Sub-division Level Temperature Patterns and Trends Across East-Coast Industrial Corridor, India

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Abstract

Temperature patterns and trends influence many sectors. The newly planned industrial corridors will have to consider the variations in temperature and other climatic parameters. The present article aims to investigate the patterns and trends of maximum and minimum temperature at the Sub-division (sub-district) level. We analyse annual and seasonal temperature data from 1958 to 2018 for the India's first east-coast corridor, the Visakhapatnam–Chennai industrial corridor (VCIC) using a combination of Getis–Ord–Gi and Mann–Kendall trend test for spatiotemporal patterns and trends. The results show domination of intensifying hot spots across the VCIC and an overall increase in both maximum and minimum temperature for annual (0.013 °C/y and 0.011 °C/y) and seasonal trends. However, the variations of pattern and trends are unambiguous within districts. There is a clear distinction in patterns and trends between southern and north-eastern districts, indicating the need for localised planning. As the industrial areas are planned at a microlevel, such studies will enable planners and decision-makers to plan and prioritise site-specific climate change adaptation and mitigation measures in industrial and urban areas.

1. Introduction

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Temperature is one of the most important hydrological and meteorological parameters and deviations from regular temperature interfere with social, economic, and industrial activities. Temperature changes cause differential heating of air, affecting the hydrological parameters like actual and potential evapotranspiration and impact various sectors. In recent decades, natural and human systems are experiencing impacts due to climate change all over the world. The global surface temperature has increased by 0.61 °C (IPCC, 2015), and are expected to rise by 1.8–4 °C by the end of the century (Hoegh-Guldberg et al., 2018). The projected impacts may include increased mean temperature over land and oceans, changes in humidity, hot summers and hotter winters, heavy precipitation, and increased drought conditions in several parts of the world (IPCC, 2018). These impacts may vary spatially and temporally. The spatial variability of temperature plays a critical role in environmental planning and climate analysis. Studying temperature trends and patterns will facilitate determining the climatic changes that, in the long term, can influence economic and social aspects among others.

Many studies conducted across the world show such trends in temperature (Mondal et al. 2015; Alemayehu and Bewket 2017; Ay 2020; Libanda et al. 2020). Hasan et al. (2016), for instance, calculated temperature trends in Brunei, Darussalam, and demonstrated a statistically significant increase temperature trend while Ay (2020) examined the temperature trend for the Western Black Sea Region, Turkey, showing statistically significant trends in the mean temperature in all regions. There is an expanding variation in the maximum and minimum temperatures in some parts of the world (Akinsanola and Ogunjobi 2014; Syed and Al Amin 2016; El Kenawy et al. 2019).

Numerous research on temperature trends have been conducted in India (Kumar et al. 1994; Sonali and Nagesh Kumar 2013; Ray et al. 2019). Pramanik and Jagannathan (1954) analysed the annual mean minimum and maximum temperature for India and concluded that there was no trend in an increase or decrease in the temperature (cited in Arora et al. 2005). Srivastava et al. (1992) showed indications of decadal temperature trends decreasing in the north of 23° N and rising trends in the south of 23° N, based on data from 1901 to 1986. Kumar et al. (1994) estimated a significant increase in the mean temperature by 0.6 °C over India in the last 100 years. In terms of regional trends, the

authors estimated maximum temperature on the east coast of India at an increasing trend of $1.2\text{ }^{\circ}\text{C}/100\text{ years}$ and trendless minimum temperature. The increase in temperature and decrease in rainfall was observed in the Ganga basin (Kothyari and Singh 1996). Arora et al. (2005), analysed trends in temperature along 125 stations across India using Mann–Kendall test. The authors observe that there is a rise in the annual mean, maximum, and minimum temperature by $0.42\text{ }^{\circ}\text{C}/100\text{ years}$, $0.92\text{ }^{\circ}\text{C}/100\text{ years}$, and $0.09\text{ }^{\circ}\text{C}/100\text{ years}$, respectively. Kumar et al. (2020) analysed spatiotemporal variation in extreme precipitation and temperature across India using climate change indices. They projected extreme temperature increase and warmer days in many regions across the country and concluded that there will be a considerable decrease in the number of cold days in Andhra Pradesh (AP) and Tamil Nadu (TN).

