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Comprehensive study of thunderstorm indices threshold favorable for thunderstorms during monsoon season using WRF–ARW model and ERA5 over India

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Abstract

Introduction The current research investigates into the application of various thunderstorm indices to predict severe thunderstorm occurrences during the monsoon season across four distinct regions in India. Methods: The study assesses the prediction model's efficacy using various skill scores and the Weather Research and Forecasting (WRF) model has been integrated for 30 h with double moment microphysics scheme NSSL-17 which accurately reproduces vertical and meteorological measures.

Objective Furthermore, it investigates fifteen thunderstorm indices derived from the ERA5 dataset to identify the most effective index for forecasting severe thunderstorms.

Results The results indicate that combining thunderstorm indices with skill scores, such as the Heidke Skill Score and True Skill Statistic, enhances the accuracy of severe thunderstorm predictions in the Indian monsoon season. The accurate predictions rely on determining optimal thresholds for each index. The study emphasizes the importance of using multiple indices rather relying solely on single measure for predicting severe thunderstorms. Advanced indices like the Energy Helicity Index (EHI) and Supercell Composite Parameter (SCP) perform well in forecasting extreme severe thunderstormsdue to their strong reliance on wind shears. The EHI (> 1), and SCP (≥ 3.5), STP (≥ 1.2) along with low SRH at 3 km (100 m^2/s^2), indicated no evidence of helicity or tornado activity during the event. On the other hand, the CAPE, K Index, and VT Index demonstrate robust predictive capabilities for non-severe category thunderstorms.

Conclusions Integrating numerous thunderstorm indices improves meteorologists' forecasts, ensuring public safety. Based on this work, future research can improve severe weather forecasting models' accuracy and reliability.

Keywords Thunderstorm indices, WRF–ARW, Lightning, Optimal threshold, Model Skill Score

Introduction

Thunderstorms, being accompanied by intense lightning, hails, and extreme rainfall causes heavy loss of life and property. (Yair et al. 2010, 2020). The vertically produced, fully matured cumulonimbus clouds are considered as thunderstorm cells, with moisture, a lifting mechanism, and atmospheric instability serving as fundamental conditions for their creation (Doswell 1987). The typical life duration of a thunderstorm is 1–12 h, and its spatial

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reach is only a few kilometres (Kunz 2007) which cover very less geographic and temporal region and make it difficult to forecast and predict (Anquetin et al. 2005; Das 2015). According to statistics, lightning is responsible for about 9% of natural hazard-related deaths in India. (Siingh et al. 2014; Yadava et al. 2020). The highest number of thunderstorms occur in the pre-monsoon months i.e., March, April, May, and early June. (Albrecht et al. 2016; Das 2017; Mondal et al. 2022; Saha et al. 2017). The intensity of the thunderstorms are severe (Hoddinott 1986; Marsham et al. 2013) over India due to the topography (Barthlott et al. 2006; Mushtaq et al. 2018). The basic criterion required for the formation of thunderstorms were outlined by many researchers (Mapes and Houze Jr 1993; Orville 1965). For decades, thermodynamic and kinematic parameters have been designed to quantify the thunderstorms formation (Guerova et al. 2019; Haklander and Van Delden 2003; Kaltenböck et al. 2009; Kunz 2007) over worldwide and India (Bondyopadhyay and Mohapatra 2023; Bondyopadhyay et al. 2021; Mukhopadhyay et al. 2003; Sahu et al. 2020; Umakanth et al. 2020). The air mass's convective characteristics and indices indicate thunderstorm potential (Stone 1985). Many research examined the effectiveness of indices generated from observed vertical profiles for thunderstorm prediction, (Fuelberg and Biggar 1994; Huntrieser et al. 1997; Johns and Doswell III 1992; Schultz 1989; Wilson and Mueller 1993).

The prediction and forecasting of thunderstorms are one of the most challenging tasks because of their spatial and temporal size (Brooks and Wilhelmson 1992) and also due to their physical and inherently nonlinear behaviour. (Litta and Mohanty 2008; Schultz 1989). The Weather Research Forecasting (WRF) model designed for both atmospheric research and forecasting application (Skamarock and Klemp 2008) which provide the user with the flexibility to change the horizontal and vertical resolution and domain selection. The modeling approach to forecast a thunderstorm required some appropriate physical parameterization schemes and variables (Bondyopadhyay and Mohapatra 2023; Rajasekhar et al. 2016). The demand for thunderstorm forecasting is steadily growing (Chaudhuri et al. 2015; Huang et al. 2022). The numerical modeling is one of the methods that have been used widely all across the world. Currently, the majority of meteorological forecasts are made using data from the NWP model combined with accessible observations (Choudhury et al. 2020; Dhawan et al. 2008; Robinson et al. 2013; Tyagi et al. 2011). Thunderstorm indices are often used for convection forecasting for many decades. The ability of a model to forecast thunderstorm events needs to be assessed and improved by employing thunderstorm indices derived from model and observational datasets (Gubenko and Rubinshtein 2017; Mukhopadhyay et al. 2003; Tajbakhsh et al. 2012).

The prerequisites for a severe thunderstorm are moisture, instability, lift, significant wind speeds, and directed storm relative wind shear (Das and Chaudhuri 2014). The indices developed to assess atmospheric static stability were based on the vertical displacement of a hypothetical air "parcel" of very small dimension, and an entire atmospheric layer of some prescribed isobaric thickness (Lamb and Peppler 1985; Peppler 1988). Up until the deployment of high resolution non-hydrostatic mesoscale models starting in 2000, all forecast techniques were dependent on the estimation of stability in terms of indices. In order to prepare an overview of the potential thunderstorm spectrum and a synopsis across broader regions, thermodynamic and kinematic vertical information in the troposphere is frequently brought together using parameters generated from radiosonde and numerical weather prediction model data (Kaltenböck et al. 2009; Majumdar et al. 2021). Over the past 40 years, numerous "indices" for quantitatively evaluating tropospheric static stability have been suggested in the literature or used in weather forecasting schemes as tools for identifying or predicting convective weather (Powers et al. 2017; Grieser 2012; Miller 1967). Some of these indices like, Shear-CAPE (Markowski et al. 1998), storm-relative helicity, (Thompson et al. 2004), Significant Tornado Parameter, (Rasmussen 2003), low level shear, K index (George 2014), Total–Total (TT) index (Miller 1972), Convective Available Potential Energy (CAPE) (Moncrieff and Miller 1976), (Johns et al. 1993) and Energy–Helicity index have been used in this study. While evaluating the likelihood of thunderstorms, meteorologists immediately evaluate stability indices and competence scores (Chaudhuri and Middey 2012; Sahu et al. 2020; Tyagi et al. 2011). Numerous researchers have made substantial efforts to predict thunderstorms using stability indices and to evaluate their success using skill scores (Kulikov et al. 2020). The advantages and disadvantages of the Critical Success Index, a commonly employed metric for assessing skills, were comprehensively analysed in the context of evaluating thunderstorm forecasting capabilities (Schaefer 1990). The efficacy of different skill scores in the prediction of rare events, specifically tornadoes and flash floods, was examined through the analysis of contingency tables (Doswell et al. 1990). Previous research have shown the use of skill score to find the optimal threshold and test the thunderstorm indices.

(Haklander and Van Delden 2003; Kunz 2007; Mukhopadhyay et al. 2003; Sahu et al. 2020).

The current study intends to assess the abilities and effectiveness of various thunderstorm indices in predicting thunderstorms of varying intensity. This also provides some helpful understanding of the properties of the pre-convective settings that are essential for the development of thunderstorms. Despite the existence of several current, complex dynamical and statistical models, there is still a need for precise thunderstorm predictions that are time and location specific (Kunz 2007). The performance of thermodynamic indices varies greatly from one location to another. It is possible that an index and its threshold that are determined for one site won't be applicable to another. In addition, forecasters are unsure whether to issue a thunderstorm warning even after obtaining the indices. This study focused on the thunderstorm indices time series analysis and ERA5 reanalysis dataset derived from the model data and observational data along with different model skill score which has been tested for all the indices over all the case studies. The Paper is organized as follows. In "Data and methodology" section, Data and methodology has been described including the brief discussion of study domain. Section "Results and discussion" are presented the results and discussion of the study. Some concluding remarks are introduced in the "Summary and conclusions" section.

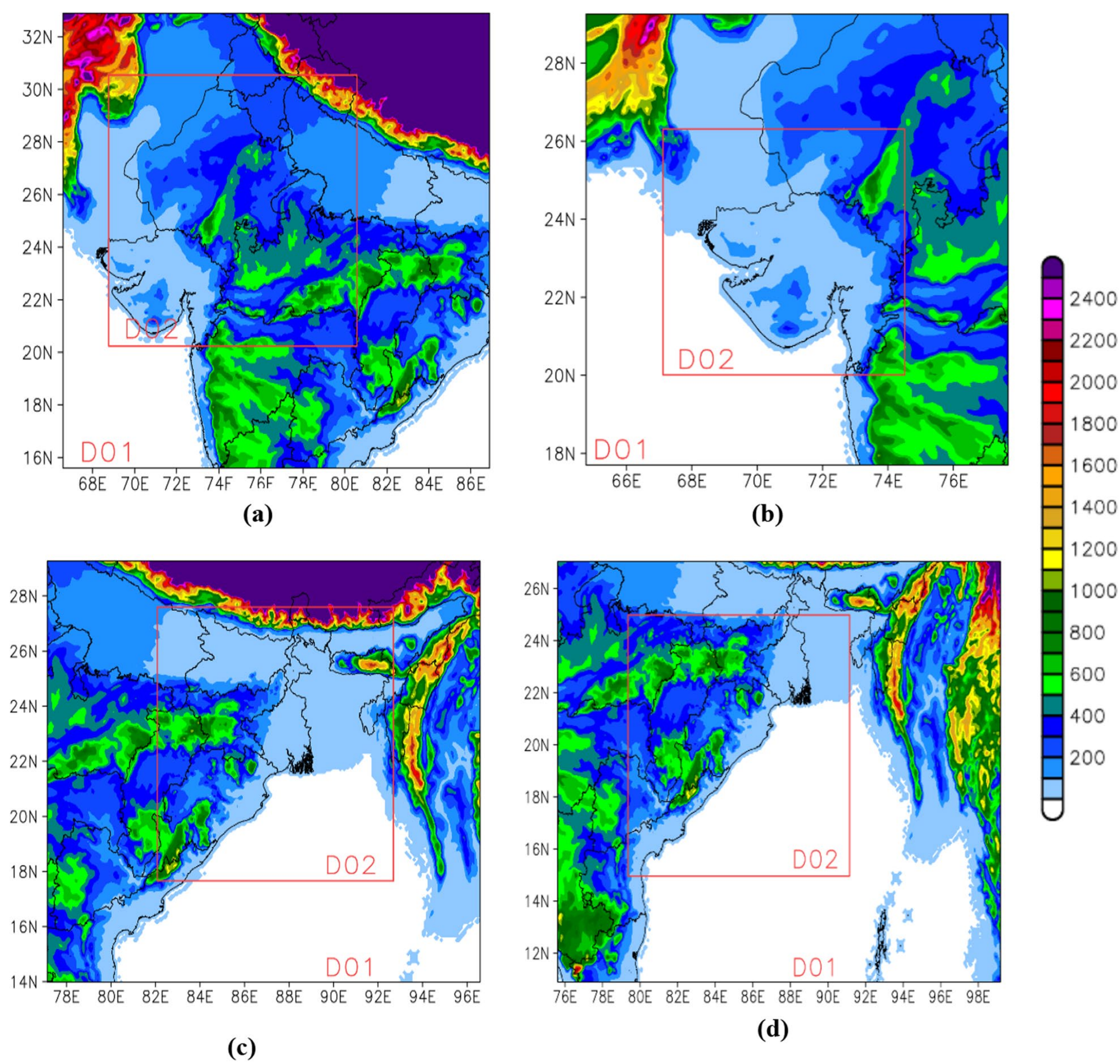

Fig. 1 WRF model double nested domain and topography (m), horizontal resolution are D01-9 km and D02-3 km resolution over **a** Udaipur, Rajasthan (11 July 2021), **b** Surendranagar, Gujarat (04 June 2021), **c** Hooghly, West Bengal (07 June 2021), & **d** Raygada, Odisha (24 June 2020)

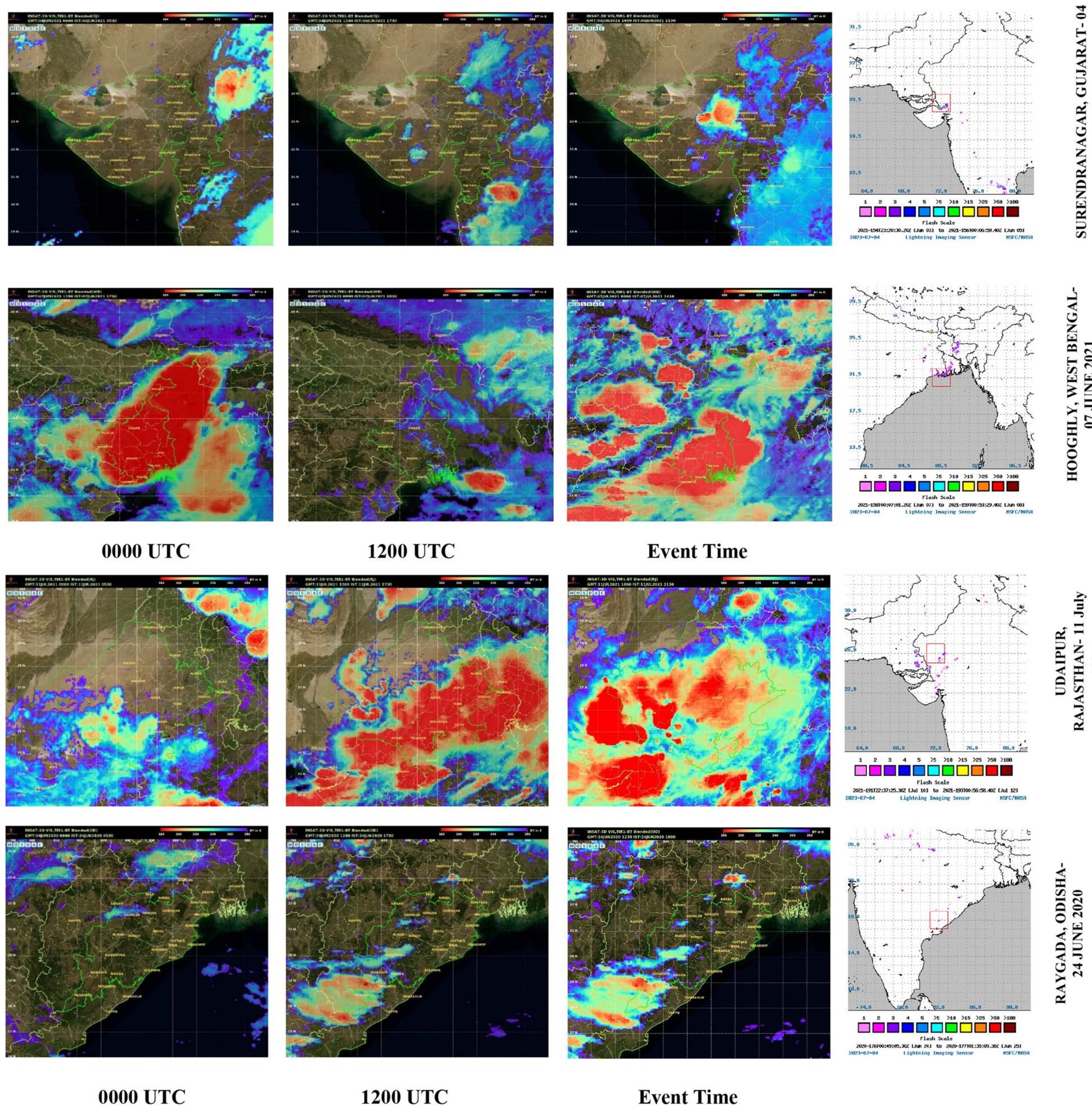

Fig. 2 Cloud Brightness Temperature (K) over the domains, 0000 UTC, 1200 UTC using INSAT-3DR and lightning flash counts using ISS-LIS

Data and methodology

Study domain

The four thunderstorm cases have been chosen from different region of India during themonsoon season for this study. Figures 1 and 2 shows the model domain resolution with topography feature of the region and synoptic condition during the event occurrences respectively. According to the IMD report for 2021, lightning and thunderstorms occurred in Rajasthan during pre-monsoon, monsoon, and post-monsoon on the following dates: 12, 22, and 23 March; 11, 13, and 14 July; 31 August; 2, 6,7,21, 22, and 28 September; 18 October; and 48 individuals died as a result of the extreme weather. 58 individuals died in West Bengal on the 11, 25, 27 May; 5, 7, 10, 12, 13 June; 2 August; 26 September. The Extremely Severe Cyclonic Storm Tauktae (14 May to 19 May) crossed Saurashtra coast on 17 May, killing 144 people from western India's Kerala in the south to Gujarat in the northwest. More than 780 people died as a result of thunderstorms and lightning in different

Table 1 Study of thunderstorm events with total number of lightning flash count over the inner domain using ISS-LIS

Events	Date	Datasets	Flash counts (number)	Box selection
Gujarat	04 June 2021	ISS-LIS	333 in 16 orbits	22.0N 24.0N 71.0E 73.0E
Odisha	24 June 2020	ISS-LIS	16 in 16 orbits	20.0N 22.0N 84.0E 86.0E
Jaipur	11 July 2021	ISS-LIS	244 in 16 orbits	24.5N 26.5N 71.5E 73.5E
Hooghly	07 June 2021	ISS-LIS	293 in 16 orbits	20.5N 22.5N 87.5E 89.5E

regions of the country. Among these, 213 deaths from Odisha, 156 deaths from Madhya Pradesh, 89 deaths from Bihar, 76 deaths from Maharashtra, 58 deaths from West Bengal, 54 deaths from Jharkhand, 49 deaths from Uttar Pradesh, and 48 deaths from Rajasthan were notably reported. Table 1 provide the details of the thunderstorm cases. The cases have been chosen based on the India Meteorological Department report and real time condition checked by using INSAT-3D and International Space Station—Lightning Imaging Sensor (ISS-LIS) satellite imageries.

