Observed and model-simulated thermodynamic processes associated with urban heavy rainfall events over Bangalore, India

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Abstract
A total of 32 rainfall events spanning the period from 2012 to 2014 over the urban Indian city of Bangalore were simulated using the Weather Research and Forecast (WRF) model. Model simulations were carried out with a four-nested domain initialized with Global Forecast System (GFS) data and the forecast was generated on an hourly basis. The forecasted rainfall at hobli level (Bangalore has 34 hobli divisions with an area of each hobli of the order of about 10 km²) was evaluated in terms of its intensity and pattern of spatial distribution by comparing it with corresponding rain-gauge observations. Also, the rainfall forecast skill of the model was evaluated statistically by computing root mean square error, bias and mean absolute error. Thermodynamic variables such as equivalent potential temperature, convective available potential energy (CAPE), convective inhibition (CIN), K index (KI), lifted index (LI) and total totals index (TTI) were also derived from the simulated model parameters for all the events and then verified against corresponding observations. The results showed that the WRF model could simulate the rainfall events and associated thermodynamic features qualitatively; however, there were few hoblis where the relative errors in the forecast were > 100%. The forecast errors were relatively lower for cases during the southwest monsoon season compared with other seasons. It was found that the model underestimated thermodynamic indices such as CAPE, dew point depression and the simulated LI were positive; these were indicative of the model’s limitation in simulating intense convection and a possible reason for underpredicted rainfall simulations.

KEYWORDS
CAPE, rainfall forecasts, thermodynamic indices, urban extreme rainfall events, WRF model

1 | INTRODUCTION

Urbanization is a complex and multidimensional phenomenon that has a great impact on socioeconomic life and the environment. By definition, urbanization is the process by which rural areas become urbanized as a result of economic development and industrialization (Peng et al., 2011). In 1950, only 30% of world population resided in urban areas, and rapid urbanization raised it to 54% in 2014, and it is projected to be 66% by 2050. With more
rapid urbanization, India is home to an urban population of 410 million, which is the second largest in the world, and is projected to add 404 million urban dwellers to that total by 2050 (UN 2014). Urban-induced precipitation events in conjunction with the increased extent of the impervious surface often result in heavy urban flooding (Shepherd et al., 2011). The magnitude and characteristics of urban-induced environmental effects usually vary with cities and climate regimes. Modified land cover in urban areas generally leads to warmer urban areas compared with the surrounding rural regions. The creation of an urban heat island (UHI) due to urbanization causes the modification of boundary layer processes in urban areas due to the different thermal properties of artificial urban surfaces, differences in albedo and other anthropogenic activities (Shepherd et al., 2002). Past studies have investigated the impact of UHI on the local climate for various cities around the world (Chow and Roth, 2006; Miao et al., 2009).

The metropolitan meteorological experiment (METROMEX) (Changnon et al., 1971) observed the urban-induced increase in warm-season rainfall, an increase in the frequency of rainy days, the numbers of thunderstorms and hail-day frequencies. It also showed that most enhancements in rainfall are pronounced at heavier intensities. After the METROMEX, there have been many studies on the effect of urbanization on weather and, especially, on precipitation that supported the METROMEX findings (Changnon, 1979; Shepherd et al., 2002; Shepherd, 2005). Kishatwal et al. (2010), with the help of a long-term daily rainfall data set and high-resolution gridded analysis of the human population, showed a significantly increasing trend in the frequency of heavy rainfall climatology over the urban regions of India during the monsoon season. Through a modelling study, Thielen (2000) showed that mesoscale processes such as convective rainfall can be affected significantly by the surface conditions in an UHI, such as sensible heat fluxes, in particular, and enhanced surface roughness. They also found a higher frequency of occurrence of rain-bearing clouds over urban areas, and that the presence of urban agglomerations resulted in enhanced precipitation, which confirmed the effects of urbanization on precipitation as observed in the METROMEX experiment. Studies have connect the increase in the frequency of thunderstorms in cities with an increase in the population (Balling and Brazel, 1987; Jaurequi and Romales, 1996).

