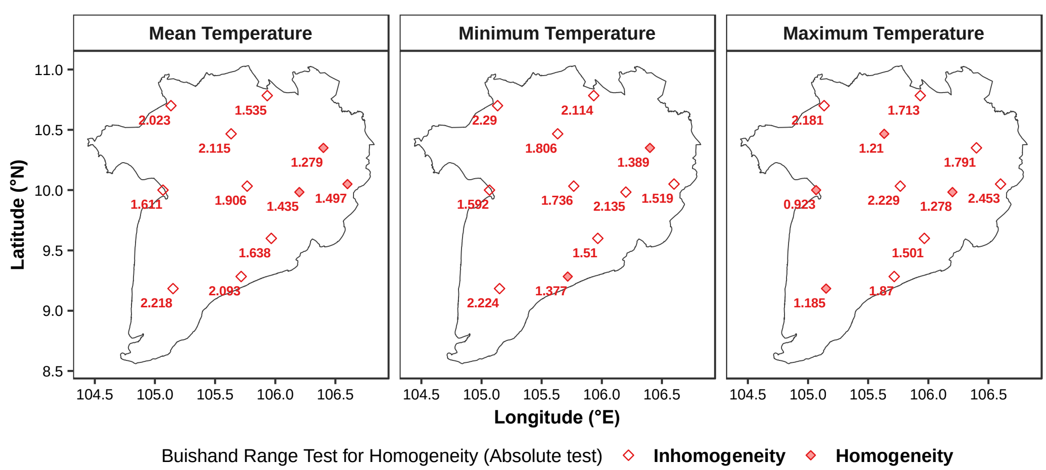


Figure 6: Homogeneity test results for all observed temperature records based on absolute test.

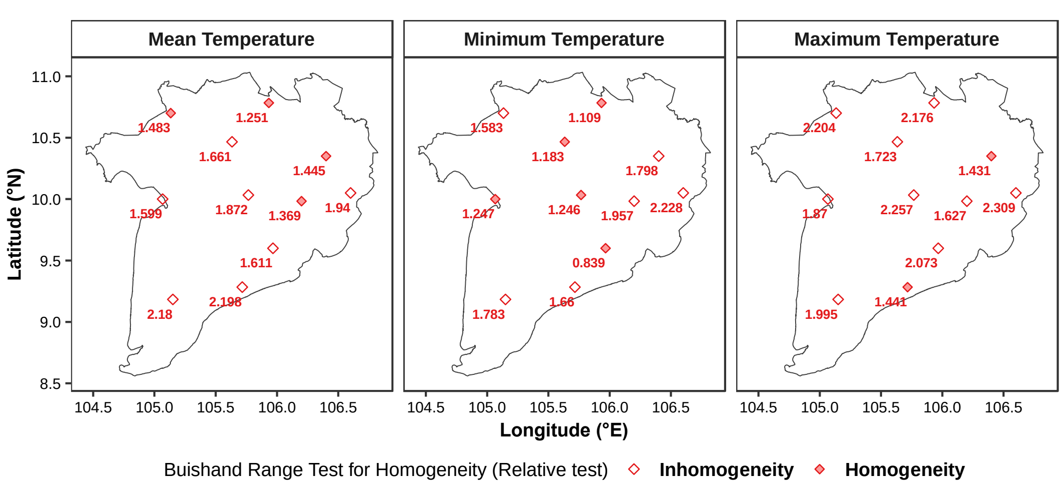


Figure 7: Homogeneity test results for all observed temperature records based on relative test.