WRF model

The numerical weather prediction model Weather Research Forecasting (WRF) model version (4.0.3) has been used for this study (Skamarock and Klemp 2008; Skamarock et al. 2021). The WRF model is mesoscale weather prediction model (Skamarock et al. 2019). The microphysics scheme that has been used for this study is NSSL-17 (Huang et al. 2022). Table 2 provides the model configuration and Table 3 provides the list of physical parameterization schemes used in the study.

Table 2 Summary of WRF model configuration

Parameter	Details
WRF version	4.0.3 version
Spatial resolution	9 and 3 km
Model integration time	24 Hr
Time step	54 Sec
Vertical resolution	34 Level
Lightning option	3 (Yair et al. 2010)

Table 3 Physical configuration of designed experiments

Physics options	Schemes
Microphysics	NSSL-2
Longwave radiation	RRTM
Shortwave radiation	RRTMG
Land surface physics	MM5
Surface layer physics	NOAH
Planetary boundary layer	YSU
Cumulus physics	GRELL-D

Data used

NCEP-FNL The WRF model has used NCEP-FNL data with $0.25^\circ \times 0.25^\circ$ resolution as an initial and boundary condition NCEP GDAS/FNL (2015). This data is prepared by using Global Data Assimilation System (GDAS) and Global Telecommunications System (GTS) for every six hours. The NCEP-FNL is the final product after using Global Forecast System (GFS) data (*NCEP GDAS/FNL 0.25 Degree Global Tropospheric Analyses and Forecast Grids*, 2015).

ERA5 ERA5 gives hourly estimates of many atmospheric, land, and oceanic climate variables. The data cover the Earth on a 30 km grid and resolve the atmosphere utilising 137 levels from the surface to 80 km. Two different level of reanalysis datasets downloaded from the ECMWF: ERA5 hourly data on single levels (10 m—U component of wind, 10 m—V component of wind, 2 m dewpoint temperature, 2 m temperature, CAPE, K Index, Total Totals Index) and ERA5 hourly data on pressure levels (U component of wind, V component of wind, Relative Humidity, Temperature) with 0.25 degree of resolution respectively. The ECMWF's fifth generation global climate and weather reanalysis is known as ERA5. Model data and global observations are combined through reanalysis using physics to provide a complete and consistent dataset. Every few hours (12 h at ECMWF), numerical weather prediction centres employ data assimilation to combine an earlier forecast with fresh observations in an efficient manner. This process results in a new analysis, or best estimate of the state of the atmosphere, from which a new and more accurate forecast is generated. The datasets are available in GRIB and NetCDF-4 format (Hersbach et al. 2019). This data has been used to evaluate the model output. The ERA5 reanalysis dataset, while widely utilised and valuable for various applications, also possess a limitation in terms of its spatial resolution. Specifically, the data provided by ERA5 is available at a resolution of 0.25 degrees.

Satellite datasets

INSAT-3D India launched INSAT-3D in 2013. This satellite using 6 channel Imager and 19 channel atmospheric sounder to provide meteorological services. Multispectral imaging systems produce six-wavelength earth images (optical radiometer). The Meteorological and Oceanographic Satellite Data Archival Centre (MOSDAC) (www.mosdac.gov.in) provides datasets and blended images of thermal infrared and visible channels to evaluate lightning case cloud coverage over research locations. Deep, mixed-phased convection cloud complexes can be tracked by a meteorological satellite. Based on cloud-top brightness temperatures, storms in the simulation domain were tracked using half-hourly data from the INSAT-3D satellite's visible (VIS) channel (0.65 m) and thermal infrared (TIR) channel (10.8 m).

ISS-LIS

The ISS-LIS lightning datasets has been used in this study to find the thunderstorm events with lightning. With a high detection efficiency, the ISS LIS instrument captures the moment when lightning strikes, analyses the radiant energy, and calculates the location both during the day and at night. The lightning datasets are provided by the NASA Global Hydrometeorology Resource Center (GHRC) DAAC, managed by the NASA Earth Science Data and Information System (ESDIS) project.

The Lightning Imaging Sensor (LIS) on board the International Space Station (ISS) makes estimates of the variability and distribution of total lightning (intra-cloud and cloud-to-ground lightning) in tropical and mid-latitude regions. The ISS LIS sensor tracks the amount of radiant optical radiation, logs the times of lightning strikes, and locates locations day and night with an average 24-h detection effectiveness of 70%. LIS data can be used for severe storm identification and analysis as well as studies the interaction of lightening with the atmosphere (Albrecht et al. 2016; Blakeslee et al. 2020). With a temporal range of 1 min to 1 h and a geographic resolution of 4–8 kms, these lightning products are accessible to the general public.

Methodology

The indices namely used in this study are as follows: K Index (KI), Cross Totals (CT Index), Totals Total Index (TTI), Convective Available Potential Energy (CAPE), Vertical Totals (VT Index), Energy Helicity Index (EHI), Potential Instability (POT), Supercell Composite Parameter (SCP), Storm Relative Humidity (SRH) 3 km, Pressure Low Condensation Level (PLCL), Deep Layer Shear (DLS), Low Layer Shear (LLS), Significant Tornado Parameter (STP) and Dew Point. These indices have been calculated by using the vertical profiles of the model simulated variable and the results have been evaluated using the ERA5 reanalysis datasets.

Energy Helicity Index (EHI) helps forecast rotating thunderstorms. It is often used to locate supercell thunderstorms. The Significant Tornado Parameter (STP) is another statistic used to identify tornado hotspots. It is derived from wind shear and instability data and utilised with other indices like the EHI. EHI considers thermodynamic and dynamic parameters to predict storms. STP, the Significant Tornado Parameter, assesses a tornado's destructive potential. SCP, the Supercell Composite Parameter, considers storm-relative helicity, low-level wind shear, and instability to predict supercell development. High CAPE values indicate that thunderstorm formation has a lot of energy, increasing the risk of severe weather like tornadoes, strong winds, and large hail. Wind shear, humidity, instability, and temperature gradients should all be considered to determine the possibility of severe weather. TTI is a meteorological indicator of thunderstorms. The lower atmosphere's stability is determined by combining the Virtual Temperature index (VT) and the Cross Totals index (CT). Based on temperature, dew point, and pressure, TTI indicates atmospheric instability. It forecasts short-term thunderstorms. Thunderstorm development and structure, including supercell and tornado formation, depends on deep layer and low-level shear. Deep layer shear, commonly measured up to 6 km above ground, is the wind difference between lower and upper atmospheric levels. It promotes mesocyclone formation by tilting and elongating updrafts. Low-level shear is the wind difference near the surface, measured within the first 1–2 km above ground. It can increase the storm's intensity, horizontally expand its clouds, and indicate oncoming severe weather. Severe weather requires high amounts of deep layer and low-level shear. EHI, STP, and SCP are meteorological indicators that predict thunderstorms and tornadoes.

The indices have been computed over the thunderstorm locations. The locations have been identified by using the ISS-LIS quality controlled browse image using ISS-LIS time domain search result [ISS LIS Quality-Controlled Browse Data for April 2023 (nasa.gov)] datasets and have been confirmed through INSAT-3DR cloud brightness temperature datasets for the real time condition confirmation. Using mathematical calculations based on temperature and moisture data at different pressure levels, instability indices show the potential for convection. The studies have examined various instability indices at various locations and provided threshold values for thunderstorm prediction using numerical weather prediction model.

In the context of severe weather forecasting, meteorologists utilise these indices among others to analyse and forecast thunderstorm activity. The determination of which indices to use and how to interpret them is based on the objectives of the research or forecasts as well as the study area. The definitions and mathematical equations have been included in Additional file 1: Appendix-I for reference.

REGRID

The model has been optimized for the double nested domain with 9 and 3 km resolution respectively for all the case studies. The inner domain of the model has been taken into consideration for the thunderstorm indices studies. The reanalysis datasets which has been taken from the ECMWF, ERA5 is with 0.25 degree of resolution. To get the accurate results the re-gridding of the datasets has been done according to the ERA5 for that the model data has been regridded to 0.25 degree of resolution for all the case studies by using CDO remapcon which avoid weird values if your variables are heterogeneous.

Box selection

The thunderstorm is typically a mesoscale system which is less in spatial and temporal size. The Box has been chosen of 2 by 2 degree where the thunderstorm has developed inside the inner domain of the model which has 3 km horizontal resolution. The box has been selected based on ISS-LIS lightning datasets. The Fig. 2 shows the box on ISS-LIS image in pink colour. The Table 1 provide the details of the box selection.

Time series

The time series analysis has been done on selected box after the regridding of both the datasets: Model and ERA5. The thunderstorm indices have been calculated from the model and ERA 5 datasets respectively. The model has undergone a 30-h integration process, during which a 6-h period was designated as a spin-up time for the model.

Model Skill Score

There are number of model skill scores (ACC, CSI, ETS, FAR, HSS, POD, TSS) used to check the model accuracy against the observational datasets. The model skill scores measure the performance of the forecast (Wheatcroft 2019). Researchers have a wide array of model skill scores to choose from, and their selection is often based on previous research, region and the specific requirements of their studies. Hence, authors carefully decided which model skill score to use in their research. The data sets are used to generate a 2×2 contingency table, and the four elements are based on whether an event was observed (YES/NO) and predicted (YES/NO) in the data sets. The index values are also subdivided into two sections by defining an optimal threshold. Some thunderstorm indices are associated with higher values of optimal threshold namely CAPE and TT Index while other depends on negative values like potential instability (POT).

Table 4 Contingency table

	Observation (yes)	Observation (no)	Total
Forecast (Yes)	Hits (YY)	False Alarm (YN)	YY + YN
Forecast (No)	Misses (NY)	Correct (NN)	NY + NN
Total	YY + NN	YN + NN	T = YY + YN + NY + NN

The optimal threshold can only be considered when the correct event forecast is maximum whereas, false alarm and surprised events (by chance) were minimum. The detailed version of the model skill scores, and contingency table have been provided in the Additional file 1: Appendix-II of the manuscript. Tables 4 and 5 provides the model skill score and contingency table used in this research.

Thunderstorm indices

The indices designed to measure the level of static stability/instability of the atmosphere provide valuable information about the vertical distribution of temperature and humidity, allowing for the assessment of atmospheric conditions and the identification of potential weather patterns or phenomena. Based on the factors in this study, thunderstorm indices are put into five groups. The first group is made up of simple indices based on temperature, like VT (Virtual Temperature), which give a general idea of how unstable the atmosphere is. In the second group are the measures like CT, TTI, and K Index that take into account both temperature and humidity. These indices give a more complete picture of the weather factors that can lead to thunderstorms. The third group is made up of wind-related measures like Deep Layer Shear (DLS) and Storm Relative Helicity (SRH). These factors measure the vertical wind shear and the chance of rotating updrafts, which are both important for the formation of tornadoes. In the fourth group, advanced factors like CAPE (Convective Available Potential Energy) and EHI (Energy-Helicity Index) are taken into account. These indices give more information about the energy and helicity of the atmosphere, which are important for the growth of severe thunderstorms and tornadoes. The fifth group is made up of thematic indices that are linked to specific weather hazards. Some of these measures are

Table 5 Model skill scores descriptions

Statistics	Formula	Definition	Range
Accuracy (ACC)	$AC = \frac{YY+NN}{YY+YN+NY+NN}$	What fraction of the forecasts were correct	0 to 1
Probability of Detection (POD)	POD = YY/YY + NY	What fraction of the observed "yes" events were correctly forecast	0 to 1
Equitable Threat Score (ETS)	$ETS = \frac{YY-YY_{random}}{YY+NY+YN-YY_{random}}$ $YY_{random} = \frac{(YY+YN)*(YY+YN)}{YY+YN+NY+NN}$	How well did the forecast "Yes" events correspond to the observed "yes" events (accounting for hits that would be expected by chance	− 1 to 1
False Alarm Ration (FAR)	FAR = YN/YY + YN	What fraction of the predicted "yes" events actually did not occur	0 to 1

STP (Significant Tornado Parameter) and SCP (Supercell Composite Parameter). They look at the exact conditions that are needed for dangers like hail, downdrafts, and lightning. The K Index is used for the non- severe thunderstorm. For severe, CT, VT, Total Totals Index and other indices have been selected. The EHI, STP, SCP and SRH are more advanced form of indices to predict the probability of the convective storms. The PLCL show the estimated height of the cloud base. The VT index is the difference between the temperature at 850 hPa and 500 hPa level. The stronger the vertical temperature gradient, the more likely are the thunderstorms. The CT, TTI and K index also included the humidity for better prediction because if humidity is low at higher level, it will decrease the chance of thunderstorm occurrences. The PLCL is important factor to discriminate between tornadic and non-tornadic supercells. It indicates the cloud base height, lower height increases the chances of supercells and tornadic thunderstorms. This is because the height of the cloud base is an indication of the amount of energy and moisture available in the atmosphere. Lower cloud base height indicates the presence of warm and humid air near the surface, which can lead to the development of stronger updrafts and increase the chances of supercells and tornadic thunderstorms. As the increase in relative humidity at lower level may increases the buoyancy in downdraft and increased probability of tornadoes. When the LCL is comparatively low compared, tornadoes are more likely to occur. Severe weather can be predicted by an extremely high dew point. A high dew point indicates unstable air because a high dew point indicates a high level of moisture in the air, which makes the air lighter and less dense, resulting in instability. Raising the dew-point temperature near the surface by evaporation and forcibly lifting the atmosphere on large scales can both make the atmosphere unstable and increase the likelihood of thunderstorm formation. Some of the indices directly depends on the latent instability such as CAPE which is very sensitive to vertical profiles of air parcel (Chaudhuri 2007). The CAPE is the most important indices in predicting the thunderstorm and it shows good correlation with thunderstorm and lightning (Murugavel et al. 2014). There is an inverse relationship between CAPE and CIN during thunderstorm formation. When CAPE is high, a highly unstable environment with tremendous convective energy is present, and CIN is often low (Chaudhuri 2011). This indicates that there is little resistance to the formation of thunderstorms. Contrarily, CIN tends to be high when CAPE is low, signifying a more stable environment with little energy available for convection, which makes it challenging for thunderstorms to form. The potential for instability (POT) metric indicates how unstable an area is by how much its value is negative. It is said that vector shear nearly around 15–20 m/s is needed to support a supercell. The DLS exceeding 15 m/s increases the likelihood that the supercell will be originated there. The LLS should be 2.5–5 m/s for significant tornado supercells. It is important to take into consideration both the DLS and LLS for predicting the thunderstorms. The SRH provides a calculation of the change in wind with respect to the magnitude and direction in relation to the storm movement. The EHI is more specific because it combines both the CAPE and SRH at 3 km. EHI estimated the tornado risk as EHI less than 1 in that case majority of instances, the occurrence of supercells and tornadoes is unlikely, where if the value greater than 1 to 5 is considered as F3 and F5 tornadoes respectively. The SCP is also used to predict the supercells. The value of SCP greater than 1 favours the supercells. If it is less than 1 it shows non supercell storm. The STP also provides the tool to differentiate between tornadic and non-tornadic supercells. It combines the CAPE, SRH at 3 km and 1 km and PLCL for calculation. Multiple indexes help to improve severe weather forecasting. First, it allows for cross-validation, which eliminates the need for a single index and associated limitations. Each index measures distinct characteristics of the atmospheric conditions that influence thunderstorm formation, such as instability, wind shear, and moisture availability. Forecasters boost forecast confidence by employing a variety of indicators. Different indexes are successful in different conditions or places. Some indices may be more helpful at recognizing hail possibility while others at predicting tornado formation. Forecasters can increase accuracy and reliability by leveraging various indices to capitalize on their strengths while adjusting for their flaws. Integrating many indices assists forecasters in identifying common patterns or trends, increasing their confidence in the upcoming severe weather event. The details of thunderstorm indices have been provided in the Additional file 1: Appendix.