Mann-Kendall trend test (MKTT) is performed to evaluate the trend analysis of hydro-meteorological parameters (Arora et al. 2005; Xu et al. 2010; Mamtimin et al. 2011; Subash and Sikka 2014; Manikandan et al. 2019; Bannayan et al. 2020; Ketema and Siddaramaiah 2020). Yan et al. (2019) analysed spatial and temporal trends using MKTT for droughts in China and revealed that the frequency of summer droughts will be increasing. Spatiotemporal investigation of temperature deviations using MKTT was carried out in the Hindukush Mountains in Pakistan by Atta-ur-Rahman and Dawood (2017) who observed an increasing trend in the maximum temperature in higher regions and a decreasing trend in the minimum temperature in higher and lower regions. Paniagua et al. (2019) analysed aridity in the Iberian Peninsula using MKTT which showed that the increase in temperature in all stations was statistically significant. MKTT was used to analyse trends in temperature extremes and their relationship to oceanic and atmospheric circulation patterns in China. Salman et al. (2017) examined the trends in temperature and temperature extremes in Iraq and detected a significant temperature increase over country that was two-to-seven times faster than the worldwide trends.

When individual entities are spatially distributed, they create spatial patterns. Such spatial autocorrelation describes how each entity is influenced by the surrounding entities (Chou 1995). These dependencies produce a clustering of similar or dissimilar values, which respectively leads to positive or negative autocorrelation. Getis–Ord–Gi

(GOG) provides an index for spatial autocorrelation and presents an indication towards hot-spots (HS) or cold spot (CS; Oyana and Margai 2015). The combination of GOG and MKTT is used to identify emerging hotspots regions in climatic patterns, urban heat islands, forest fires, and diseases (Rumiantsev and Ivanova 1995; Luković et al. 2014; Javari 2016, 2017; Abdrakhmanov et al. 2017; Rousta et al. 2017; Wangdi et al. 2018; Rayadurgam & Rao, 2021). Bajat et al. (2013) carried out spatial pattern analysis of monthly, seasonal, and annual rainfall across Serbia and the emerging HS analysis was used to identify HSs to understand the clustering of low and high values of precipitation. Dai et al. (2010) carried out spatiotemporal analysis for spatial heterogeneity and temporal variation of surface temperature. Javari (2017) carried out spatial variability of rainfall caused by temperature and elevation. Murumkar et al. (2020) conducted trend and pattern analysis on meteorological variables in Sub-Saharan floodplains. Spatial and temporal variability analysis was carried out in the western United States for minimum temperature (Svejcar et al. 2016). Rayadurgam & Rao (2021) carried out Spatio-temporal analysis for rainfall patterns and trends using data from 1901-2015 and concluded there is a positive trend in rainfall across the VCIC corridor.

Previous studies have addressed the temperature trends for a large area, for instance, the east coast of India, which covers about a 2545 km coastline and 33 districts as a single value (Mondal et al. 2015; Nengzouzam et al. 2019; Ray et al. 2019). Some studies have been carried out at the sub-district- or state level, providing the temperature trends covering all 10 districts of AP and TN that are part of the Visakhapatnam–Chennai Industrial Corridor as a single value (e.g., Geetha et al. 2019). These studies enable decision-makers for climate-resilient planning at the national or regional levels. Some studies have been carried out at the city level too to understand the temperature trends (Jeganathan and Andimuthu 2014; Jhajharia et al. 2014). However, the nature of temperature and rainfall trends differs across spatial and temporal scales, necessitating examination of temperature and rainfall fluctuations at the district administrative level. (Subash and Sikka 2014; Rayadurgam & Rao, 2021). Even then, few studies have been carried out at the district- or Sub-division level. This is important for planning an industrial or agricultural area as these are planned at the microscale and financial and resource are allocated accordingly. The size of industrial areas in AP and TN varies from

50 ha to 10,000 ha. Further, adaptation and mitigation measures for any climate change are planned for industrial or urban areas. The present study evaluates the local trends and patterns in temperature using spatial and temporal data, which enables the decision-makers to take site-specific climate change adaptation (CCA) measures (Pingale et al. 2014) for various sectors like industrial, urban, or agricultural. The present study introduces analysis at sub-division level which is required for planning purposes. Further, the research contributes towards temperature pattern analysis for the region, which is first of its kind. The present study starts with the importance of temperature patterns and trends, literature review, and the importance of the study area, followed by the data used. Then we describe the methods adopted, followed by results and conclusion.