Predicting urban localized rainfall events is still a challenging issue in weather forecasting due to their high spatial and temporal variability (Orlanski, 1975). Earlier studies showed that urbanization and changes in urban–rural boundaries can have significant feedback on the spatiotemporal patterns of precipitation (Niyogi et al., 2006; Mote et al., 2007; Lei et al., 2008; Kutty et al., 2018). Refining the skill of quantitative precipitation forecasting (QPF) is one of the biggest challenges with mesoscale modellers (Anquetin et al., 2005). Anquetin et al. (2005) showed that low-resolution simulations failed in QPF (rainfall were underestimated) forecast and spatial distribution. However, there were case studies using high-resolution (3 km) WRF-nonhydrostatic mesoscale model showing better results in thunderstorm prediction and suggested that high-resolution models have the potential to provide distinctive and valuable information for severe thunderstorm forecasters (Anquetin et al., 2005; Litta and Mohanty, 2008). Another high-resolution (WRF 500 m grid spacing) modelling study found that rapid urbanization results in significant modifications in the surface properties and atmospheric circulations while convergence zones in urban areas are correlated to building height distribution (Miao et al., 2009). Similarly, Pielke et al. (2007) summarized that urbanization alters rainfall patterns as a result of local circulations through changes in convective available potential energy (CAPE). Higher resolution models also help to make use of high-resolution input data (Miao et al., 2009). Rakesh and Goswami (2015) examined the impact of assimilation of in-situ data on the simulation of heavy rainfall events over the Indian region and showed that there are strong seasonality and location dependence in the impact of data assimilation. Mohapatra et al. (2017) examined the skill of a high-resolution configuration of the WRF model when simulating localized and non-localized heavy rainfall events over Bangalore and found that model skill was relatively poor in the case of localized rainfall events. Accurate simulation of urban localized rainfall is generally difficult for mesoscale models, mainly due to their inability to simulate complex thermodynamic processes which lead to such rainfall events (Guo et al., 2006).

However, studies that investigated the model skill in simulating thermodynamic features associated with urban localized rainfall are limited over the Indian region, except for a few case studies. In the present study, an attempt has been made to investigate the skill of the Weather Research and Forecast (WRF) model in simulating the thermodynamic features of urban localized rainfall by analysing 32 events over Bangalore, a megacity in southern India (12.65–13.5°N, 77.18–77.95°E), that occurred during the three years between 2012 and 2014. Since the current study centred over Bangalore, which is located in the Tropics, most of the extreme weather events that occur there are convective in nature and advance and the accurate forecast of these heavy rainfall events has a high socioeconomic impact, especially in cities (Litta and Mohanty, 2008). Such studies within the city and beyond need detailed examination, which has
importance in weather forecasting, urban planning, water resource management and anthropological impact on climate and the environment and sustainable development (Shepherd et al., 2002).

2 | METHODOLOGY

2.1 | Model configuration and experiment design

The WRF model, a popular numerical weather prediction system, was used and applied in both atmospheric research and forecast. It has been an extensively used model recently, especially in heavy rainfall research over the Indian region (Fadnavis et al., 2014; Chawla et al., 2018; Karki et al., 2018; Madhulatha and Rajeevan, 2018; Reshmi et al., 2018). A recent study by Chawla et al. (2018) found that the WRF-simulated rainfall exhibit less bias compared with national centers for environmental prediction final (NCEP-FNL) reanalysis data. The WRF model is a highly customizable model with several radiation, planetary boundary layer (PBL), cloud microphysics and convection physics options. The selection of appropriate physics schemes is crucial for the dependable prediction of intensive rainfall (Ratnam et al., 2017; Karki et al., 2018). The influence of various combinations of parameterization schemes on rainfall simulation is still an active area of research in India (Chawla et al., 2018).