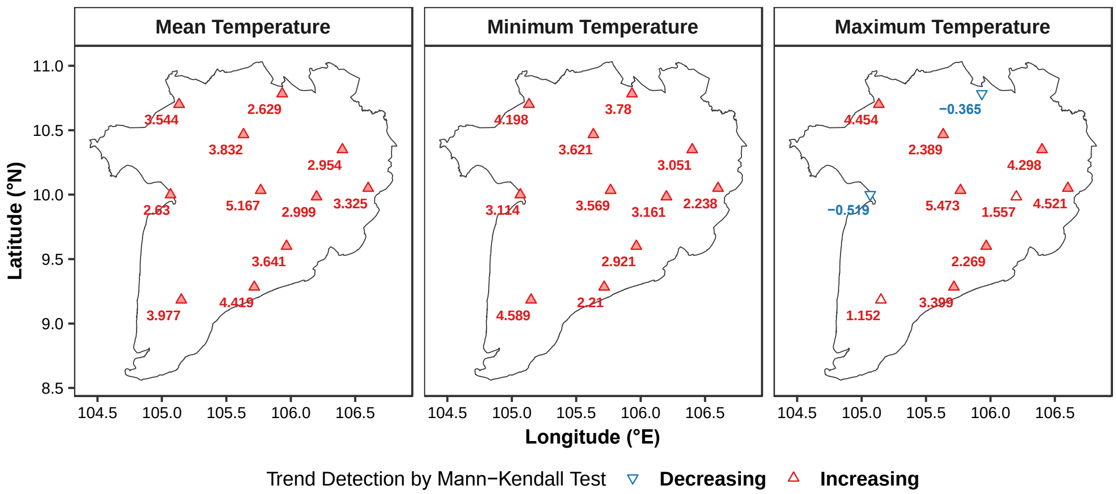


Figure 8: Trend detection results for all observed temperature records.

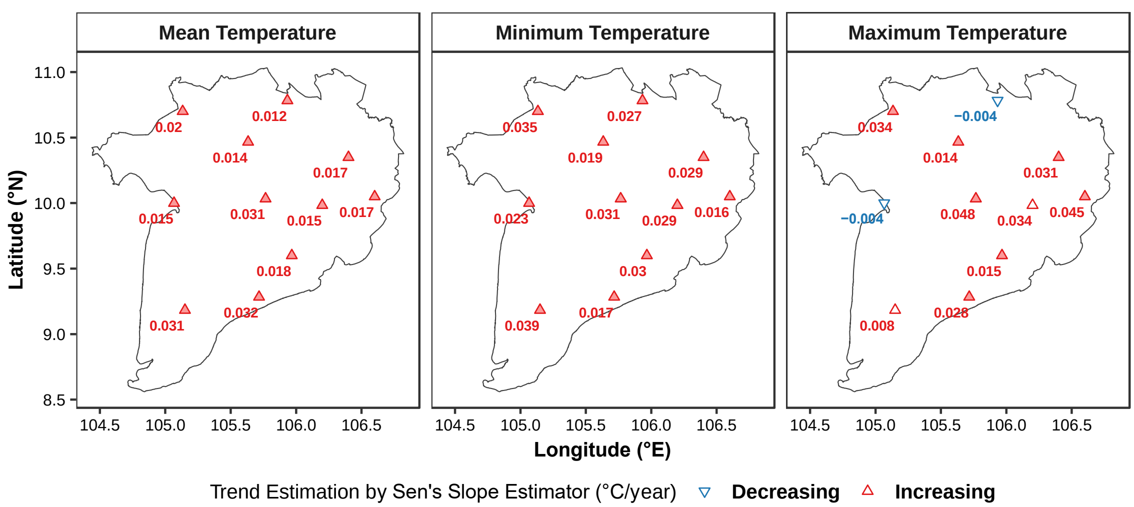


Figure 9: Trend estimation results for all observed temperature records.