2. Background of the study area

The Visakhapatnam–Chennai Industrial Corridor (VCIC) forms a key component of the East Coast Economic Corridor, which aligns with the Golden Quadrilateral and India's Act East Policy that links the East Asian economies. VCIC is 800 km long and passes through eight districts of AP and two districts of TN (Fig. 1). It will be spatially categorized into nine industrial zones under four nodes. It is estimated that the present output of industries in VCIC in 2015–16 will rise from Rs. 1110 billion to Rs. 3000 billion under the business as usual (BAU) scenario by 2035–36 whereas it may increase to Rs. 7823 billion if the potential of VCIC is fully utilised in the next 20 years (Mitra et al. 2016). Around 95% of industries are comprised of micro, small, and medium-sized enterprises (MSME). These industries are susceptible to fluctuations and changes in temperature and other extreme climatic events. Future urban agriculture and industrial planning require an understanding of temperature trends and patterns for prioritising site-specific CCA and mitigation measures.

Fig. 1 Districts of VCIC

3. Data and methods

The monthly temperature gridded data from 1958 to 2018 with a resolution of ~5 km was

downloaded from TerraClimate Data
(<http://www.climatologylab.org/terraclimate.html>) in the network common data form
(NetCDF) format. Abatzoglou (2018) has derived TerraClimate data from WorldClim,
Climate Research Unit (CRU) and the Japanese 55-year reanalysis aided in interpolation.
The monthly minimum and maximum temperature data were aggregated as seasons
and annual data. Seasons in India are divided into four categories (Rao 1981) with
January and February (JF) as winter months, March to May (MAM) as pre-monsoon,
June to September (JJAS) as monsoon and October to December (OND) as post-
monsoon. Fig. 2 shows the annual homogeneous temperature of all districts along VCIC
and for the overall VCIC.

Fig 2 Average annual maximum and minimum temperature

These districts receive rainfall from both southwest and northeast monsoons, affecting
the deviation of temperature across seasons. The southern districts receive rainfall from
the northeast monsoon (OND) and the north-eastern and central districts receive
rainfall mainly from the southwest monsoon (JJAS).

3.1 Statistical analysis

In this article, hot spots (HSs) are defined as locations with high values that are
surrounded by areas with high values of temperature at 90% significance. Similarly, if
the region has low temperature surrounded by low temperature at 90% significance,
then this region is called a cold spot (CS). When the time series is considered for HS
analysis, it is called an emerging HS analysis. Spacetime (ST) cube approach is adopted
to test the temperature pattern along VCIC. ST cube is used to analyse positive or
negative patterns, which helps in analysing HS or CS in the data (Maxwell et al. 2019).
Each bin in the ST cube is represented by a geographic location (X and Y coordinates)
and time (T) (Marumbwa et al. 2019). The minimum and maximum temperature space-
time analysis has been carried out using the emerging HS Analysis tool in ArcPro 2.4
(ESRI, 2020). EHSA uses MKTT to test whether a statistically significant temporal trend
exists in the series of Z-score resulting from the GOG statistic. This tool does not provide
the magnitude of the slope of the trend; hence it was estimated from the time series
data using MKTT.

Equation 1 denotes the estimate of GOG statistics (Ord and Getis 1995), which is used to identify the presence of distinct spatial clustering patterns.

$$G_i^* = \frac{\sum_{j=1}^n w_{i,j} y_j - \bar{Y} \sum_{j=1}^n w_{i,j}}{S \sqrt{\frac{[\sum_{j=1}^n w_{i,j}^2 - (\sum_{j=1}^n w_{i,j})^2]}{n-1}}}$$

1

where y_j is the feature j attribute value, w_{ij} is the spatial weight among feature i and j , n is the total number of features and

$$\bar{Y} = \frac{\sum_{j=1}^n y_j}{n}$$

2

$$S = \sqrt{\frac{\sum_{j=1}^n y_j^2}{n} - (\bar{Y})^2}$$

3

The analysis of HSs calculates the GOG for all bins in the data and the Z-score shows that the data are clustered in large or small values. The high G_i^* results indicate HSs and high negative G_i^* value indicates CSs. The G_i^* statistic is a Z-score, so no further calculations are required. The Mann–Kendall trend test is carried out by Equation 4. The Kendall tau statistic is calculated using the following formula:

$$S = \sum_{j=1}^{n-1} \sum_{k=i+1}^n \text{sign}(y_k - y_j)$$

4

where n is the dataset, while y_j and y_k are the data at time j and k , respectively.