The present study used a configuration (Figure 1) with four nested domains (with domains 1–4 having horizontal resolutions 36, 12, 4 and 1.33 km, respectively) with model physics options such as the microphysics-WSM6 scheme, rapid radiative transfer model (RRTM) long wave and Dudhia short wave, cumulus parameterization–New Kain–Fritsch scheme, and PBL-yonsei university (YSU) scheme. A nested configuration was used to downscale dynamically the initial condition and to incorporate the effect of large-scale circulation on urban extreme events through feedbacks between the outer domain and the inner domains. Ratnam et al. (2017), using a set of 17 experiments, tested various combinations of physics schemes of the WRF model and found that a configuration similar to the above was suitable for simulating rainfall over the Indian region. The model configuration has 48 vertical levels and a topmost level set at 50 hPa, with a higher number of levels in the lower troposphere. The simulations were carried out for 32 rainfall events over Bangalore where the model was initiated at 0000 UTC for each case with a 36 hr period of integration. The three hourly forecast data, archived in near real-time from the NCEP Global Forecast System (GFS) (0.5° × 0.5°) (NCEP/NCAR), enhanced by the assimilation of local observations such as radiosondes, telemetric weather station (TWS) installed by the Karnataka State Natural Disaster Monitoring Centre (KSNDMC), automatic weather stations (AWS) observations from the India Meteorological Department (IMD), and CSIR Climate Observation and Modelling Network (COMoN) using the WRF three-dimensional variational (3D-Var) assimilation scheme, was used to generate the model’s initial conditions (Rakesh and Goswami, 2015). The basic model parameters such as temperature, wind vector, pressure and humidity from the TWS observations were assimilated in the model outer domain (domain 1). The profiler data from upper air soundings (about 70 locations) over South Asia from the University of Wyoming (http://weather.uwyo.edu) were also assimilated in domain 1. The model background and observation errors covariances used in the present study were similar to those used by Rakesh and Goswami (2015). The model land-surface parameters such as terrain height, land-use (USGS-25 Category) and vegetation fraction were extracted from the US Geological Survey data sets. The model boundary conditions (for the outer domain) were updated hourly using the forecasted GFS data, and the interpolated fields from the outer domain were used to update the boundary for the inner domains.

2.2 | Thermodynamic indices

It is well known that atmospheric instability is a key factor determining the possibility of thunderstorm development, especially in the Tropics. Thermodynamic stability
indices can be used to predict the possible atmospheric instability and thereby thunderstorm development. The usefulness of different stability indices in assessing forecast skills had been studied extensively in the past (Peppler, 1988; Hantuiers et al., 1997; Haklander and Delden, 2003; Manzato, 2005; Kunz, 2007). However, it should be noted that the theoretical values of different indices are not definite, but may vary with geographical location, season and synoptic situation (Dalezios and Papamanolis, 1991; Haklander and Delden, 2003). It has been found that no single index can predict or describe the instability of atmosphere (Tyagi et al., 2011) and different indices work for different thunderstorm types (Haklander and Delden, 2003). The present study selected a few thermodynamic indices based on past studies over the Indian region (Tyagi et al., 2011; Jayakrishnan and Babu, 2014), which explained the development of instability in the atmosphere that triggers convection. While the K index (KI) was selected as an indicator for determining non-severe convective showers and thunderstorms, lifted index (LI) and total totals index (TTI) were selected as indicators for severe convection together with the CAPE and convective inhibition (CIN) as measures of positive and negative buoyant energy of the parcel.

### 2.2.1 Convective available potential energy (CAPE)

CAPE (J·kg\(^{-1}\)) is essentially the positive area integrated in the skew T-log P sounding chart, where the air parcel temperature is warmer than the ambient temperature starting from the level of free convection (LFC) to the level of neutral buoyancy (LNB). Rather a measure of instability, CAPE represents vertically integrated positive buoyancy of an adiabatically rising air parcel (Miller, 1972). It is related to the vertical extent and updraft strength of a convective storm. A CAPE < 1,000 J·kg\(^{-1}\) is considered as weak instability; 1,000–2,500 J·kg\(^{-1}\) as moderate; 2,500–4,000 J·kg\(^{-1}\) as strong; and > 4,000 J·kg\(^{-1}\) as extreme instability (https://www.spc.noaa.gov/exper/mesoanalysis/help/begin.html). Tyagi et al. (2011) reported a CAPE ≥ 1,000 J·kg\(^{-1}\) as the threshold for possible convection, while Mukhopadhyay et al. (2003) showed that a CAPE ≥ 896.8 J·kg\(^{-1}\) triggered convection.

\[
\text{CAPE} = \int_{\text{LFC}}^{\text{LNB}} (T_{vp} - T_{ve}) R_d d(lnP)
\]

where LFC is the height at which a parcel of air becomes warmer than its surroundings when lifted dry-adiabatically until saturated and saturated adiabatically, thereafter; LNB is the level at which the ascending or descending parcel of air attains the same density as its environments; \(P\) is the pressure through which a parcel rises; \(T_{vp}\) is the virtual temperature of the parcel; \(T_{ve}\) is the virtual temperature of the environment; and \(R_d\) is the ideal gas constant for dry air. CAPE analysis is a very popular method with which to evaluate the convective potential of the atmosphere (Manzato, 2005).