Optimal threshold calculation

The optimal threshold for the different thunderstorm indices has been calculated using the model skill scores values. The model skill score method which has been already used in the past research (Haklander and Van Delden 2003; Huntrieser et al. 1997; Kunz 2007; Sahu et al. 2020) has been followed in this study. Some indices with low values indicate increased thunderstorm probabilities, while the opposite is also possible. The optimal threshold has been calculated for all the indices for 0000 UTC, 1200 UTC and during the event of occurrence. The maximum, minimum, and standard deviation values of the model were simulated and ERA5 datasets were used to establish the best threshold of the indices. The mean value of the area has been computed for the geographical region in which the thunderstorm event occurred. Figure 3 shows the example of choosing the optimal threshold for the thunderstorm indices. CT index for the Surendranagar, Gujarat case has been considered to explain the process how to calculate optimal threshold. CT index ranges for Surendranagar, Gujarat are − 5 °C to 25 °C, with an increasing interval of 1 °C to verify performance or determine the ideal threshold. The graph indicates the surge at 18 °C, and we also verify the model skill score values for more precision. The model skill scores on value 18 °C are: 0.73 ACC, 0.64 POD, 0.01 FAR, 0.32 ETS, 0.63 CSI, 0.61 TSS, and 0.49 HSS, which is the greatest among all the other values if other optimal threshold values are considered. The optimal threshold for the distinction of thunderstorm is then allocated to the index value at which an appropriate skill score reaches its maximum (Kunz 2007; Sahu et al. 2020). The TSS and Heidke are both often cited in literature as indicators of forecast skill, however, there appears to be a significant variation between their traits. It appears that the TSS seeks a somewhat high POD, but the Heidke Skill Score seeks to bring the FAR down to acceptable levels (Haklander and Van Delden 2003).

Results and discussion

Thunderstorm indices quantify atmospheric parameters for thunderstorm development and objectively analyse severe weather potential. They assist forecasters in swiftly assessing thunderstorm activity and predicting hail, damaging winds, and tornadoes. However, thunderstorm indices may not accurately capture local atmospheric conditions and are indirect indicators of thunderstorm presence. Their accuracy depends on the quality of input data, and determining optimal thresholds can be challenging. Understanding thunderstorm indices requires knowledge of atmospheric dynamics, and misinterpretation can lead to incorrect estimates or false alarms. Despite these limitations, thunderstorm indices provide a systematic approach to assess severe weather risk and support decision-making for public safety. The use of multiple indices helps assessing atmospheric conditions and thunderstorm potential. Easy to

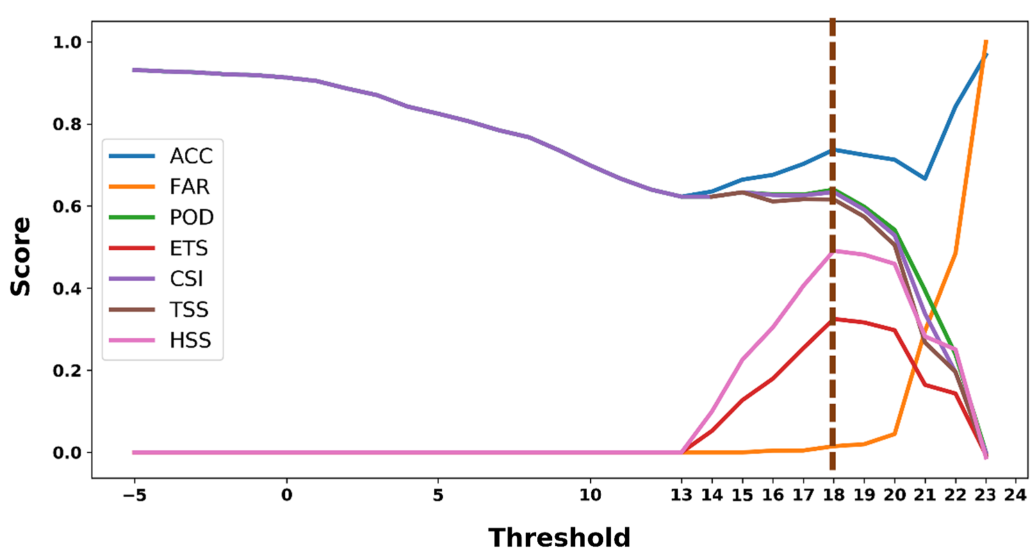

Fig. 3 Assessment of optimal threshold using several model skill score parameters for the Cross Totals (CT index) over Surendranagar, Gujarat

cross-validate information and mitigate the limitations of individual indices, enhances severe weather predictions. Thus, improved severe weather forecasts, allows forecasters to produce more accurate predictions and give timely public safety alerts.

Temperature, moisture, and wind profiles must be precise to calculate EHI. EHI is limited by the difficulty of obtaining such data in real-time operational conditions. Due to atmospheric dynamics and storm features, EHI may work differently in different regions. In places with unusual storm structures or meteorological circumstances, its dependability and accuracy may be decreased. SCP, STP and SRH heavily relies on bulk wind shear, which may not adequately reflect the complicated wind profiles within supercell thunderstorms. In cases where wind shear profiles depart from the predicted structure, bulk shear may limit its accuracy. Advance indices such as STP, SRH and SCP does not offer microscale specifics regarding particular storm aspects and attributes. It may not capture storm behaviour at smaller sizes. The parameter thresholds or weighing factors employed in SCP, SRH and STP calculation can affect its performance. Validation may be needed to determine the optimal threshold values for individual geographies or weather patterns. Careful evaluation of these problems and continuous research to improve their performance can increase their applicability and dependability in severe weather forecasting.

Weather circumstances that are prone to create severe thunderstorms are identified using various parameters. All follow simple conceptual models of convection circumstances. However, false alarm rates are high and detection rates low. Most parameters are convection dependent. These parameters can be categorized based on their underlying physical processes or variables. Temperature-only indices, such as the Vertical Total Index, provide insights into the temperature profile of the atmosphere. Humidity-related indices, such as the Cross Total, K Index, Total Totals, and Dew Point, are used to assess moisture levels in the atmosphere. Wind-related indices, including Deep Level Shear, Low Level Shear, and Storm Relative Helicity, are used to characterize the wind patterns and their potential to produce severe weather. There are also advanced indices that incorporate themes related to hail, downdrafts, and lightning, such as the Supercell Composite Parameters (SCP) and Significant Tornado Parameter (STP). By categorizing these parameters, researchers and forecasters can better understand the physical processes that govern atmospheric phenomena and use this knowledge to improve their predictions and assessments of weather and climate-related risks. The model skill scores have been computed based on optimal threshold for 0000 UTC, 1200 UTC, and the time of event occurrence. Since it would not provide an overall outcome about the skill scores, graphs for the entire time period have been plotted to provide a better understanding of the skill score for the thunderstorm indices.

Verification of model simulated thunderstorm indices with ERA-5

The thunderstorm indices have been calculated and plotted in time series graph for all the case studies to understand the difference in the model simulated datasets and reanalysis datasets. The time series graphs enable us to understand where the model worked well in accordance with the observed datasets and where it did not. The thunderstorm indices were chosen based on different studies that has been done all over the world and also in India and also testify some new indices for the case study. The time series have been plotted for the 24 h carrying hourly output of both the datasets. Based on the analysis of Figs. 4, 5, 6, and 7, it is apparent that the indices simulated by the model exhibit a high degree of agreement with the indices calculated from reanalysis data. However, it should be noted that some of the model-calculated indices did not perform as well as the reanalysis indices in certain case studies. The optimal threshold has also been calculated for all the thunderstorm indices for 0000UTC, 1200 UTC and during the occurrence of event over the region. This will give us better understanding of the threshold value of the indices at different time periods.

Assessment of thunderstorm indices over Udaipur, Rajasthan

On 11 July 2021, a thunderstorm event occurred in Udaipur, Rajasthan, which resulted in the unfortunate loss of 11 lives due to lightning strikes. The incident took place in the late afternoon, between 1600 and 1900 UTC. Figure 4 depicts the calculated model simulated thunderstorm indices over the reanalysis ERA-5 indices in a time series graph. The maximum, minimum, mean, and standard deviation of all the thunderstorm indices for both the model simulated indices and the ERA-5 derived indices are provided in Tables 6 and 7. The event occurrence time, as determined by the study of the graph and datasets, is 1900 UTC, which is consistent with the report, observational datasets, and synoptic imageries.

Figure 4 demonstrates that all indices have optimal thresholds, where the optimal thresholds for the K, VT, CT, and TTI indices are 30 °C, 24 °C, 19 °C, and 44 °C, respectively. In conjunction with the literature review, these values significantly indicate the likelihood of a thunderstorm. During the event, the dew point temperature was also elevated, around 21 °C and the PLCL was approximately 860 hPa, which is high enough to indicate a non-tornado thunderstorm. The POT value of − 56 K

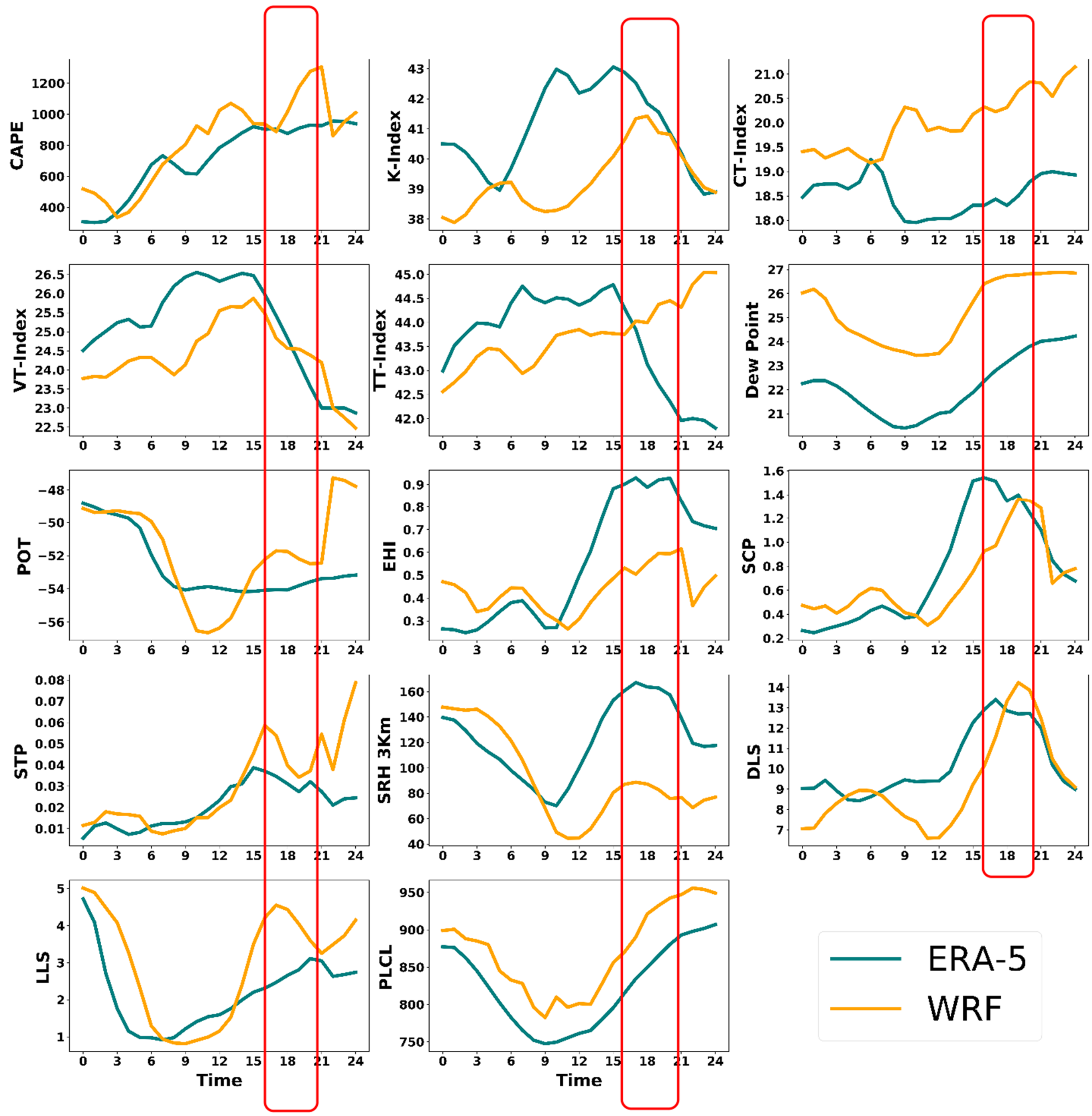

Fig. 4 Time series comparison of calculated thunderstorm indices using WRF model and ERA5 datasets over domain [24.5N 26.5N 71.5E 73.5E], the vertical box in red showing the time of event occurrence, at Udaipur, Rajasthan on 11 July 2021

indicates a region of instability that is favourable for the thunderstorm. The CAPE value is approximately 1300 J/Kg, indicating the likelihood of convection. The DLS and LLS values of 15 m/s and 7 m/s, respectively, provide an updraft for the air parcel. The EHI value of 0.5 suggests the possibility of a supercell, but it did not indicate any convective activity and there was no helicity during the event. The SCP and STP values of 1 and − 0.1 indicate that it was not a supercell tornado. The SRH value of approximately 60 m^2/s^2 was quite low for intense storm motion.