Sen's estimator (Sen 1968) is used to evaluate the value of a trend in a time series, while the MK test is used to determine the statistical significance of the trend. These techniques are commonly utilised in the study of hydrological and meteorological time series (Chou 1995; Yue and Hashino 2003; Jain et al. 2013; Pingale et al. 2014; Mondal et

al. 2015; Salman et al. 2017). The slope of trend (Z_i) of all data pairs are initially calculated by

$$Z_i = \frac{t_j - t_k}{j - k} \text{ for } i = 1, 2, 3, \dots, N$$

5

where t_j and t_k are data values at time j and k , respectively. The median of these N values is Sen's slope estimator; a negative slope indicates a falling trend, whereas a positive slope indicates an increasing trend.

The feature data was transformed into a NetCDF format data cube structure by aggregating 61-years of monthly temperature data. Each ST bin is made of spatial distribution of 8 km and 5 years of data. We express the results in terms of increasing or decreasing trends of new, intensifying, diminishing, persistent, or sporadic patterns (ESRI 2018). The ST cube aggregated 5,59,370 points into 11,648 hexagon grid locations over 61-time step intervals. Each location had a height of 8 km, a width of 9.24 km, sides of 4.62 km, and an area of 55.43 sq, km.

3.2 Output

The output maps are classified into seventeen categories, as indicated in Table 1, comprising eight HS, eight CS, and one non-significant category that represents different categorizations of spatiotemporal analysis at 90% level of statistical significance (ESRI 2020). For the whole study area, statistically significant (90 percent) slopes for each season were analysed and interpolated using inverse distance weight (IDW) (Mair et al. 2013; Pingale et al. 2014; Sharma et al. 2016; Javari 2017). Additionally, the data were aggregated at the subdivision level. The dominant pattern and slope of the trend are provided in Annexures 1 and 2 for the subdivision, district, and VCIC, respectively.

Table 1 Definition of different types of spatiotemporal patterns

4. Results and discussion

Analysis was carried out on the spatiotemporal data for VCIC from 1958 to 2018 for the area of 1,09,563 sq. km from Kancheepuram district to Vizianagaram district. The trend and pattern analysis for the VCIC region as Subdivision- and district-wise is represented in Fig. 3–6. Annexures 1 and 2 reproduce the dominating spatiotemporal patterns and trends for each Subdivision, district and the entire VCIC.

4.1 Maximum temperature

Fig. 3 and 4 provide the trends and spatiotemporal patterns for seasonal and annual maximum temperature along VCIC. The VCIC districts experience an annual average maximum temperature of 28.2 °C to 33.7 °C, with the mean and median at 33.3 and 32.4 °C respectively. The annual temperature in the region is dominated by intensifying HS (42%) and diminishing CS (22%), showing that a rise in the temperature over the years has been consistent. Further, Chennai, Guntur, Kancheepuram, Krishna, Nellore, Prakasam, and Tiruvallur are dominated by intensifying HS whereas the north-eastern districts, Visakhapatnam and Vizianagaram are dominated by diminishing CS and East Godavari are dominated by a non-significant or no pattern. However, within districts, at the Subdivision level, there are significant variations in the temperature pattern. In terms of Sen's slope, the annual average maximum temperature trend is +0.013 °C/y but it ranges from +0.003 °C/y in Chintapalle Sub-division of Visakhapatnam to +0.024 °C/y in Kuppam Sub-division of Chittoor. At the district level, the trend analysis shows a statistically significant value of +0.021 °C/y for Chittoor and +0.004 °C/y for Visakhapatnam. Fig. 1 shows the temperature trend and pattern along VCIC for the interior parts of AP. The interior districts of Chittoor, Nellore, and Prakasam have higher slopes than the north-eastern districts. The results also indicate a gradual increase in the slope from north-eastern districts to southern districts (Nengzouzam et al. 2019).