### 2.2.2 Convective inhibition (CIN)

CIN (J·kg\(^{-1}\)) is the amount of work required to lift an air parcel through an original layer that is warmer than the parcel and allow these parcels to ascend above the LFC. It is computed like CAPE and is defined as:

\[
\text{CIN} = \int_{\text{Surface}}^{\text{LFC}} (T_{vp} - T_{ve}) R_d d(lnP).
\]

The marginal values of CIN in the range 0–50 J·kg\(^{-1}\) indicate weak inhibition; 51–199 J·kg\(^{-1}\) indicate moderate inhibition; and > 200 J·kg\(^{-1}\) show strong inhibition. The analysis performed by Frank and Colby (1984) showed that low convective inhibition is an important predictor for convective outbreaks.

### 2.2.3 K index (KI)

KI (George, 1960) measures the convective potential of the lower troposphere. It uses the lapse rate and moisture content of the lower troposphere by combining the difference between 850 and 500 hPa temperature, known as vertical totals (VT) and the 850 hPa dewpoint (a direct measure of low-level moisture content) minus the 700 hPa dewpoint depression (an indirect measure of the vertical extent of the moist layer). In general, marginal values evaluated for the KI in the range 15–25 K indicate small convective potential; 26–39 K indicate moderate convection; and > 40 K show high potential. The study by Tyagi et al. (2011) over Kolkata found that for KIs ≥ 24 K moderate convection occurred.

\[
\text{KI} (K) = (T_{850} - T_{500}) + T_d850 - (T_{700} - T_d700)
\]

where \(T\) is the temperature (K); and \(T_d\) is the dew point temperature (K) at the corresponding levels.

### 2.2.4 Total totals index (TTI)

TTI (Miller, 1967) is a severe weather index used to calculate storm strength. This index is useful to assess the
storm strength, but it fails to consider the latent instability at < 850 hPa (Miller, 1972). This is because the TTI is computed using the temperature and dewpoint at 850 hPa and the temperature at 500 hPa. It is a combination of VT and cross-totals (CT = Td850 − T500). If TTI < 44 K, convection is not likely (Miller, 1967, 1972). Tyagi et al. (2011) showed a threshold TTI to trigger convection is ≥ 46 K.

\[ TTI = (T850 − T500) + (Td850 − Td500) \]

where \( T \) is the temperature; and \( T_d \) is the dew point temperature at the corresponding levels.

2.2.5 Lifted index (LI)

LI (Sadowski and Rieck, 1977) is a stability index that assesses the parcel instability at the lower troposphere at a level usually < 500 hPa. Marginal values are in the range of 0 to −4 K for marginal instability, from −4 to −7 K for large instability, and −8 K or less for extreme instability (Tyagi et al., 2011).

\[ LI = T500 − T_p500 \]

where \( T \) is the temperature (K); and \( T_p \) is the parcel temperature (K) at the corresponding levels.

2.2.6 Equivalent potential temperature (\( \theta e \))

An air parcel can be brought to its equivalent potential temperature (\( \theta e \); K) by raising the parcel from its original level to a greater level where all its moisture has condensed and then brought adiabatically to 1,000 hPa (Holton, 1973). The \( \theta e \) is calculated using temperature and dewpoint at different pressures and is performed using the simplified procedure of Bolton (1980), which stands valid in tropical regions. The calculations are performed as follows.

\[ \theta e = T_K \left( \frac{1000}{p} \right)^{0.2854(1−0.28×10^{-3}r)} \times \exp \left[ \left( \frac{3.376}{T_L} - 0.00254 \right) \times r(1 + 0.81×10^{-3}r) \right] \]

where \( T_K \), \( p \) and \( r \) represent the absolute temperature (K), pressure (hPa) and mixing ratio (kg·kg\(^{-1}\)) at the initial level (1,000 hPa), respectively; and \( T_L \) is the temperature (K) at the lifting condensation level (LCL), computed from temperature (\( T_K \)) and dew point temperature (\( T_D \)), which is given by:

\[ T_L = \frac{1}{T_D - 56} + \frac{\ln(T_K/T_D)}{800} + 56 \]

While examining the mesoscale convective system, \( \theta e \) is a useful measure to determine the static stability of the unsaturated atmosphere. During normal, stably stratified atmospheric conditions, \( \theta e \) increases with height:

\[ \frac{\partial \theta e}{\partial z} > 0 \]

and the vertical motions in the atmosphere are normally suppressed.