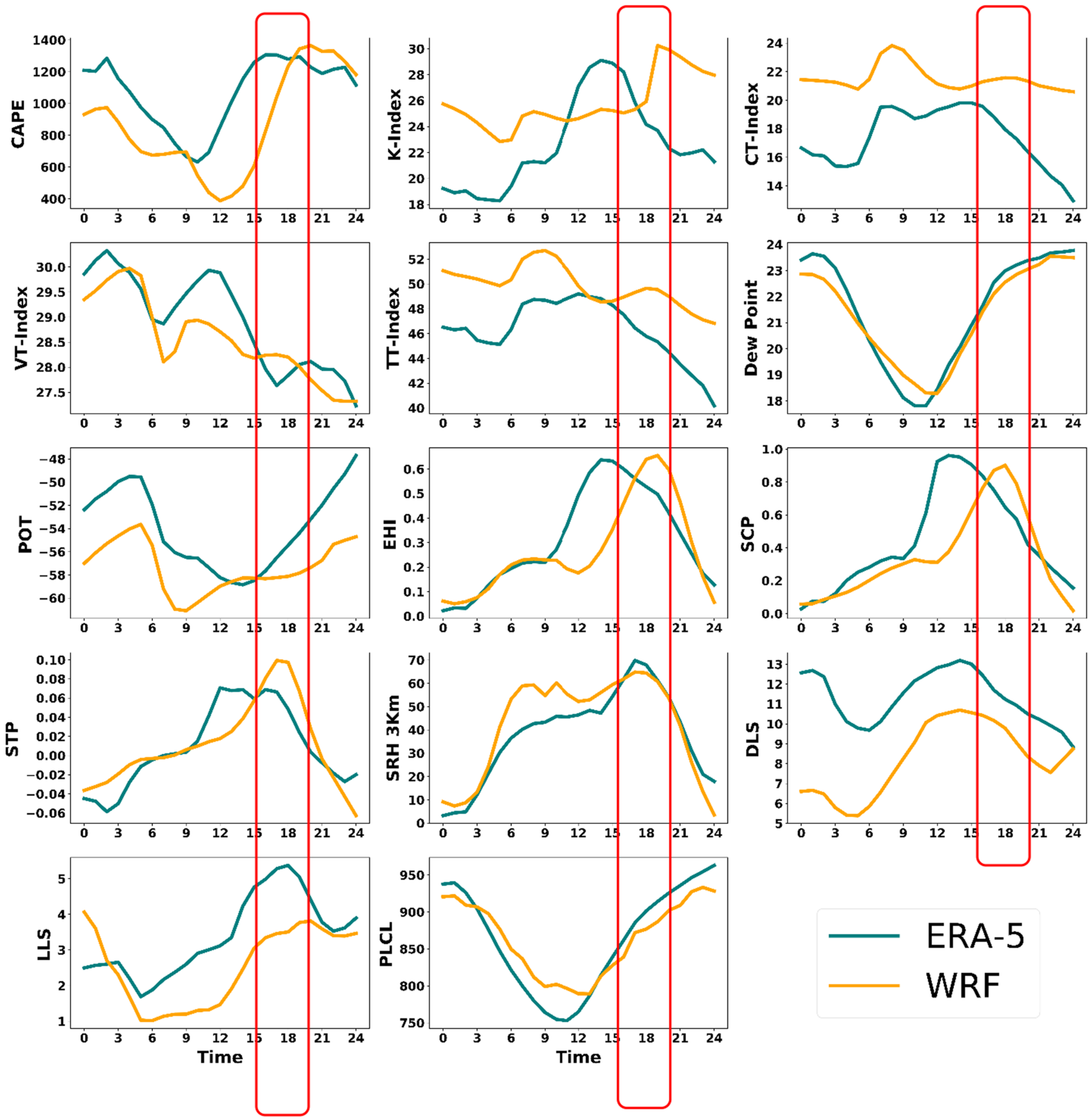

Fig. 5 Time series comparison of calculated thunderstorm indices using WRF model and ERA5 datasets over domain [22N 24N 71E 73E] the vertical box in red showing the time of event occurrence, at Surendranagar, Gujarat on 04 June 2021

The time series graph and table for all the thunderstorm indices provide results indicating that the thunderstorm in Udaipur, Rajasthan was in the low or weak category. The table provides the maximum and minimum of all the thunderstorm indices for the entire time, derived from the model simulated and reanalysis datasets. These values indicate that convective storm activity occurred. WRF simulated a drastic

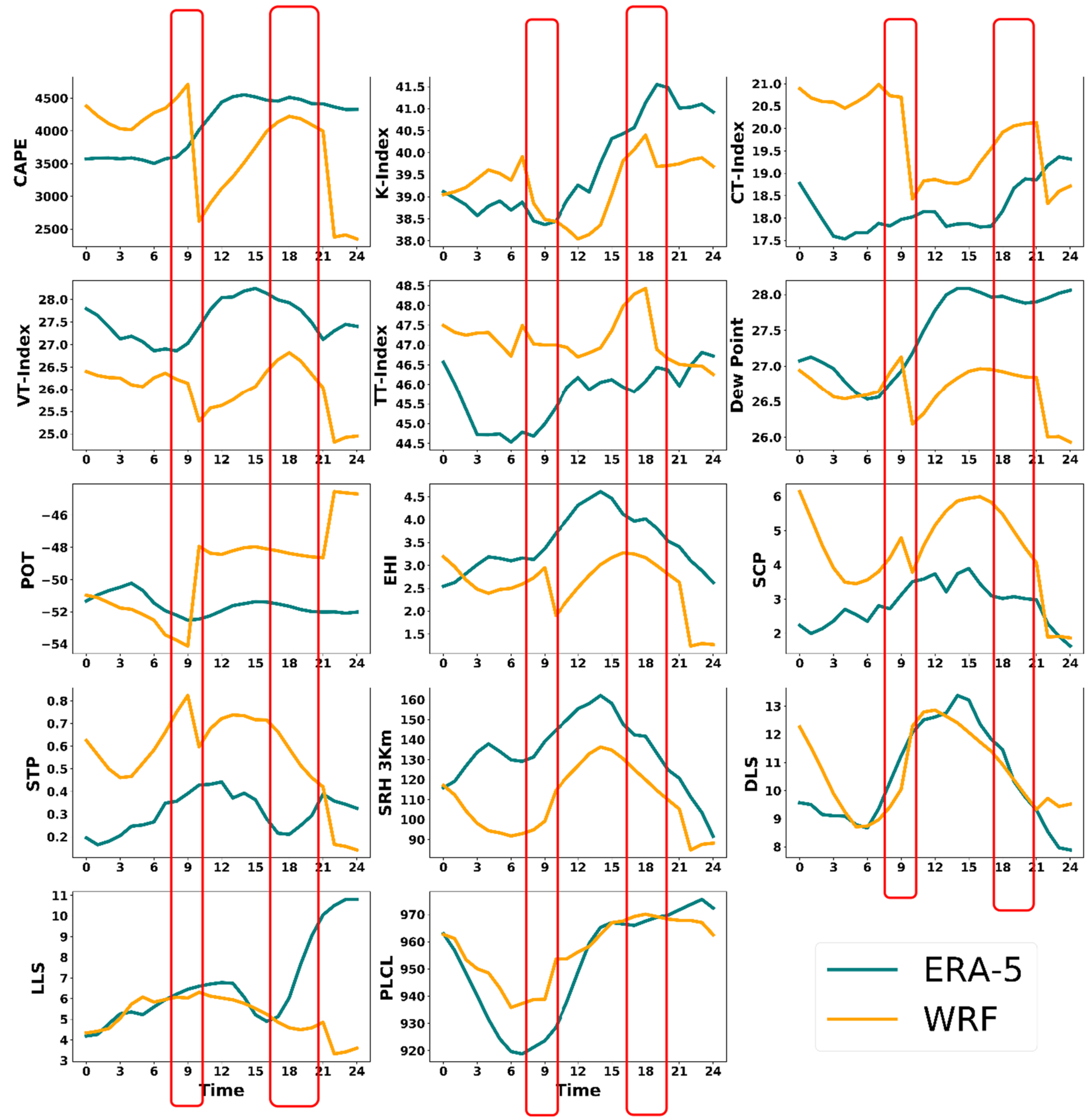

Fig. 6 Time series comparison of calculated thunderstorm indices using WRF model and ERA5 datasets over domain [20.5N 22.5N 87.5E 89.5E] the vertical box in red showing the time of event occurrence, at Hooghly, West Bengal on 07 June 2021

increase (800–2100 J/Kg) in CAPE when the event was recorded, although the ERA5 CAPE increased comparatively slowly (800–850 J/Kg). All indices showed similar trends between the model and ERA5 except for the TT-Index, which is showing a decreasing trend in ERA5 and an increasing trend in WRF. WRF also overestimated several indices, including the CT-Index, Dew Point, EHI, and SRH indices, with significant numbers. The indices with the best ability to forecast the occurrence of thunderstorms using the best

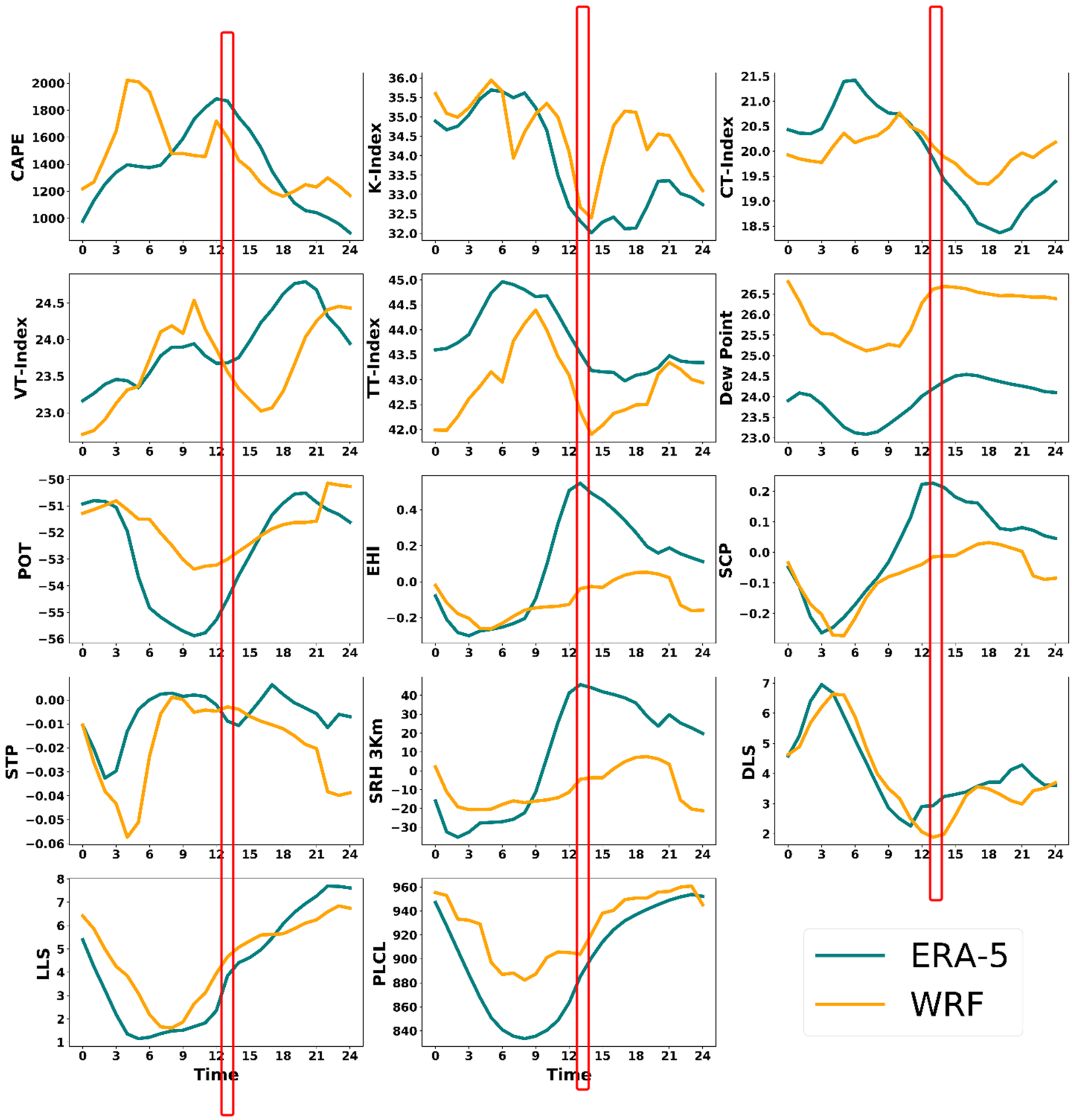

Fig. 7 Time series comparison of calculated thunderstorm indices using WRF model and ERA5 datasets over domain [20.0N 22.0N 84.0E 86.0E] the vertical box in red showing the time of event occurrence, at Raygada, Odisha on 24 June 2020

threshold are CAPE, KI, DLS, LLS, DLS whereas EHI, STP, SRH have the worst forecasting abilities. Prior to assessing the indices' precision, it is crucial to keep in mind that many of them were created to forecast particular kinds of thunderstorms.

Assessment of thunderstorm indices over Surendranagar, Gujarat

On June 04, 2021, a thunderstorm hit Surendranagar, Gujarat between 1600 to 2000 UTC in local time 2130 to 0030 IST. Figure 5 compares the model-simulated

Table 6 Maximum, minimum, mean, and standard deviation computed for all thunderstorm indices over Udaipur, Rajasthan (Max = Maximum, Min = Minimum, Mean = mean, Std = Standard Deviation)

Index	WRF				ERA-5			
	Max	Min	Mean	Std	Max	Min	Mean	Std
CAPE	2561.5	0	847.39	441.71	3879.77	0	617.91	527.89
KI	45.84	27.51	39.77	2.13	45.47	2.29	37.15	1.75
CT	22.05	11.38	18.75	1.6	24.8	12.36	19.85	1.01
VT	36.78	18.95	24.19		35.49	18.35	23.69	2.36
TTI	51.96	35.43	42.94	2.17	50.35	22.28	42.35	2.45
DEW	27.32	− 1.97	22.37	2.86	33.85	16.61	25.06	2.05
POT	− 35.72	− 63.31	− 52.75	4.24	− 28.96	− 70.35	− 51.74	4.64
EHI	3.18	− 0.46	0.32	0.32	3.46	− 0.22	0.2	0.24
SCP	5.37	− 0.43	0.39	0.49	4.97	− 0.4	0.31	0.45
STP	0.5	− 0.25	0	0.04	0.74	− 0.28	0.01	0.04
SRH 3	321.4	− 59.87	62.01	50.41	269.58	− 42.74	52.44	41.35
DLS	22.68	0.2	8.59	4.44	23.64	0.02	8.17	4.17
LLS	15.39	0.03	3.22	2.64	12.42	0	3.35	2.52
PLCL	992.95	531.74	843.04	84.7	992.62	515.65	85.05	67.48

thunderstorm indices with ERA-5 indices, while Tables 8 and 9 provide the maximum, minimum, mean, and standard deviation of thunderstorm indices derived from both sources. The report, observational datasets, and synoptic images align with the 1700 UTC event time indicated by the graph and datasets.

The CAPE's optimal threshold of 1700 J/kg suggests the occurrence of a thunderstorm. The CT, VT, TTI, and K index during the event were 18 °C, 27 °C, 46 °C, and 26 °C, respectively, indicating favourable conditions for convection. The time series graph shows an increase in values during and after the event, followed by a sudden decrease indicating the dissipation of the convective storm. The dew point temperature is around 23 °C. The DLS and LLS values are 13 m/s and 5 m/s, respectively, indicating the availability of ample wind updrafts for the formation of a thunderstorm. The optimal PLCL threshold is around 920 hPa, while before the event, it was around 750 hPa. The EHI is negligible, indicating the absence of helicity during the event. The SCP is low, but the graph approaches 1, consider in level 1 which indicates a weak category of thunderstorm and a very low likelihood of super cell formation. (https://www.saakeskus.fi). The STP values are low or negative, indicating the absence of a tornado during the event. The SRH at 3 km is around 60 m^2/s^2, which is inadequate for an extremely severe thunderstorm.

The table provides optimal thresholds for all indices, indicating that advanced indices such as STP, SCP, and EHI are only useful during extremely severe thunderstorm events. The indices gradually increased before the event and decreased after the event. Both WRF and ERA5 data showed the same pattern during the event. However, the WRF overestimated the CT-Index, while the DLS was underestimated. CAPE, LLS, DLS, TTI are most capable of forecasting the occurrence of thunderstorms using the optimal threshold, while STP, EHI, VT, have the lowest forecasting abilities. The threshold values of thunderstorm indices and graph analysis suggest that the thunderstorm that occurred was weak and not an extremely severe thunderstorm.