The winter temperature patterns are highly variable, and no pattern dominates the region. However, sporadic HS, oscillating HS, and intensifying HS are also prevalent in this area. In terms of districts, Chennai, Nellore, Tiruvallur, and West Godavari are dominated by sporadic HS and Chittoor and Kancheepuram by oscillating HS. The districts of East Godavari and Visakhapatnam are dominated by persistent CS and

Vizianagaram by intensifying CS, implying little change decrease in the temperature over the years. In terms of temperature trend, Parvathipuram of Vizianagaram has the lowest trend in temperature (-0.005 °C/y) during winters and Kuppam the highest trend (0.028 °C/y).

Pre-monsoon patterns are also extremely varied and are characterised by a mix of diverse patterns, such as intensifying HS in Guntur, Krishna, and Prakasam, persistent CS in Visakhapatnam and Vizianagaram, and no pattern in the remaining areas. The reason for persistent CS maybe because of the pre-monsoon cyclones hitting these areas. In terms of the slope of trend during pre-monsoon, which is mainly summer in India, the lowest trend in maximum temperature is -0.005 °C/y for Bhuminipatnam of Visakhapatnam and the highest temperature trend is 0.021 °C/y in Kupam and Madanapalle of Chittoor. Certain regions of Visakhapatnam and Vizianagaram's eastern districts are not statistically significant. During monsoon, the region is dominated by intensifying HS in the southern and central regions of VCIC. The north-eastern districts of Visakhapatnam and Vizianagaram are dominated by no pattern. Temperature trends are lowest in several Subdivisions of East Godavari (0.003 °C/y) during monsoons and highest in Kupam (0.025 °C/y), Chittoor, within VCIC.

Temperatures during monsoon seasons are consistently higher than those of other seasons, which is a significant contributor to the annual temperature rise. This may also have an effect on the region's rainfall, particularly during the monsoon season. This season brings more than 75% of the yearly rainfall to the East Godavari, Prakasam, and Guntur districts. Temperature trends are elevated in areas like as Chennai, Nellore, Kancheepuram, and Tiruvallur, which get only around 20%–25% of annual rainfall during the monsoons. This may result in an increase in hot days. These areas will see increased temperatures and humidity, resulting in decreased production in sectors such as agriculture, industry, and construction (Balakrishnan et al. 2010).

The majority of the post-monsoon rainfall in VCIC (including Chennai, Nellore, Tiruvallur, and Kancheepuram) falls in the southern districts. Tropical cyclones are prevalent during this time of year along VCIC, resulting in greater temperatures. However, increasing HS predominates in Chennai, Guntur, Kancheepuram, Krishna, Nellore, Prakasam, and Tiruvallur. The eastern districts of Visakhapatnam and

Vizianagaram show no trend, which may be because of the frequent tropical cyclones occurring post-monsoon. Rampa Chodavaram ($0.007\text{ }^{\circ}\text{C}/\text{y}$), East Godavari, and Giddalur ($0.025\text{ }^{\circ}\text{C}/\text{y}$), Prakasam districts have the lowest and greatest post-monsoon temperature trends, respectively. Sen's slope is steeper in the majority of VCIC's southern districts, and these districts get 75%–80% of their annual rainfall during the post-monsoon.

Fig 3 Spatiotemporal patterns of maximum temperature across all seasons and annual data along VCIC

Fig 4 Sen's slope of maximum temperature for all seasons and annual data across VCIC

Minimum temperature

VCIC districts experience an annual average minimum temperature of $22.1\text{ }^{\circ}\text{C}$ to $23.5\text{ }^{\circ}\text{C}$ with mean and median at $22.9\text{ }^{\circ}\text{C}$. The annual minimum temperature pattern along VCIC is intensifying HS. Only Chittoor, Visakhapatnam, and Vizianagaram have diminishing CS pattern and remaining are intensifying HS. In both cases, this indicates an increase in the minimum temperature along VCIC (Mondal et al. 2015). The annual minimum temperature varies from $0.004\text{ }^{\circ}\text{C}/\text{y}$ in Tuni, East Godavari, to $0.016\text{ }^{\circ}\text{C}/\text{y}$ in Giddalur, Prakasam. Fig. 5 and 6 show the details of spatiotemporal patterns and Sen's slope for minimum temperature across VCIC.