If \( \theta e \) decreases with height:

\[ \frac{\partial \theta e}{\partial z} < 0 \]

then the atmosphere is categorized as unstable and vertical motions are permitted with a likelihood of convection.

2.3 Verification methodology

The high-resolution rainfall forecasts at hobli (a cluster of villages each having an area of about 10 km\(^2\)) level were verified against the observations at comparable resolution from the telemetric rain-gauge (TRG) network installed and maintained by the KSNDMC; the study area of Bangalore consists of 34 hobli divisions. There were 52 rain gauges over Bangalore, and since they were not uniformly distributed, a Thiessen polygon method was used to average the data to obtain the rainfall for each hobli at a horizontal resolution of the order of 10 km\(^2\) (Rakesh and Goswami, 2015). In the present study, the 24 hr-accumulated rainfall forecasts over the 34 hobli divisions in Bangalore extracted from domain 4 were verified against the corresponding rain-gauge observations. From 36 hr forecasts, the initial 0300 hours were not considered due to model spin-up and the next 24 hr (valid for 0300 to 0300 UTC of the next day)-accumulated rainfall was used for validations. Interpolated (bilinear interpolation) model values at the TRG locations were used to obtain average (Thiessen polygon method) rainfall over hobli divisions from the model forecasts (Rakesh and Goswami, 2015). Thermodynamic stability indices calculated from the model were validated with a moderate-resolution imaging spectroradiometer (MODIS). The vertical profiles, mainly temperature and humidity profiles, obtained from MODIS level 2 products were used to
calculate the stability indices defined in Section 2.2. The indices were calculated for 0530 and 1730 UTC for the selected days of the event. A comparative study of stability indices derived from radiosonde and MODIS data (Jayakrishnan and Babu, 2014) showed that they closely match each other, and most of the parameters derived from MODIS were in good agreement with radiosonde data, justifying the use of MODIS-derived products where radiosonde observations are not available. It was also shown that many model-derived parameters, which cannot be derived from radiosonde observations, are helpful at understanding thermodynamic processes associated with heavy rainfall (Haklander and Delden, 2003).

### 3 | RESULTS AND DISCUSSION

The spatial distribution of three heavy rainfall events (the top three rainfall events in terms of intensity were shown here from 32 events) from the KSNDMC, IMD observations and WRF simulations over Bangalore are shown in Figure 2. It is clear that the spatial variability of urban heavy rainfall was better depicted in the high-resolution KSNDMC observation compared with the IMD (0.25 × 0.25° daily gridded precipitation) observation (Figure 2). Besides, the observed high-intensity localized rainfall in the KSNDMC observation was not visible in the IMD observation due to its coarse resolution. This indicated the necessity of high-resolution station observations in order to study the spatial distribution and intensity of urban rainfall events and to examine the skill of numerical model in simulating such rainfall events. The simulated rainfall events over Bangalore using the WRF showed widespread rainfall over the city, but significantly underestimated quantitative rainfall when compared with the observations. In subsequent discussions, forecast errors were computed by comparing with the KSNDMC observations for different hobli divisions (34) in Bangalore.
In the present study, in addition to the average statistics of all the cases, the model skill is analysed for the cases during the monsoon and non-monsoon seasons separately because of the contrasting thermodynamic structure of the urban atmosphere during these seasons. During the monsoon season, the clouds are mostly stratiform with a lot of convective downdraft, while during the non-monsoon season, clouds usually have large vertical growth and updraft predominates. Hence, it will be interesting to see whether the forecast errors in rainfall during these seasons are consistent with the model’s skill at simulating the contrasting thermodynamic structure of the atmosphere.