Assessment of thunderstorm indices over Hooghly, West Bengal

On June 7th, 2021, a severe convective storm occurred in Hooghly, West Bengal, resulting in the unfortunate deaths of 27 individuals. This event comprised two back-to-back thunderstorm occurrences, with the first taking place during the morning hours between 0800 to 1000 UTC in local hour 1330 to 1530 IST. Synoptic images and observational datasets indicate the event time to be around 0900 UTC.

An analysis of time series graphs produced by model simulations and ERA5 revealed that the morning thunderstorm was severe, with CAPE values ranging from 3900 to 4300 J/Kg in the afternoon thunderstorm. Figure 6 shows a graph analysis of various indices, including the K-Index value at 31 °C, CT-Index at 17 °C,

Table 7 Threshold values and skill scores of thunderstorm indices for event time, 0000 UTC and 1200 UTC over Udaipur, Rajasthan

Index	19 UTC								00 UTC								12 UTC							
	Threshold	ACC	POD	FAR	ETS	CSI	TSS	HSS	Threshold	ACC	POD	FAR	ETS	CSI	TSS	HSS	Threshold	ACC	POD	FAR	ETS	CSI	TSS	HSS
CAPE	**≥ 1300**	0.71	0.26	0.85	0.01	0.1	0.04	0.03	**≥ 800**	0.8	0.42	0.6	0.17	0.25	0.3	0.29	**≥ 1100**	0.63	0.61	0.66	0.11	0.27	0.25	0.19
KI	**≥ 30**	0.93	0.94	0.01	0.18	0.93	0.47	0.3	**≥ 35**	0.84	0.92	0.1	0.21	0.83	0.32	0.35	**≥ 31**	0.93	0.94	0.01	0.19	0.93	0.5	0.32
CT	**≥ 19**	0.62	0.63	0.13	0.08	0.57	0.22	0.16	**≥ 19**	0.66	0.58	0.09	0.21	0.54	0.44	0.35	**≥ 19**	0.49	0.42	0.11	0.06	0.4	0.2	0.11
VT	**≥ 24**	0.91	0.93	0.15	0.7	0.79	0.84	0.82	**≥ 25**	0.91	0.93	0.25	0.63	0.71	0.84	0.77	**≥ 24**	0.89	0.94	0.19	0.65	0.77	0.81	0.78
TTI	**≥ 44**	0.82	0.83	0.44	0.38	0.49	0.66	0.55	**≥ 44**	0.83	0.78	0.57	0.29	0.37	0.62	0.46	**≥ 44**	0.79	0.84	0.52	0.31	0.43	0.62	0.47
DEW	**≥ 21**	0.77	0.76	0	0.12	0.76	0.76	0.22	**≥ 23**	0.37	0.35	0	0.01	0.35	0.35	0.03	**≥ 21**	0.75	0.72	0.01	0.24	0.71	0.66	0.39
POT	**≤ -56**	0.76	0.75	0.03	0.24	0.73	0.61	0.39	**≤ -48**	0.83	0.59	0.15	0.42	0.53	0.54	0.59	**≤ -58**	0.8	0.85	0.07	0.17	0.79	0.36	0.3
EHI	**≥ 0.5**	0.81	0.64	0.57	0.25	0.34	0.41	0.4	**≥ 0.5**	0.88	0.31	0.79	0.1	0.14	0.23	0.18	**≥ 0.5**	0.85	0.45	0.74	0.14	0.19	0.34	0.45
SCP	**≥ 1**	0.88	0.55	0.49	0.3	0.36	0.48	0.46	**≥ 0.5**	0.84	0.44	0.61	0.19	0.25	0.34	0.32	**≥ 0.5**	0.81	0.49	0.5	0.24	0.33	0.38	0.38
STP	**≥ − 0.1**	0.82	0.83	0.01	0.04	0.82	0.38	0.08	**≥ − 0.1**	0.84	0.84	0	0	0.84	NA	NA	**≥ − 0.1**	0.81	0.81	0.006	0	0.81	− 0.18	− 0.01
SRH	**≥ 60**	0.79	0.75	0.27	0.39	0.58	0.57	0.56	**≥ 70**	0.75	0.61	0.29	0.3	0.49	0.46	0.47	**≥ 70**	0.82	0.6	0.5	0.28	0.37	0.48	0.44
DLS	**≥ 15**	0.9	0.84	0.61	0.31	0.35	0.74	0.48	**≥ 16**	0.97	0.92	0.6	0.36	0.38	0.89	0.53	**≥ 15**	0.94	0.87	0.49	0.44	0.47	0.82	0.61
LLS	**≥ 7**	0.87	0.59	0.34	0.38	0.45	0.53	0.55	**≥ 7.5**	0.88	0.42	0.78	0.13	0.16	0.33	0.23	**≥ 7**	0.97	0.24	0.73	0.13	0.14	0.23	0.24
PLCL	**≥ 860**	0.75	0.68	0.01	0.32	0.67	0.65	0.49	**≥ 920**	0.83	0.63	0.04	0.47	0.61	0.6	0.64	**≥ 940**	0.95	0.52	0.12	0.46	0.48	0.51	0.63

The optimal threshold of the thunderstorm indices, highlighted in bold, at a specific time

Table 8 Maximum, minimum, mean, and standard deviation computed for all thunderstorm indices over Surendranagar, Gujarat (Max = Maximum, Min = Minimum, Mean = mean, Std = Standard Deviation)

Index	WRF				ERA-5			
	Max	Min	Mean	Std	Max	Min	Mean	Std
CAPE	3761.99	1.56	1544.88	601.74	4070.24	0	1297.55	631.77
KI	45.91	− 6.34	22.14	12.19	42.67	2.09	23.82	9.03
CT	25.92	− 5.43	16.08	6.21	26.33	12.55	20.05	2.94
VT	36	22.27	29.99	2.3	34.62	23.57	29.12	1.91
TTI	58.35	27.03	46.07	5.33	55.18	32.44	47.33	4.54
DEW	27.25	9.56	22.85	3.19	28.91	13.64	22.57	2.3
POT	− 36.71	− 72.93	− 52.55	7.2	− 34.89	− 71.82	− 54	7.29
EHI	5.27	− 1.48	0.56	0.61	4.09	− 0.81	0.38	0.45
SCP	17.66	− 3.84	1.1	1.49	8.98	− 2.37	0.92	1.31
STP	1.53	− 1.37	0	0.16	1.57	− 1.31	0	0.14
SRH	287.88	− 96.78	56.02	51.41	2.38	− 72.67	46.85	43.64
DLS	29.96	0.54	13.52	6.18	25.71	0.02	11.59	6.29
LLS	13.38	0.14	2.86	1.8	9.77	0	2.35	1.8
PLCL	996.32	660.25	895.29	82.5	979.23	687.37	885.61	61.45

VT-Index at 25 °C, and TTI at 44 °C, all of which indicated a strong severe thunderstorm during the morning hours. Tables 10 and 11 provide comprehensive statistics regarding the event.

The EHI during this event rose to 4.5, signifying the severity of the thunderstorm. The SCP varied from 4 to 6 throughout the day, indicating an extreme severe weather event of category third. The OT of SRH at 3 km peaked at 615 m^2/s^2 in model simulation and 429 m^2/s^2 in ERA5, which is quite high. The STP was low as no tornadoes occurred. The DLS at 11 m/s and LLS at 7 m/s were adequate updraft winds for the thunderstorm.

The Hooghly, West Bengal case was observed at 0900 UTC, and it was noted that WRF recorded sharp increases and decreases in various indices such as CAPE, CT-Index, VT-Index, Dew Point, POT, EHI, SCP, and STP just before or after 0900 UTC. In contrast, ERA5 exhibited smooth changes. Additionally, WRF and ERA5 represented indices such as K-Index, Dew Point, LLS, and DLS. Of all cases, the Hooghly, West Bengal case recorded the highest CAPE threshold, reaching 4300 J/Kg at 1200 UTC, indicating the severity of the event. The indices that exhibit the highest predictive capacity for forecasting the onset of thunderstorms, when utilising the optimal threshold, includes CAPE, KI, VT, CT, TT, EHI, SCP, SRH DLS and LLS. All indices perform well during this thunderstorm event. Overall, the Hooghly, West Bengal convective storm was an extreme severe weather event, and all thunderstorm indices indicated its severity.

Assessment of thunderstorm indices over Odisha

According to the INSAT-3D and ISS-LIS datasets, the thunderstorm occurred on June 24, 2020, at around 1300 UTC during the midday in local time zone 1830 IST. Because the optimal threshold of CAPE is currently around 1300 J/kg, it is rather evident that a thunderstorm is beginning to develop. At the time that the occurrence took place, the relevant values for the CT, VT, TTI, and K index OT were 18 °C, 23 °C, 42 °C, and 34 °C. The maximum and minimum values for all the thunderstorm indices show the formation of convective storm. For example, CAPE reaches to 3900 J/Kg, TTI around 46 °C, K Index around 43 °C, CT around °C and TTI around 47 °C respectively. Figure 7 figures suggest that there is a possibility for convection to take place given the conditions. The time series graph also shows a spike in values during the occurrence, which depicts the dissipation of the convective storm, and then a steep drop in values after the incident. Tables 12 and 13 provides the computed scores for the event. The dew point is often found somewhere around 23 °C. The examination of graphs indicates that there is enough wind updraft available for the generation of thunderstorms with a DLS of approximately 6 m/s and an LLS of approximately 3.5 m/s. A little over 940 hPa was the OT of PLCL just before the disaster occurred. Due to the exceptionally low EHI, there is no evidence of helicity during the event. The SCP is quite low, the graph hits 0.5, which implies that there is no probability of a supercell but there is a 15% chance of a thunderstorm occurring. The readings of the STP, which are similarly

Table 9 Threshold values and skill scores of thunderstorm indices for event time, 0000 UTC and 1200 UTC over Surendranagar, Gujarat

Index	17 UTC								00 UTC								12 UTC							
	Threshold	ACC	POD	FAR	ETS	CSI	TSS	HSS	Threshold	ACC	POD	FAR	ETS	CSI	TSS	HSS	Threshold	ACC	POD	FAR	ETS	CSI	TSS	HSS
CAPE	**≥ 1700**	0.72	0.79	0.4	0.28	0.51	0.47	0.44	**≥ 1730**	0.71	0.96	0.59	0.25	0.39	0.62	0.4	**≥ 1900**	0.77	0.97	0.67	0.23	0.32	0.72	0.38
KI	**≥ 26**	0.83	0.74	0.02	0.51	0.73	0.71	0.38	**≥ 27**	0.71	0.46	0.25	0.23	0.41	0.35	0.37	**≥ 29**	0.77	0.63	0.23	0.34	0.53	0.5	0.51
CT	**≥ 18**	0.73	0.64	0.01	0.32	0.63	0.61	0.49	**≥ 18**	0.74	0.64	0.05	0.34	0.62	0.58	0.5	**≥ 17**	0.79	0.75	0.009	0.35	0.74	0.72	0.52
VT	**≥ 27**	0.88	0.89	0.02	0.46	0.87	0.75	0.63	**≥ 31**	0.78	0.82	0.35	0.37	0.57	0.58	0.54	**≥ 31**	0.7	0.8	0.65	0.18	0.31	0.48	0.31
TTI	**≥ 46**	0.75	0.69	0.07	0.32	0.65	0.56	0.49	**≥ 48**	0.76	0.69	0.11	0.36	0.64	0.56	0.53	**≥ 44**	0.84	0.82	0.03	0.43	0.8	0.71	0.6
DEW	**≥ 23**	0.74	0.77	0.13	0.24	0.69	0.24	0.38	**≥ 23**	0.71	0.75	0.13	0.13	0.67	0.28	0.23	**≥ 23**	0.83	0.79	0.2	0.49	0.65	0.66	0.66
POT	**≤ -50**	0.8	0.83	0.4	0.38	0.53	0.62	0.55	**≤ -46**	0.84	0.67	0.21	0.44	0.57	0.59	0.61	**≤ -48**	0.91	0.84	0.21	0.6	0.68	0.77	0.75
EHI	**≥ 1**	0.81	0.67	0.44	0.31	0.43	0.52	0.48	**≥ 0.5**	0.72	0.7	0.55	0.21	0.37	0.42	0.35	**≥ 0.5**	0.76	0.4	0.47	0.34	0.5	0.35	0.51
SCP	**≥ 4**	0.94	0.65	0.09	0.57	0.6	0.65	0.72	**≥ 0.5**	0.77	0.74	0.22	0.37	0.61	0.54	0.54	**≥ 2**	0.85	0.89	0.48	0.39	0.49	0.74	0.57
STP	**≥ − 0.1**	0.69	0.77	0.14	0.03	0.67	0.07	0.06	**≥ − 0.2**	0.84	0.02	0.05	0.04	0.83	0.24	0.09	**≥ − 0.1**	0.77	0.83	0.08	− 0.02	0.77	− 0.07	− 0.05
SRH	**≥ 140**	0.87	0.53	0.72	0.18	0.22	0.43	0.3	**≥ 80**	0.82	0.57	0.81	0.11	0.16	0.41	0.2	**≥ 100**	0.85	0.89	0.55	0.35	0.42	0.74	0.52
DLS	**≥ 17**	0.9	0.19	0.16	0.66	0.77	0.81	0.8	**≥ 12**	0.85	0.96	0.21	0.54	0.75	0.7	0.7	**≥ 14**	0.83	0.93	0.22	0.5	0.73	0.65	0.67
LLS	**≥ 7.5**	0.94	0.25	0.95	0.03	0.04	0.2	0.06	**≥ 6.5**	0.94	0.56	0.59	0.28	0.3	0.52	0.44	**≥ 5.5**	0.94	0.5	0.97	0.01	0.02	0.44	0.03
PLCL	**≥ 920**	0.83	0.99	0.25	0.5	0.73	0.68	0.67	**≥ 860**	0.9	0.89	0	0.29	0.89	0.89	0.45	**≥ 920**	0.94	0.95	0.13	0.77	0.83	0.9	0.87

The optimal threshold of the thunderstorm indices, highlighted in bold, at a specific time

Table 10 Maximum, minimum, mean, and standard deviation computed for all thunderstorm indices over Hooghly, West Bengal (Max = Maximum, Min = Minimum, Mean = mean, Std = Standard Deviation)

Index	WRF				ERA-5			
	Max	Min	Mean	Std	Max	Min	Mean	Std
CAPE	5624.77	0	1680.3	1572.65	6995.75	0	1359.22	1185.97
KI	44.03	19.81	37.62	3.62	43.49	− 20.29	34.5	5.68
CT	23.27	10.94	18.04	1.89	24.09	12.88	19.31	1.48
VT	33.18	19.44	26.67	2.59	31.09	18.51	24.99	1.99
TTI	50.78	36.67	44.71	2.32	50.32	14.69	43.86	3.26
DEW	29.01	0.47	22.56	4.6	30.04	16.81	24.9	1.64
POT	− 38.8	− 61.51	− 49.77	3.46	− 28.89	− 66.6	− 49.44	5.28
EHI	9.38	− 0.85	1.41	1.48	6.69	− 0.79	0.83	0.96
SCP	26.17	− 0.44	1.89	2.37	19.05	− 0.35	1.36	1.78
STP	2.94	− 0.31	0.17	0.26	2.56	− 0.15	0.15	0.23
SRH 3	615	− 82.77	100.78	73.24	419.23	− 45.71	93.08	63.64
DLS	22.578	0.59	9.77	4.02	20.01	0	8.77	3.49
LLS	18.62	0.02	4.86	3.09	16.19	0	4.75	3.08
PLCL	998.4	592.98	872.07	98.18	998.43	523.44	905.6	72.07

low or headed toward zero, indicate that there was no tornado activity throughout the event. The SRH at 3 km is only 70 m^2/s^2, which is a very substantial amount lower than what one would anticipate for a truly powerful thunderstorm. The Raygada, Odisha case has represented better the agreement between the ERA5 and WRF, among all cases. It showed that given model configuration in the present study has simulated comparatively better thunderstorms. When using the optimum threshold, the following indices have the highest accuracy in predicting for thunderstorm occurrence CAPE, TT, KI, On the other hand, advanced indices exhibit the lowest estimating performance. The interpretation of the optimal threshold of thunderstorm indices and graph analysis that was just described suggests that the thunderstorm that occurred in this instance was a moderate one and not an exceedingly severe one.