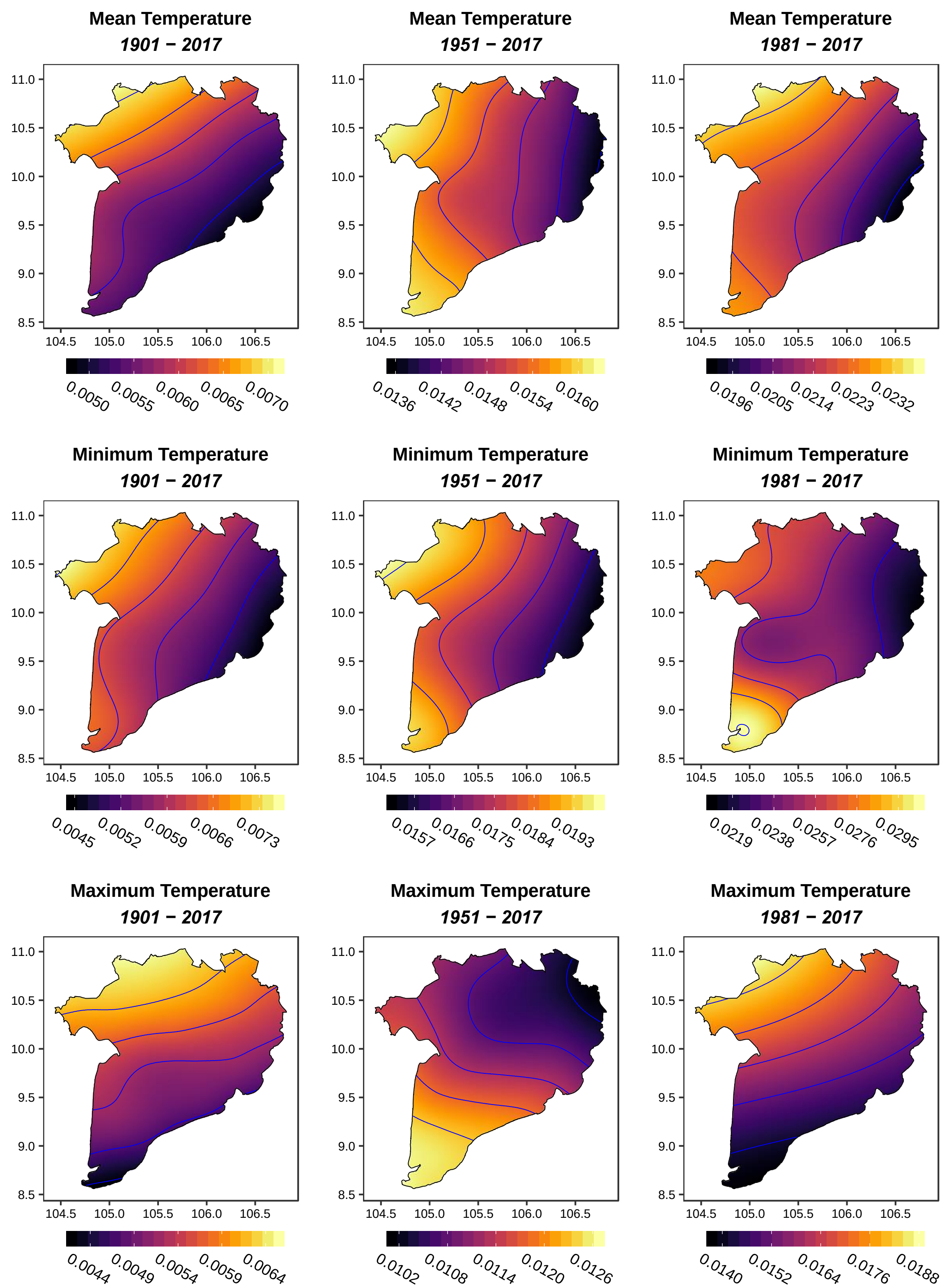


Figure 10: Spatial distribution of Sen's slope estimator (°C/year) for gridded temperature anomalies relative to the base period 1961–1990.

5. Conclusion

A well–conducted evaluation of statistical characteristics forms a crucial role of hydrology and climatology studies. However, the application of statistical methods in such field is frequently restricted to the detection and identification of trend component in a given time series. In the present study, a number of powerful statistical methods were employed to analyze the annual mean and extreme temperatures in order to investigate warming tendency in the VMD over three recent decades. Firstly, graphical tools (i.e. box plot and density plot) were applied to expound an initial assessment concerning temporal variations in each temperature records. Then, all of the observed temperature records were subjected to normality and homogeneity test by utilizing the Shapiro–Wilk and Buishand Range test prior to proceeding with the examination of trend possibilities by making use of the well–known Mann–Kendall test and Sen's slope estimator in combination with the trend–free pre–whitening procedure. Meanwhile, the high–resolution gridded dataset (CRU TS4.02) was also incorporated in the spatio–temporal trend analysis.