A statistical evaluation of forecast error in rainfall is carried out by computing bias (observation model), mean absolute error (MAE) and root mean squared error (RMSE). Figure 3 shows the spatial distribution (over 34 hobli divisions) of bias (top), MAE (middle) and RMSE (bottom) in model-simulated rainfall computed for all the 32 events (left), for events during the southwest monsoon season (middle) and for events during the non-monsoon season (right). The positive biases showed that the WRF forecast underestimated the observed rainfall (Figure 3, top), a model feature consistent with previous findings (Fadnavis et al., 2014; Reshmi et al., 2018). It is also noted that the forecast errors are relatively smaller for events during the monsoon period (bias = −5 to 10 mm; 15 mm; 30 mm).
MAE < 20 mm; RMSE < 25 mm for most hoblis) with respect to non-monsoon events (bias = > 10 mm; MAE > 20 mm; RMSE > 25 mm for most hoblis). One possible reason for larger errors with the model in simulating non-monsoon events may be due to the localized nature of rainfall events during that season, and mesoscale models generally have limitations at simulating quantitative rainfall associated with such localized events (Mohapatra et al., 2017). The precipitation pattern during the monsoon season is mostly governed by large-scale circulation, which is at a resolvable scale for most of the models. On the contrary, most of the rainfall events during the non-monsoon season are the result of intense local convection, and in order to simulate such events correctly, the model convection physics should be able to reproduce the thermodynamic structure of the unstable atmosphere. A similar analysis of forecast errors is done for each day (averaging over all hoblis), which is shown in Figure 4. The mean bias of all events was 10.3 mm, while for monsoon and non-monsoon seasons the values were 6.5 and 16.6 mm, respectively. Similarly, the MAE and RMSE for monsoon events (RMSE = 23.5 mm;
MAE = 16.4 mm) were relatively smaller compared with those for all events (RMSE = 25.4 mm; MAE = 18.5 mm) and for events during the non-monsoon season (RMSE = 28.4 mm; MAE = 22.1 mm). Similar to the spatial distribution of errors, hobli-averaged errors also showed that forecast errors were higher for non-monsoon events compared with monsoon rainfall events.

Urban heavy rainfall events, particularly over the Tropics, are generally attributed to organized convection in the lower part of the atmosphere either at the local scale or as part of large-scale circulations (Tokay and Short, 1996). Generally, the skill of mesoscale models in predicting urban heavy rain events depends on their ability to simulate deep moist convection (Holley et al., 2014). Thermodynamic properties, such as temperature/moisture profiles and thermodynamic indices, are crucial parameters determining deep moist convection, and examining those parameters gives valuable insights into forecast errors in rainfall (Lepore et al., 2015). From the conventional thermodynamic indices available in the past literature, those indices that better explain the instability in the atmosphere which triggers convection were chosen to examine how the model simulates atmospheric instability. In what follows, the model skill in simulating these thermodynamic indices was examined by comparing it with the corresponding observations.

The WRF model-simulated equivalent potential temperature ($\theta_e$) profiles (averaged over all 32 events; a model profile for each event is generated by averaging simulated values over 34 hoblis in Bangalore) are verified against the MODIS observations (the mean observed profile for each event is generated by averaging all available observation over Bangalore) (Figure 5). The $\theta_e$ is a critical parameter that can be used operationally to figure out the regions with a most unstable atmosphere and thus having intense convection. Since $\theta_e$ is a measure of both the moisture content and temperature of the atmosphere, a high value indicates a warm and humid parcel state. Therefore, if the $\theta_e$ curve decreases with altitude, it represents an unstable atmosphere; an increasing $\theta_e$ profile indicates a stable atmosphere. Note that the model-simulated $\theta_e$ profile differed significantly from observations at lower (warm and moist bias) and upper (cold and dry bias) levels (Figure 5). A rapidly decreasing $\theta_e$ profile in the MODIS observation in the lower troposphere (1,000 to 800 hPa) was a clear indication of convective activity (Figure 5). The WRF model simulations hardly picked the MODIS observed vertical variations in $\theta_e$ at 0530 UTC (left) and 1730 UTC (right). This indicated the model's failure at simulating the observed dew point depression, which is an indicator for higher instability in the atmosphere favouring the convection (Figure 5). To some extent, the forecast errors in rainfall can be related to the incorrect simulation of the vertical thermal and moisture structure of the atmosphere. However, it is important to examine how the misrepresentation of the thermal and moisture structure of the atmosphere affects other model-simulated thermodynamic stability indices such as the CAPE, CIN, LI, KI and TTI, which in turn can further explain the forecast errors in rainfall simulation.