Model Skill Score analysis

The categorical verification provides a methodical way to assess the accuracy of different indices and select appropriate thresholds. To evaluate the optimal threshold different skill scores have been tested. The Probability of Detection (POD) and False Alarm Ratio (FAR) are widely employed metrics in research. POD is the proportion of accurately predicted events. In addition, the False Alarm Ratio (FAR) is utilised. Both metrics range from 0 to 1. In comparison to other meteorological indices, the FAR skill score for Dew Point, PLCL, POT, STP, CT, and K is significantly higher for all events. Negative skill is absent from these indices, highlighting the good performance of the model. POD, which ranges from 0 to 1, achieves a perfect score of 1 when overpredicting events, excluding false events, as shown in Fig. 8. As shown in Fig. 9, the False Alarm Rate (FAR) increases when events are underpredicted. In Fig. 8, indices such as K, CT, VT, Dew Point, PLCL, and DLS demonstrate high skill scores across all events. EHI, SCP, and STP are superior indicators for the West Bengal competition. The Accuracy (ACC) ranges from 0 to 1 in Fig. 10, representing the proportion of accurate forecasts. With the exception of the CAPE and VT Index of Odisha, all of the indices perform well. In most circumstances, indices produce commendable results exceeding 0.6. The Equitable Threat Score (ETS) in Fig. 11 ranges from − 1/3 to 1. Between 0.2 and 0.8 ETS skill scores validate accurate predictions of thunderstorm events. Complex scores such as ETS, CSI, HSS, and TSS are useful for verification. Figure 12 depicts the Critical Success Index (CSI), which quantifies the ratio of results to the total number of events and false alarms and ranges between 0 and 1. Across regions, K, CT, Dew Point, and VT skill scores stand out. CSI focuses on predicting issues and disregards accurately predicted non-events. However, it can be laborious and subject to event frequency bias. True Skill Statistics (TSS), depicted in Fig. 13, are calculated as the difference between the probability of expected events and the occurrence of unanticipated non-events. TSS ranges between − 1 and 1. The instance of thunderstorms in Gujarat yields atypical results for the majority of indices. Indices such as STP,

Table 11 Threshold values and skill scores of thunderstorm indices for event time, 0000 UTC and 1200 UTC over Hooghly, West Bengal

Index	09 UTC								00 UTC								12 UTC							
	Threshold	ACC	POD	FAR	ETS	CSI	TSS	HSS	Threshold	ACC	POD	FAR	ETS	CSI	TSS	HSS	Threshold	ACC	POD	FAR	ETS	CSI	TSS	HSS
CAPE	**≥ 3800**	0.92	0.46	0.43	0.3	0.34	0.43	0.47	**≥ 3900**	0.95	0.31	0.3	0.25	0.27	0.3	0.41	**≥ 4300**	0.95	0.92	0.86	0.12	0.13	0.88	0.22
KI	**≥ 31**	0.92	0.98	0.07	0.48	0.91	0.56	0.65	**≥ 26**	0.91	0.96	0.05	0.41	0.91	0.58	0.62	**≥ 31**	0.9	0.97	0.08	0.43	0.9	0.51	0.6
CT	**≥ 17**	0.57	0.56	0.007	0.02	0.56	0.42	0.05	**≥ 17**	0.67	0.65	0.03	0.13	0.63	0.47	0.23	**≥ 16**	0.79	0.8	0.02	0.1	0.78	0.42	0.19
VT	**≥ 25**	0.87	0.95	0.13	0.58	0.82	0.71	0.73	**≥ 26**	0.76	0.92	0.29	0.34	0.66	0.51	0.51	**≥ 25**	0.84	0.96	0.18	0.5	0.78	0.64	0.67
TTI	**≥ 44**	0.72	0.7	0.15	0.28	0.62	0.46	0.43	**≥ 42**	0.82	0.9	0.12	0.3	0.79	0.44	0.46	**≥ 44**	0.8	0.82	0.13	0.41	0.73	0.59	0.58
DEW	**≥ 24**	0.75	0.62	0.03	0.35	0.61	0.58	0.52	**≥ 24**	0.52	0.45	0.02	0.09	0.44	0.39	0.17	**≥ 24**	0.67	0.57	0.002	0.23	0.57	0.57	0.37
POT	**≤ -44**	0.92	0.23	0.4	0.18	0.2	0.22	0.3	**≤ -44**	0.84	0.17	0.55	0.1	0.14	0.14	0.18	**≤ -52**	0.74	0.72	0.08	0.26	0.67	0.5	0.41
EHI	**≥ 0.5**	0.8	0.76	0.17	0.43	0.65	0.6	0.6	**≥ 0.5**	0.81	0.77	0.14	0.46	0.68	0.63	0.63	**≥ 0.5**	0.71	0.72	0.32	0.27	0.54	0.43	0.42
SCP	**≥ 0.5**	0.82	0.76	0.09	0.48	0.7	0.66	0.65	**≥ 0.5**	0.79	0.69	0.06	0.42	0.66	0.62	0.59	**≥ 0.5**	0.74	0.69	0.13	0.31	0.62	0.51	0.48
STP	**≥ 0.2**	0.85	0.63	0.3	0.38	0.49	0.55	0.56	**≥ 0.2**	0.79	0.42	0.2	0.27	0.38	0.37	0.43	**≥ 0.2**	0.78	0.67	0.38	0.32	0.47	0.5	0.49
SRH	**≥ 220**	0.98	0.89	0.56	0.4	0.41	0.87	0.57	**≥ 190**	0.95	0.92	0.31	0.61	0.64	0.88	0.76	**≥ 230**	0.96	0.69	0.19	0.57	0.59	0.68	0.72
DLS	**≥ 11**	0.77	0.88	0.4	0.36	0.55	0.61	0.53	**≥ 10**	0.78	0.84	0.3	0.4	0.61	0.59	0.57	**≥ 9**	0.75	0.78	0.15	0.3	0.68	0.48	0.46
LLS	**≥ 7**	0.93	0.54	0.52	0.3	0.33	0.5	0.47	**≥ 4**	0.93	0.92	0.04	0.74	0.89	0.86	0.85	**≥ 5**	0.61	0.29	0.33	0.09	0.25	0.17	0.18
PLCL	**≥ 880**	0.88	0.77	0.001	0.63	0.77	0.77	0.77	**≥ 940**	0.88	0.81	0.005	0.63	0.8	0.8	0.77	**≥ 900**	0.86	0.75	0.007	0.58	0.75	0.74	0.73

The optimal threshold of the thunderstorm indices, highlighted in bold, at a specific time

Table 12 Maximum, minimum, mean, and standard deviation computed for all thunderstorm indices over Raygada, Odisha (Max = Maximum, Min = Minimum, Mean = mean, Std = Standard Deviation)

Index	WRF				ERA-5			
	Max	Min	Mean	Std	Max	Min	Mean	Std
CAPE	3939.28	0	1659.65	730.49	4169.33	0	1215.75	612.81
KI	43	23.88	34.37	3.94	41.99	23	34.08	2.96
CT	22.7	13.92	19.22	1.38	23.1	14.88	19.08	1.36
VT	26.9	20	23.36	1.01	25.8	19.84	23.18	0.96
TTI	46.94	37.46	42.59	1.63	46.62	37.02	42.04	1.52
DEW	27.58	18.18	24.85	1.89	30.19	18.65	25.48	1.16
POT	− 40.25	− 62.36	− 50.77	4.81	− 36.69	− 60.33	− 49.47	4.22
EHI	3.18	− 0.82	0.33	0.39	2.71	− 0.86	0.18	0.28
SCP	4.51	− 0.57	0.23	0.33	3.43	− 0.72	− 0.21	0.35
STP	0.8	− 0.36	0	0.04	0.39	− 0.2	0	0.03
SRH 3	213.51	− 63.58	27.98	32.21	217.41	− 58.32	21.92	30.82
DLS	24.69	0.26	6.31	2.98	16.2	0.03	6.07	2.85
LLS	13.59	0.08	2.8	2.13	13.74	0	2.87	2.28
PLCL	1033.27	755.43	924.45	57.5	996.68	759.67	936.87	36.02

DLS, SCP, and VT reached "0" in the Gujarat region prior to the event. Figure 14 depicts the Heidke Skill Score (HSS) for determining optimal thresholds for forecasts and ranking indices by their prediction capability. HSS, which ranges from − 1 to 1, highlights advanced indices such as EHI, SCP, STP, and SRH for the event in West Bengal. HSS performs admirably during event occurrences in all regions.

The majority of indices that exhibited superior performance in terms of the maximum Heidke Skill Score (HSS) and TSS also demonstrated a notable level of accuracy in predicting thunderstorm occurrences. In the investigation of both the maximum thunderstorm probability and the skill scores, it becomes evident that the accurate prediction of thunderstorms with varying characteristics cannot be accomplished through the utilisation of a single thunderstorm index that aligns optimally with the ERA5 reanalysis data or any other observational datasets. In order to enhance comprehension prior to analysis, it is helpful to employ cross checking techniques utilising both the indices graph and model skill score. That also applies to the problem of finding an appropriate threshold. When summarizing the results, the indices with the highest skills for thunderstorm prediction based on the event time are K Index, CT Index, VT Index, Dew Point. The advanced indices like EHI, SRH, STP, SCP performed well and scores high in model skill scores during the severe thunderstorm events, for example Hooghly case. When assessing the skill of the indices, it must be taken into account that while several indices were designed for the prediction of a special kind of thunderstorm some other indices were designed to forecast severe thunderstorms. CAPE, CIN, K Index can be used for every category of thunderstorm. The severity of thunderstorm accompanied by hails, heavy wind gust and tornado effect can be predicted by the thematic indices. However, when considering severe thunderstorm (Hooghly), a high prediction skill was found for EHI, SCP, STP, VT Index. Indices considering additional dynamic information like SCP, STP, EHI, SRH Index exhibit significantly low skill scores for all types of non-severe category of thunderstorms. It is interesting to note that several other indices are more suitable to predict thunderstorms than the CAPE. The study revealed that an index-based prediction of severe thunderstorms that are associated with hail or storm/flood damage is a big challenge. When compared to the prediction of thunderstorm vs. non-thunderstorm days, skill scores for the prediction of severe thunderstorms and their maximum the probability are quite low.

Summary and conclusions

The Weather Research Forecasting (WRF) model, in conjunction with the 0.25 Global Data Assimilation System (GDAS) Final dataset, has been utilized to simulate four distinct thunderstorm events. The model was implemented using a double nested domain with horizontal resolutions of 9 and 3 kms and was integrated over a period of 24 h with an additional 6-h spin-up time. To

Table 13 Threshold values and skill scores of thunderstorm indices for event time, 0000 UTC and 1200 UTC over Raygada, Odisha

Index	13 UTC								00 UTC								12 UTC							
	Threshold	ACC	POD	FAR	ETS	CSI	TSS	HSS	Threshold	ACC	POD	FAR	ETS	CSI	TSS	HSS	Threshold	ACC	POD	FAR	ETS	CSI	TSS	HSS
CAPE	**≥ 1300**	0.55	0.87	0.51	0.09	0.45	0.19	0.17	**≥ 1400**	0.82	0.89	0.25	0.48	0.68	0.67	0.65	**≥ 1200**	0.6	0.9	0.45	0.13	0.51	0.24	0.23
KI	**≥ 34**	0.91	0.87	0.06	0.69	0.82	0.82	0.82	**≥ 35**	0.79	0.7	0.11	0.42	0.64	0.6	0.6	**≥ 34**	0.87	0.83	0.08	0.6	0.77	0.75	0.75
CT	**≥ 18**	0.83	0.9	0.15	0.47	0.77	0.62	0.63	**≥ 20**	0.69	0.46	0.49	0.15	0.31	0.26	0.26	**≥ 18**	0.83	0.89	0.13	0.45	0.78	0.6	0.62
VT	**≥ 23**	0.72	0.81	0.24	0.26	0.64	0.4	0.41	**≥ 24**	0.87	0.86	0.22	0.56	0.69	0.73	0.72	**≥ 24**	0.75	0.7	0.63	0.2	0.31	0.46	0.33
TTI	**≥ 42**	0.72	0.91	0.43	0.3	0.53	0.53	0.46	**≥ 42**	0.77	0.88	0.22	0.35	0.7	0.5	0.52	**≥ 42**	0.7	0.9	0.43	0.28	0.53	0.49	0.44
DEW	**≥ 23**	0.78	0.78	0	0.001	0.78	0.78	0.003	**≥ 23**	0.71	0.71	0.001	0.009	0.71	0.53	0.01	**≥ 24**	0.69	0.67	0.001	0.1	0.67	0.65	0.18
POT	**≤ -50**	0.88	0.77	0.01	0.61	0.76	0.75	0.76	**≤ -48**	0.74	0.67	0.33	0.29	0.5	0.46	0.46	**≤ -50**	0.87	0.76	0.02	0.6	0.74	0.74	0.75
EHI	**≥ 1**	0.89	0.37	0.71	0.15	0.19	0.3	0.26	**≥ 0.5**	0.89	0.55	0.58	0.26	0.13	0.48	0.42	**≥ 0.5**	0.65	0.76	0.76	0.11	0.22	0.4	0.2
SCP	**≥ 0.5**	0.84	0.65	0.55	0.28	0.36	0.53	0.44	**≥ 0**	0.74	0.76	0.15	0.29	0.67	0.47	0.45	**≥ 0.5**	0.84	0.62	0.55	0.27	0.34	0.5	0.42
STP	**≥ − 0.1**	0.92	0.92	0	0	0.92	0	0	**≥ − 0.1**	0.92	0.93	0.006	− 0.01	0.92	− 0.06	− 0.01	**≥ − 0.1**	0.92	0.92	0.001	− 0.01	0.92	− 0.7	− 0
SRH	**≥ 70**	0.91	0.61	0.35	0.4	0.45	0.56	0.57	**≥ 50**	0.89	0.47	0.32	0.33	0.38	0.43	0.49	**≥ 70**	0.89	0.51	0.41	0.32	0.37	0.46	0.49
DLS	**≥ 6**	0.74	0.78	0.36	0.32	0.54	0.51	0.48	**≥ 6**	0.89	0.92	0.1	0.66	0.83	0.79	0.79	**≥ 6**	0.76	0.77	0.31	0.35	0.54	0.52	0.51
LLS	**≥ 3.5**	0.87	0.67	0.14	0.5	0.6	0.62	0.66	**≥ 2.5**	0.79	0.81	0.16	0.39	0.7	0.56	0.56	**≥ 2**	0.79	0.69	0.19	0.4	0.59	0.56	0.57
PLCL	**≥ 940**	0.92	0.94	0.11	0.72	0.84	0.84	0.84	**≥ 960**	0.88	0.88	0.09	0.6	0.8	0.76	0.75	**≥ 940**	0.93	0.93	0.07	0.77	0.86	0.87	0.87

The optimal threshold of the thunderstorm indices, highlighted in bold, at a specific time