In terms of seasonal variations, the intensifying HS dominates the region during winter except in Chittoor and Vizianagaram, which experience diminishing CS. The winter temperature trends show an increase in the minimum temperature ($0.01\text{ }^{\circ}\text{C}/\text{y}$) with the slope ranging from $0.002\text{ }^{\circ}\text{C}/\text{y}$ in a few districts of East Godavari to $0.015\text{ }^{\circ}\text{C}/\text{y}$ in Parvathipuram, Vizianagaram. Intensifying HS dominates pre-monsoon, monsoon and post-monsoon seasons for minimum temperature, indicating an increase in spatial temperature clustering. In terms of MKTT, the temporal trends also indicate an increase in the minimum temperature in all seasons. The slope of pre-monsoon minimum temperature ranges from $0.00\text{ }^{\circ}\text{C}/\text{y}$ in several Sub-divisions of Visakhapatnam districts

to 0.015 °C/y in Giddalur and Malkapur of Prakasam. The near zero slope of Visakhapatnam also reflects the persistent CS pattern. Sen's slope during monsoons ranges from 0.003 °C/y in Pithapuram and Kakinada of East Godavari to 0.015 °C/y in Kuppam and Palmaner of Chittor . The post monsoon trends show maximum deviations ranging from 0.007 °C/y in Pratipadu and Tuni of East Godavari to 0.02 °C/y in Giddalur of Prakasam.

Fig 5 *Spatiotemporal patterns of minimum temperature for all seasons and annual data across VCIC*

Fig 6 *Sen's slope of minimum temperature for all seasons and annual data across VCIC*

Fig 7 *Distribution of spatial pattern for seasonal and annual maximum (Tmax) and minimum (Tmin) temperature across VCIC*

VCIC exhibits 12 out of 17 patterns of HS/CS. Fig. 5–7 summarise the spatiotemporal pattern for VCIC. Table 2 compares the results with other authors. The comparison cannot be made directly because of spatial and temporal variation; however, it provides an indication towards the prevalent trends.

Table 2 *Comparison of trends in maximum and minimum temperature with other authors*

Districts and Sub-divisions

Analysis shows that there is a rise in temperature over VCIC, which are consistent with the results from coastal and southern India by Arora et al. (2005).

However, there are differences among VCIC districts and sub-divisions. Kancheepuram, the VCIC's southernmost district, has a warmer temperature pattern and trend than the majority of the VCIC. Except for the pre-monsoon season, there is little change in slope ($0.001-0.002$ °C/y) or pattern across sub-divisions. The highest variance in trend within district is 0.003 C/y between Chegalpattu and Uttiramerur. In terms of pattern, Kancheepuram is dominated by intensifying HS. In winter, oscillating and sporadic HS are predominant, and no pattern prevails for maximum temperature in the pre-monsoon season.

Fig 8 Sub-district map of VCIC districts

Chennai covers a small area, where maximum and minimum temperature trend is higher than VCIC but within Chennai, there is not much variation in trends and patterns. The annual trends in maximum and minimum temperature in Chennai are 0.016 °C/y and 0.009 °C/y, respectively (Jeganathan and Andimuthu 2014).

The maximum temperature trend is higher and minimum temperature trend is lower than the VCIC for Tiruvallur. Within districts, there is considerable variation in maximum and minimum temperature trends: the difference in trends of Pallipattu and Gummidipundi is around 0.004 °C/y for annual temperature and increases to 0.006 °C/y for monsoon temperature. With the exception of sporadic HS in Pallipattu for minimal temperature, all sub-divisions of Tiruvallur district are witnessing intensifying HS. Pre-monsoon maximum temperature has no pattern in Thiruvallur.

The variation within Nellore district is prominent and ranges from 0.004 °C/y to 0.005 °C/y in all seasons for both maximum and minimum temperatures. The variations are high between Atmakur and Udayagiri of Nellore. It is also observed that in case of Tiruvallur and Nellore, the slope of temperature near coastal Sub-divisions is less than in the Sub-divisions away from the coast. Nellore also experiences a similar pattern as Tiruvallur, with intensifying HS dominating this region and sporadic HS for maximum

373 temperature during winter and pre-monsoon seasons.