The results of normality test by the SW test show that most of temperature records are likely normal. According to the BR test, there is strong evidence of departures from homogeneity detected in most of temperature records. However, the main causes of these inhomogeneities are still inconclusive. It is advisable to involve historical metadata for further investigations. According to the classical/modified Mann–Kendall test and Sen's slope estimator, significantly increasing trends were detected for the majority of annual temperature records. In the meantime, the application of spatial interpolation in combination with statistical trend tests for the examination of spatio–temporal trend possibilities also indicate significant increase in all temperature anomalies (especially as for the minimum temperature from 1981–2017), implying profound warming tendency in the VMD over three recent decades. Thus, it is recommended to employ the high–resolution gridded dataset (e.g. CRU TS) for the purpose of spatio–temporal assessment. Such a station–wise and grid–wise trend analysis will yield a large number of scientific merits in climate–related studies in the context of climate change and variability.

Appendix

Shapiro–Wilk test

The Shapiro–Wilk test, which was originally developed by Shaphiro and Wilk (1965), is such an effective method for assessing the assumption of normality. Mendes and Pala (2003); Razali and Wah (2011) shown that the SW test is more powerful than Kolmogorov–Smirnov, Lilliefors and Anderson–Darling tests via a set of Monte Carlo simulations. It is advisable to apply the SW test to environmental datasets (Gilbert, 1987) as well as climatic datasets (Steinskog et al., 2007). Shaphiro and Wilk (1965); Gilbert (1987) presented a very clear step–by–step procedure to perform the SW test. Generally, given a random sample of size $n \leq 50$ ($x_1, x_2, \ldots, x_n$), an increasing ordered sample ($y_1 \leq y_2 \leq \ldots \leq y_n$) can be obtained by sorting in ascending manner so that y_1 and y_n are the smallest and largest sample values respectively. The test statistic (W) is defined as follows:

$$W = \frac{b^2}{S^2} = \frac{\left(\sum_{i=1}^{k} a_{n-i+1}\left(y_{n-i+1} - y_i\right)\right)^2}{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2} \tag{1}$$

Where the values of coefficients a_{n-i+1} were given by Shaphiro and Wilk (1965), while $k = n/2$ (if n is even) or $k = (n-1)/2$ (if n is odd).

The test statistic (W) value lies between 0 and 1. Small values of W indicate departures from normality. Then, the null hypothesis of normal distribution can be rejected at the α significant level if the test statistic (W) value is less than the percentage points given by Shaphiro and Wilk (1965).

Buishand range test

The Buishand range test proposed by Buishand (1982) is an effective test for homogeneity based on the adjusted partial sums or cumulative deviations from the mean, which can be expressed as follows:

$$S_0^* = 0; \quad S_k^* = \sum_{i=1}^{k} \left(Y_i - \bar{Y} \right), \quad k = 1, \ldots, n \tag{2}$$

When a given time series is homogeneous, the values of S_k^* 's fluctuate around zero. In case there is an existence of break in year K, then the S_k^* reaches the highest or lowest point near the year $k = K$ as for negative or positive shift. Rescaled adjusted partial sums are then obtained by dividing the S_k^* 's by the sample standard deviation as follows:

$$S_k^{**} = \frac{S_k^*}{\sqrt{\frac{\sum_{i=1}^{n} \left(Y_i - \bar{Y} \right)^2}{n}}}, \quad k = 0, \ldots, n \tag{3}$$

It is found that the values of S_k^{**} 's are not affected by linear data transformation (e.g. unit conversion). Therefore, homogeneity tests are also based on the rescaled adjusted partial sums. In order to assess the significance of shift in the mean of a given time series, the statistic range (R), which is sensitive to departures from homogeneity, can be used. High values of R indicate an indication of shifts in the mean (i.e. non–homogeneity). Buishand (1982) provided a number of critical values for $R/\sqrt{n}$.