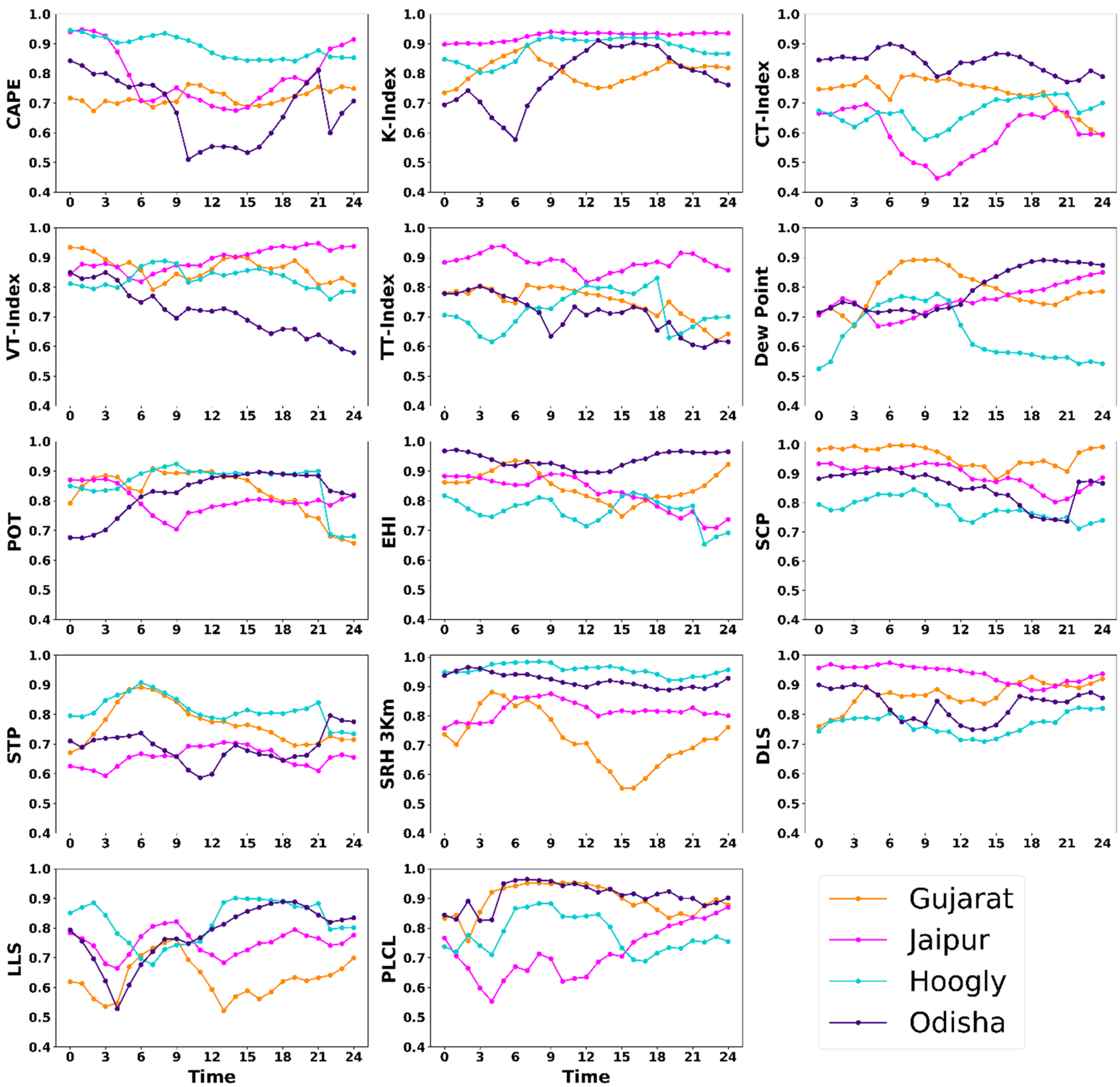

Fig. 8 Model skill score comparison of Accuracy (ACC) for different thunderstorm indices over all the case study domains

assess the accuracy of the model, thunderstorm indices were computed and compared to data from the ERA5 reanalysis dataset. The results of this comparison were then analysed and formalized. The link between these many indices and numerical weather prediction models might vary. Severe thunderstorm potential is measured using a number of different indices. Overall, there is the potential for substantial association between these indices and numerical weather prediction models. Forecasting severe thunderstorms is a difficult endeavour even with the greatest models and indices since there are numerous variables that might influence how a thunderstorm develops. All these indices are inter-related, they are used together to identify the likelihood of severe weather conditions, forecast the potential of severe thunderstorms, tornadoes and other severe weather conditions. High values indicate a high potential for the development of thunderstorms. Thunderstorm indices

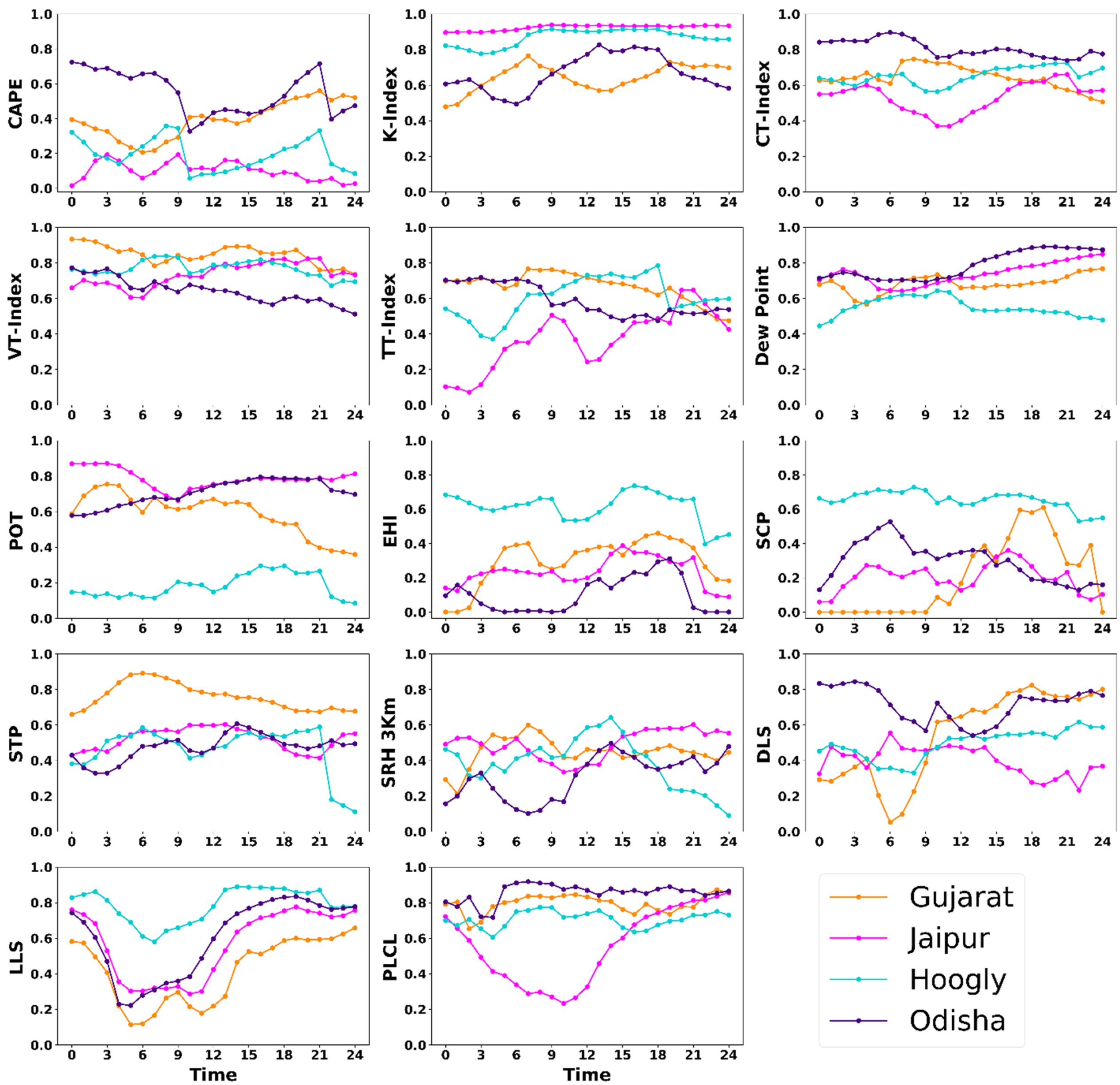

Fig. 9 Model skill score comparison of Critical Success Index (CSI) for different thunderstorm indices over all the case study domains

should be used in conjunction with other forecasting tools, such as radar and satellite imagery, to help predict severe weather events.

Thunderstorm indices CAPE showed significant values, with CAPE reaching above > 1200 J/kg and TTI around > 46 °C, suggesting the formation of a convective storm. The Wind updraft potential was sufficient for thunderstorm generation, with DLS of 10 m/s and LLS of 10 m/s. The EHI (> 1), and SCP (≥ 3.5), STP (≥ 1.2) along with low SRH at 3 km (100 m^2/s^2), indicated no evidence of helicity or tornado activity during the event. The Hooghly, West Bengal case recorded the highest CAPE threshold of 4300 J/Kg at 1200 UTC, indicating the severity of the event. These included CAPE values ranging from 3900 to 4300 J/Kg, EHI reaching 4.5, SCP indicating extreme severe weather, significant SRH and STP values, as well as adequate DLS and LLS wind conditions for updrafts. Despite EHI suggesting the possibility of a

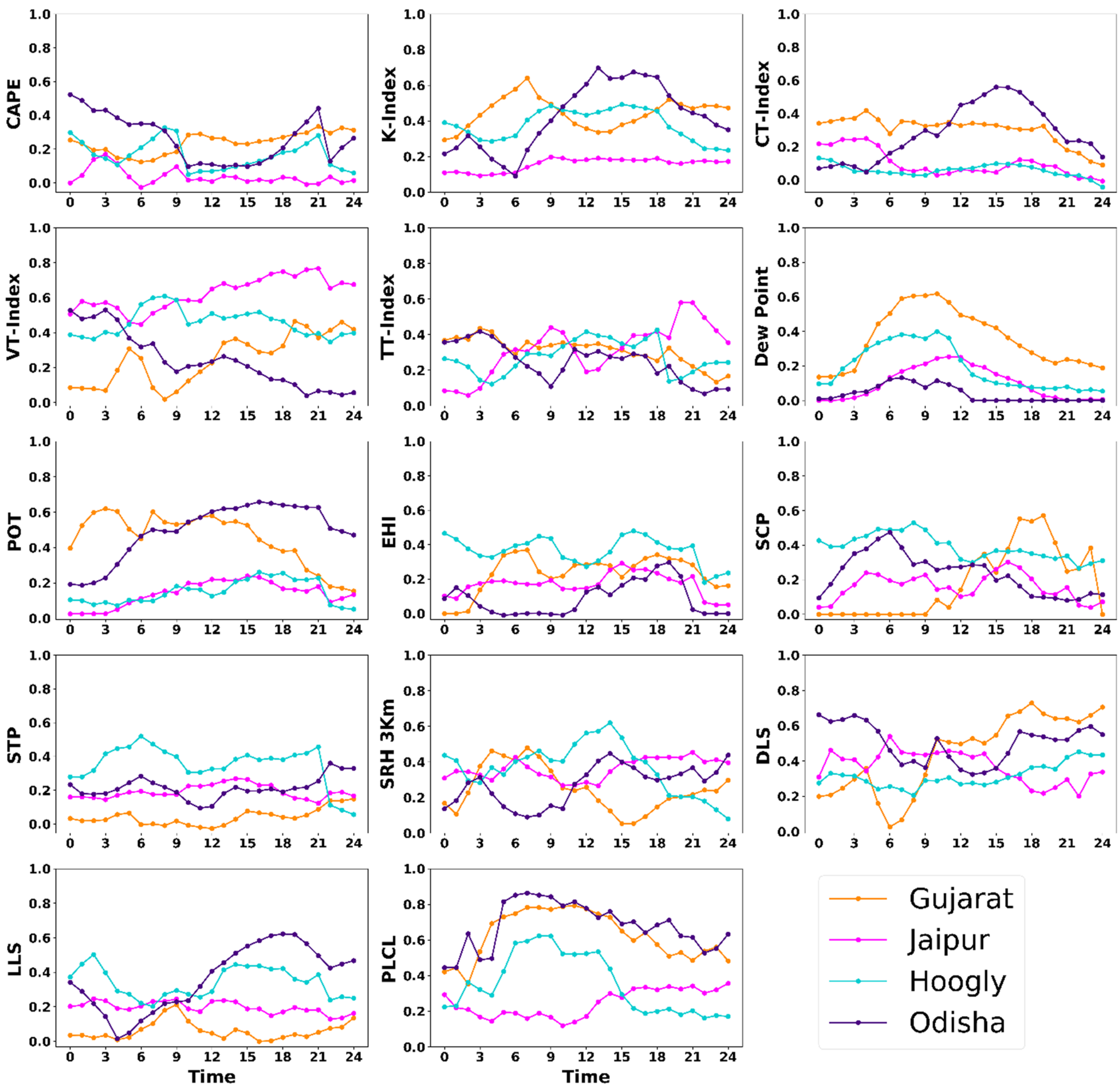

Fig. 10 Model skill score comparison of Equitable Threat Score (ETS) for different thunderstorm indices over all the case study domains

supercell in Rajasthan, there was no convective activity or helicity during the event. SCP and STP values suggested it was not a supercell tornado. Favourable conditions for convection were indicated by CT, VT, TTI, and K index values of > 18 °C, > 27 °C, > 45 °C, and > 30 °C, respectively exhibited high predictive capacity for forecasting the onset of thunderstorms. The simplistic indices such as VT, CT, TTI works well with the weak and non-supercell thunderstorms such as for Udaipur, Rajasthan, Surendranagar, Gujarat, and Raygada, Odisha cases. The supercell thunderstorm happened at Hooghly, West Bengal was predicted well by EHI, SCP, STP and SRH (advance indicators). The DLS, LLS and PLCL also indicated the supercell or non-supercell thunderstorm category. The CAPE is the most potent indices for predicting the thunderstorm either weak or strong, but the limitation is it

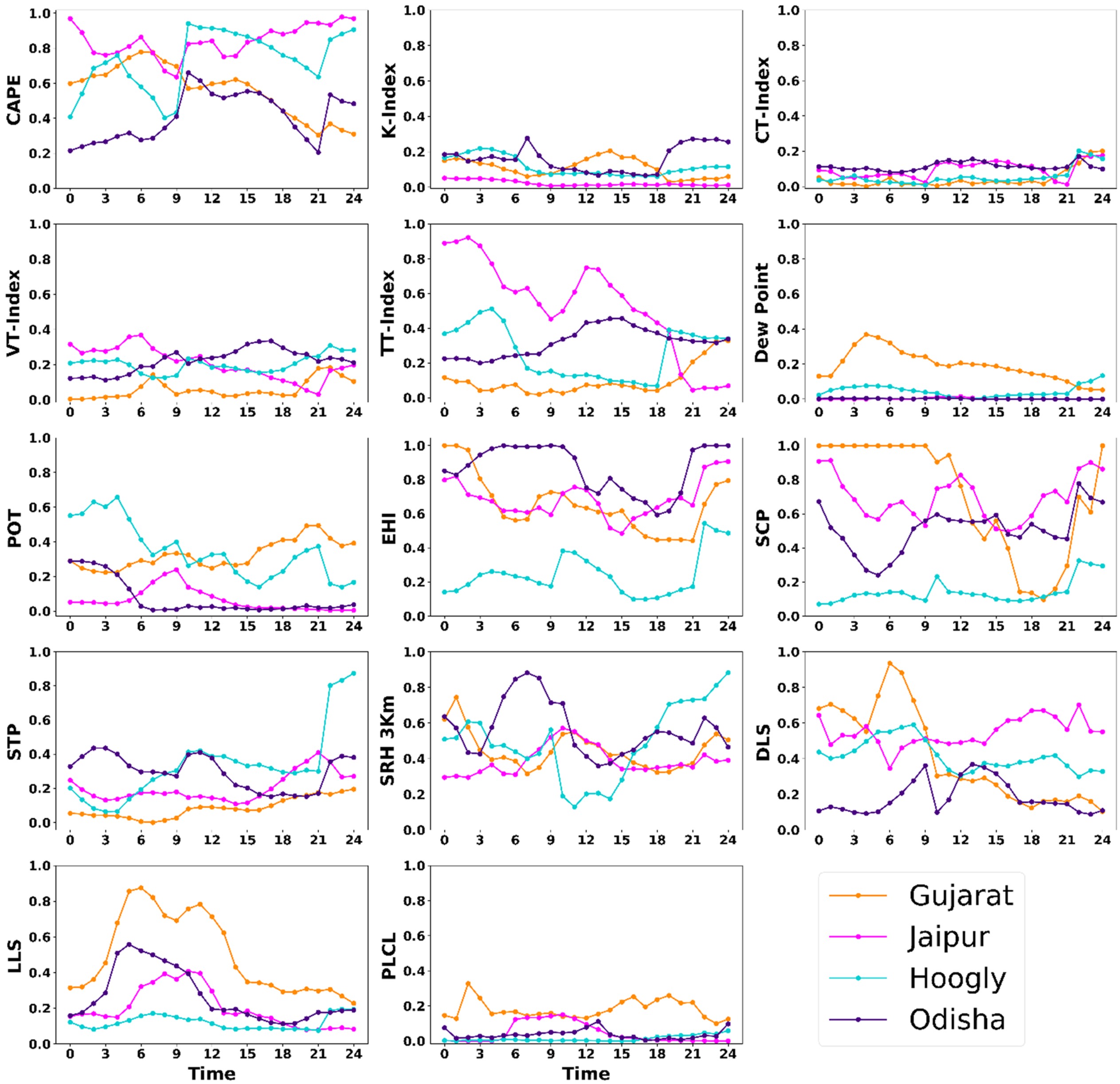

Fig. 11 Model skill score comparison of False Alarm Ratio (FAR) for different thunderstorm indices over all the case study domains

cannot predict the supercell or other categories alone. But combining with EHI, SRH and SCP it can predict the thunderstorms.