374 Chittoor's average trend is the highest of the VCIC districts. Satyavedu has the lowest
375 temperature trend of all Chittoor Sub-divisions, whereas Kupam, Madanepalle, and
376 Palmaner have the highest. Temperature trends vary by 0.005 to 0.007 degrees Celsius
377 per year between the lowest and highest slopes in all seasons, and by 0.003 to 0.005
378 degrees Celsius per year for minimum temperature trends. The Chittoor district is
379 characterised by a diminishing CS pattern. The pattern for maximum temperature
380 varies with the seasons, and diminishing CS dominates the pattern for minimum
381 temperature, suggesting a rise in the surrounding temperatures. Within Chittoor
382 district, the pattern varies from Diminishing CS to Consecutive HS.

383 Prakasam's trend is significantly greater than the average VCIC, and the fluctuation is
384 greatest within districts, ranging from 0.005 °C/y to 0.008 °C/y (post-monsoon) between
385 Chirala and Giddalur. In Prakasam, the annual maximum and minimum temperatures
386 are influenced by intensifying HS, with the exception of Giddalur for the minimum
387 temperature. Districts vary significantly in terms of pattern, particularly during the
388 winter and pre-monsoon maximum temperatures.

389 The average temperature trend in Guntur is slightly higher than the average for VCIC.
390 There are higher variations (0.004 to 0.007 °C/y) in maximum temperature trends
391 between Tenali and Vinukonda. The variations in minimum temperature trends (0.003
392 °C/y to 0.005 °C/y) between Guruzala and Narasaraopet in all seasons. This district is
393 also dominated by intensifying HS pattern for annual maximum and minimum
394 temperature. There are variations within the district showing sporadic HS for Bapatla,
395 Repale, and Tenali for maximum temperature pattern and Guruzala for minimum
396 temperature pattern.

397 Krishna district has a lower annual average temperature than VCIC. Sub-divisions of
398 Krishna likewise exhibit an intensifying HS pattern, with an exception of Avanigadda
399 and Gudivada displaying no pattern and sporadic HS for maximum temperature,
400 respectively. Also, sporadic HS for minimum temperature in Tiruvuru. Maximum
401 temperature patterns in the Kaikalur Subdivision vary according to season, from new
402 HS in winter to sporadic HS in the pre- and post-monsoon seasons.

The bulk of East Godavari's Sub-divisions are statistically insignificant; nonetheless, temperature changes within the Sub-divisions are modest. Rampa Chodavaram has the lowest maximum temperature trends (significant only on an annual basis) and the highest in Amalapuram, Razole, and Mummidivaram. In the East Godavari district, no pattern dominates the annual maximum temperature pattern, while the HS for lowest temperature is intensifying. The Addatigala and Rampa Chodavaram are characterised by diminishing CS values for maximum and minimum temperatures. Pratipadu's highest temperature is dominated by diminishing CS.

In West Godavari, sporadic HS and intensifying HS dominate the annual average maximum and minimum temperature pattern, respectively. However, for maximum temperature, no pattern dominates Bhimavaram, Narsapur, Tadepallegudam, and Tanuku Sub-divisions of West Godavari. There exist variations within seasons among various Sub-divisions of West Godavari for maximum temperature. The average trend in West Godavari is much lower than VCIC and the variations within different Sub-divisions are less than $0.003\text{ }^{\circ}\text{C/y}$.

The average temperature trend in Visakhapatnam is much lower ($0.004\text{ }^{\circ}\text{C/y}$) than the average trend in VCIC ($0.013\text{ }^{\circ}\text{C/y}$). The variations within Visakhapatnam district are low ($< 0.003\text{ }^{\circ}\text{C/y}$). Visakhapatnam has diminishing HS for both maximum and minimum temperature pattern with a considerable domination of persistent CS in winter and pre-monsoon maximum and minimum temperature. The variations within districts are consistent with maximum temperature; however, the annual minimum temperature pattern varies from diminishing CS to intensifying HS. It is observed that winter and pre-monsoon trends for Visakhapatnam are positive and non-significant; however, the annual minimum and maximum temperature trends are positive and statistically significant at 95% and 99%, respectively.