$$R = \max_{0 \le k \le n} S_k^{**} - \min_{0 \le k \le n} S_k^{**} \tag{4}$$

Mann–Kendall test and Sen's slope estimator

The non–parametric rank–based Mann–Kendall test originated by Mann (1945); Kendall (1975) is commonly applied to detect monotonic trends in hydro–meteorological and environmental records. The MK test is applicable to non–normal and skewed data, and also robust to the presence of outlier or extreme values (Jaagus, 2006; Partal & Kahya, 2006). The MK statistic (S_{MK}) is defined as follows:

$$S_{MK} = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn\left(x_j - x_k \right) \tag{5}$$

$$sgn\left(x_j - x_k \right) = \begin{cases} +1 & if \quad x_j - x_k > 0 \\ 0 & if \quad x_j - x_k = 0 \\ -1 & if \quad x_j - x_k < 0 \end{cases} \tag{6}$$

Where x_j, x_k are the sequential data in the series and n is the length of the data series.

In cases where sample size ≥ 10, the standardized test statistic Z_{MK} is calculated as follows:

$$Z_{MK} = \begin{cases} \dfrac{S_{MK} - 1}{\sqrt{Var\left(S_{MK} \right)}} & if \quad S_{MK} > 0 \\ 0 & if \quad S_{MK} = 0 \\ \dfrac{S_{MK} + 1}{\sqrt{Var\left(S_{MK} \right)}} & if \quad S_{MK} < 0 \end{cases} \tag{7}$$

$$Var(S_{MK}) = \frac{\left[n(n-1)(2n+5) - \sum_{t=1}^{m} t(t-1)(2t+5)\right]}{18} \tag{8}$$

Where *t* stands for the extent of any given tie and *m* denotes the number of tied groups.

To access the statistical significance of possible trends in a given time series, positive and negative values of Z_{MK} show upward and downward trends respectively. Then, the null hypothesis (H_0) of no trend can be rejected at the specific α significance level when $|Z_{MK}|$ is greater than $Z_{1-\alpha/2}$ obtained from the standard normal cumulative distribution table. In the present work, the significance levels of α = 0.05 and 0.01, which yield strong evidence against H_0 (Kundzewicz & Robson, 2000), were adopted so $Z_{1-\alpha/2}$ = 1.96 and 2.576, respectively.

In order to quantify the magnitude of trends, the non–parametric Sen's slope approach, which was initially introduced by Sen (1968), was applied here. This slope estimator is calculated as follows:

$$\beta_{SS} = median\left(\frac{x_j - x_k}{j-k}\right) \text{ for all } j < k \tag{9}$$

Where β_{SS} is Sen's slope estimator and x_j, x_k are the data values at times *j* and *k* respectively. The positive and negative signs of the estimated slopes show increasing and decreasing trends respectively.

Trend–free pre–whitening procedure

The trend–free pre–whitening procedure was proposed by Yue et al. (2002) for the purpose of taking the effect of serial correlation into consideration. The TFPW procedure outperforms compared to the previous approach, i.e. pre–whitening procedure introduced by Kulkarni and von Storch (1995). The key merit of the TFPW procedure is removing significant serial correlation from detrended series. Yue et al. (2002); Khaliq et al. (2009); Oguntunde et al. (2011); Sonali and Nagesh Kumar (2013); Viola et al. (2014) summarized a number of key steps to implement the TFPW procedure. Generally, this approach consists of four major steps as follows: (i) detrending sample data with an assumption of linear trend (Eq. (10)), where β_{SS} is the Sen's slope estimator (Eq. (9)); (ii) removing AR(1) from the detrended series X_t' (Eq. (11)), where r_1 is the lag–1 serial correlation coefficient (Eq. (12)); (iii) combining the identified trend T_t and the residual Y_t' (Eq. (13)); and (iv) applying the MK test to the blended series Y_t.

$$X_t' = X_t - T_t = X_t - \beta_{SS} t \tag{10}$$

$$Y_t' = X_t' - r_1 X_{t-1}' \tag{11}$$

$$r_1 = \frac{\frac{1}{n-1}\sum_{t=1}^{n-1}(X_t - \bar{X}_t)(X_{t+1} - \bar{X}_t)}{\frac{1}{n}\sum_{t=1}^{n}(X_t - \bar{X}_t)^2} \tag{12}$$

$$Y_t = Y_t' + T_t \tag{13}$$

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