The performance of a forecast model can be assessed using a contingency table using the True Skill Statistic (TSS), Probability of Detection (POD), False Alarm Ratio (FAR), Heidke Skill Score (HSS), and Accuracy. The percentage of correct forecasts, the percentage of predicted events that occurred, the percentage of predicted events that didn't happen, the improvement in forecasting skill compared to a reference forecast, and the percentage of correct forecasts relative to the total number of forecasts are all measured by these scores. These scores measure the forecast's performance and are computed using the items of the contingency table. The CSI, TSS and HSS can be used for the forecasting skill score that are more complicated and need more useful verification parameters.

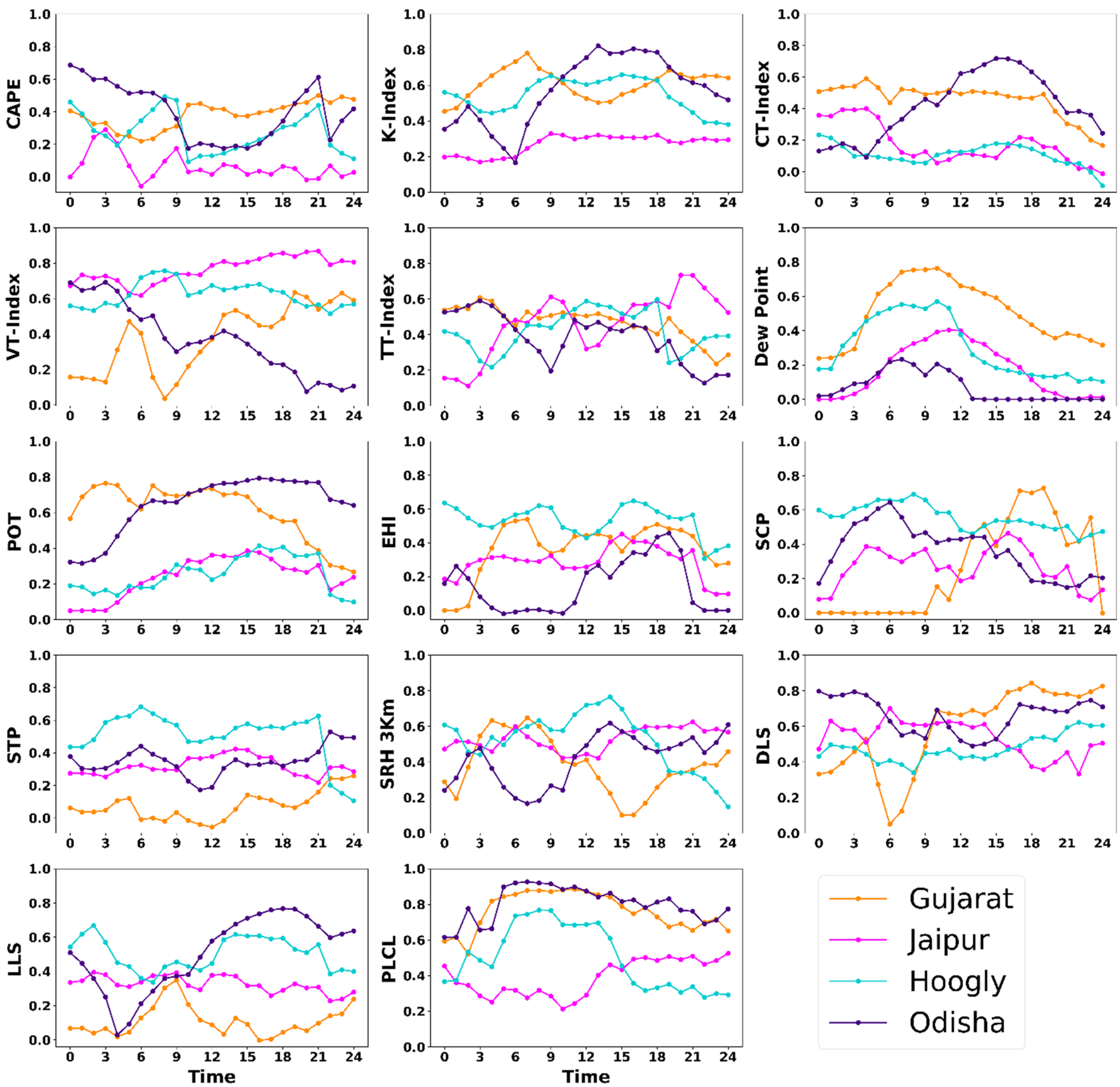

Fig. 12 Model skill score comparison of Heidke Skill Score (HSS) for different thunderstorm indices over all the case study domains

This study aimed to determine the capability of the model to track real-time events and its validity can be checked through the thunderstorm indices. The model's skill score was used to validate its performance, and the simulated thunderstorm indices produced by the model were compared with the ERA5 dataset. The model-generated indices showed good performance, except for an underestimation in the Raygada, Orissa case. To further analyse the data, weightage was given to the True Skill Statistics (TSS) and Heidke Skill Score (HSS), which consider only the correct forecasts, and not merely those made by chance. The optimal threshold of the indices obtained from both the model-simulated and reanalysis datasets demonstrated a positive correlation in almost all events and cases. The WRF–ARW model successfully simulates the surface and vertical meteorological conditions in the current experiment. The model's overestimation and underestimation were minimal, and no time lag or lead was observed. These findings suggest that the model can be used to predict the real-time occurrence

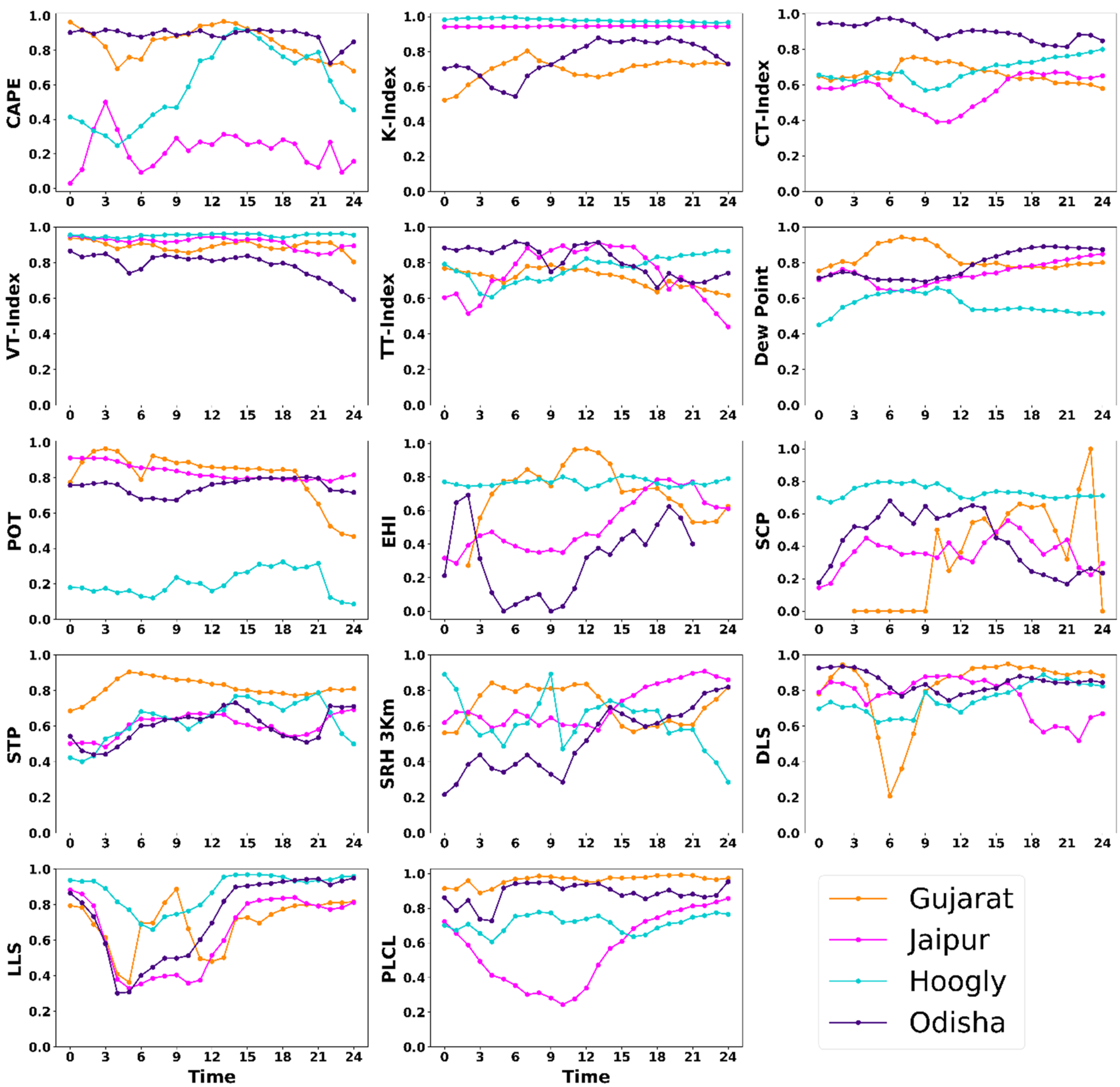

Fig. 13 Model skill score comparison of Probability of Detection (POD) for different thunderstorm indices over all the case study domains

of thunderstorms, regardless of their strength. The various indices, coupled with the implementation of skill scores, can effectively predict thunderstorms. Thunderstorm indices help with the quick assessment of thunderstorm activity and related dangers by assessing atmospheric parameters for forecasting and analysing the potential for severe weather. They do, however, act as a secondary indicator of storms and may not accurately represent regional variations. Data quality and optimal threshold setting are key to accuracy for thunderstorm assessment. Due to these indices' complexity, incorrect interpretation could result in false alarms. Despite their drawbacks, they offer a systematic way to assess the danger of severe weather so that decisions can be made with knowledge. Through cross-validation, using different indices enhances forecasting by capturing many factors that affect thunderstorms. Integrating several indices improves accuracy, helps to spot patterns, and gives

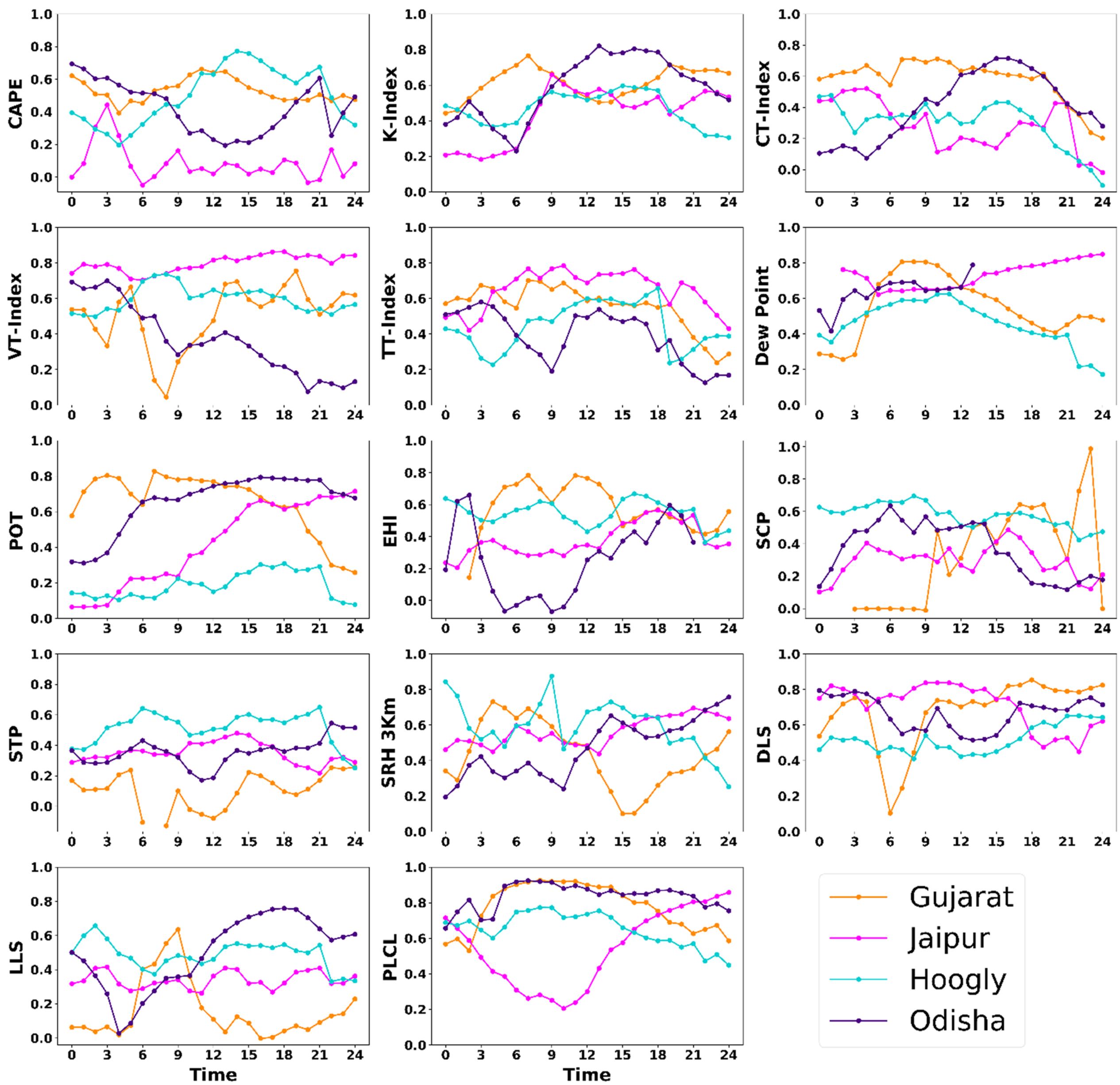

Fig. 14 Model skill score comparison of True Skill Statistic (TSS) for different thunderstorm indices over all the case study domains

forecasters more confidence when it comes to predicting severe weather events. Despite their limits, thunderstorm indices improve predictions and enable prompt public safety alerts, thereby helping in effective risk assessment and mitigation.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40677-023-00262-5.

Additional file 1. This additional files has a comprehensive explanation of thunderstorm indices and model skill score, including their equations.

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Author contributions

Authors contributed to the study conception and design—UM, SKP. Material preparation, data collection and analysis were performed by UM, SKP, AK and SD. The first draft of the manuscript was written by UM, and all authors commented on earlier versions of the manuscript. All authors read and approved the final manuscript."

Availability of data and materials
The datasets generated during and/or analysed during the current study are publicly available at ECMWF https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=overview and NCAR https://rda.ucar.edu/datasets/ds083.3/ website repository.

Declarations

Ethics approval
This article is based on analyses of secondary data and do not contain any experiments conducted on human participants and animals.
The authors have no relevant financial or non-financial interests to disclose.

Competing interests
The authors declare that they have no conflicts of interest.

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