Diminishing CS and intensifying HS dominate annual maximum and minimum temperature patterns, respectively, in Vizianagaram. Intensifying CS and persistent CS patterns dominate winter and pre-monsoon maximum temperature. Within districts, no pattern is observed in Bobbili and Vizianagaram for maximum temperature and Parvathipuram for minimum temperature. The average trend in Vizianagaram is lower than VCIC and there is a low variation within the district. The winter and pre-monsoon

trends show negative and non-significant trends whereas the slope of the trends for annual minimum temperature is more than that of the annual maximum temperature.

5. Conclusion

The purpose of this study was to determine the minimum and maximum temperature patterns and trends along the VCIC during all seasons. Spatiotemporal analysis was carried out for assessing the intensity of clustering and slope of trends using ST cubes. The investigation of the temperature trend has been carried out for the period 1958–2018, which represents the trends of the parent dataset. The data was analysed for each district and Sub-division of VCIC. The following points were observed during the study.

- Intensifying HS dominates both maximum and minimum temperature across VCIC.
- It is evident that there is a positive and significant trend in both maximum and minimum temperature along VCIC, and there are substantial variations in trends within VCIC.
- The spatiotemporal temperature patterns are more dominated by intensifying HS in the southern and central districts and diminishing CS and no pattern in the north-eastern districts.
- Temperature trends are higher in the southern districts and gradually decrease towards the north-eastern districts.
- The variations in patterns within seasons and districts are more prominent in the north-eastern districts than in the southern districts.
- The variations in temperature trend within districts are higher in the southern districts than in the north-eastern districts.
- The slope of the trends is higher for minimum temperature than maximum temperature in the north-eastern districts, whereas it is opposite in the case of southern districts.
- The central part of VCIC forms a transition area for both patterns and trends.
- Earlier studies consider the entire east coast or coastal AP as a single value;

however, it can be seen from present study that it varies within the districts.

The VCIC is an industrial corridor with a diverse range of climatic conditions. The industrial corridor is subject to two separate rainfall seasons, each of which has an effect on the region's temperature patterns. The southern districts of Kancheepuram, Chennai, Tiruvallur, and Nellore experience northeast monsoons and central districts Prakasam, Chittoor, and Guntur experience mainly southwest monsoon but also northeast monsoons. The northern districts East and West Godavari, Visakhapatnam, and Vizianagaram receive rainfall mainly from the southwest monsoon. It is evident from the present study that the maximum and minimum temperature patterns and trends are changing along VCIC.

This corridor also experiences tropical cyclones frequently during post-monsoon seasons and intermittently during pre-monsoon seasons, which changes the temperature and the micro-climate of the region. Therefore, some adjustments are required for the present industrial areas and industrial units, especially the MSME ones, to adapt to local climatic changes, taking both soft and hard measures. Climate risk assessment of MSME sectors will enable industries to cope with extreme climate risks.

The objective of the present study will be leading towards planning of urban and industrial areas. These areas require long term planning (>30 years), where changes in the global and local micro-climate should be considered. The industrial areas range from 50 ha to 10,000 ha in the VCIC districts from AP and TN and also include non-processing zones like residential, commercial, and institutional areas. Hence, during the planning stage, variations in climate should be considered and appropriate climate change adaptation and mitigation measures need to be taken. The study enables the VCIC authorities to work towards planning and implementation of CCA measures in line with the national policies and sustainable development goals.

***Annexure 1** Spatiotemporal patterns of maximum and minimum temperature in each sub-division of VCIC*

***Annexure 2** Maximum and minimum temperature trends in each district (in bold) and Sub-division of VCIC*

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Figures

Figure 1

Districts of VCIC

Figure 2

Average annual maximum and minimum temperature

Figure 3

Spatiotemporal patterns of maximum temperature across all seasons and annual data along VCIC

Figure 4

Sen's slope of maximum temperature for all seasons and annual data across VCIC

Figure 5

Spatiotemporal patterns of minimum temperature for all seasons and annual data across VCIC

Figure 6

Sen's slope of minimum temperature for all seasons and annual data across VCIC

Figure 7

Distribution of spatial pattern for seasonal and annual maximum (Tmax) and minimum (Tmin) temperature across VCIC

Figure 8

Sub-district map of VCIC districts

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [Annexure1SpatiotemporalPatternsofTmaxandTmin.docx](#)
- [Annexure2TrendsofTmaxandTmin.docx](#)