Figure 6 shows the spatial distribution of the CAPE calculated at 0530 UTC (left) and 1530 UTC (right) for different hoblis averaged over all events (top), events during the southwest monsoon (middle) and events during the non-monsoon (bottom). The WRF model heavily underestimated the CAPE values compared with the MODIS observation; MODIS CAPE values ranged from 1,500 to 3,200 J·kg$^{-1}$ (while model values ranged from 300 to 1,100 J·kg$^{-1}$) at 0530 UTC; they ranged from 1,400 to 4,000 J·kg$^{-1}$ (the model ranged from 300 to 800 J·kg$^{-1}$) at 1730 UTC (Figure 6). As CAPE is an important indicator of atmospheric instability and convection, the significantly lower CAPE values in the model simulation compared with the MODIS observation clearly explain the underprediction of rainfall by the model (Figure 6). The MODIS data showed higher CAPE values at 1730 UTC for the events during the non-monsoon season compared with those during the monsoon season, a feature completely missing by the model simulations (Figure 6). The deviation of the model-simulated $\theta_e$ profiles from observation is consistent with the underprediction of CAPE values by the model, since the CAPE corresponds...
to the area where the parcel temperature is warmer than the environmental temperature from LFC to equilibrium level (EL). Generally, the numerical weather prediction (NWP) models have limitations at simulating middle- and upper level humidity (Yang et al., 2017), and the results from the analyses are consistent with previous studies (Peters et al., 2017). Since the above discussed results were the average of all the events or those during a particular season, and the simulated CAPE was found to be considerably underestimated by model, the simulated CAPE for individual cases was also compared with the observations. The model-simulated CAPE for five selected heavy rainfall events (the top five rainfall events in terms of intensity were selected) were individually compared against the corresponding observations (Figure S1). For the two events selected (August 31 and September 2, 2013), the model could simulate the observed CAPE values and spatial distribution reasonably well, and in these cases the observed CAPE values were mostly < 2,000 J·kg\(^{-1}\). In the other three events (May 20 and September 1, 2013, and May 27, 2014), when the observed CAPE values were very high, the model underestimated their values significantly (Figure S1). These results highlight the model limitations to simulate high CAPE values associated with severe heavy rainfall events, as seen in the observations.

Figure 7 shows a comparison of the model-simulated CIN with the MODIS observed values averaged over all events (top), cases during the monsoon season (middle) and cases during the non-monsoon season (bottom). A value of ≥ 200 J·kg\(^{-1}\) is considered a strong CIN and is sufficient to suppress a convection process. Even though the model underestimated the observed CIN values, it is clear that there is no strong CIN (> 200 J·kg\(^{-1}\)) in both observation and the model at 0530 UTC (left) and 1730 UTC (right).
and 1730 UTC, which implies the possibility of convection. Most of the CIN values were < 50 (except for a few hoblis at 1730 UTC in the MODIS observation) at 0530 and 1730 UTC, which is considered a weak CIN and is a favourable condition for convection to occur (Figure 7). Note that the CIN is measured from the surface to the LFC, and that the model-simulated temperature and humidity profiles were relatively better at lower levels, which accounts for the relatively better simulation of the CIN by the model. The MODIS-observed CIN values were relatively lower during the non-monsoon season compared with the monsoon season; however, the model simulations do not show large variations between the monsoon and non-monsoon seasons (Figure 7). The underestimation of the observed CAPE, CIN and rainfall by the model in the present study concurs with the findings of Fadnavis et al. (2014), who also reported that the simulated CAPE and CIN from the model were less than the radiosonde observations, resulting in rainfall underestimation.

Figure 8 shows the observed and simulated LI at 0530 and 1730 UTC averaged over all events (top), monsoon events (middle) and non-monsoon events (bottom). A negative LI indicates instability in the planetary boundary level, and convection may occur in such a situation. Instability increases by increasing the negative value, where $\leq -4$ (Tyagi et al., 2011) indicates the probability of severe convection. The 0530 and 1730 UTC MODIS observations were found to be predominantly negative; most fell in the range 0 to $-3$ for all the cases examined (Figure 8). While the simulated LI values at 0530 UTC showed reasonably good agreement with observations (with absolute differences with observation < 1 for most hoblis), at 1730 UTC the model simulated mostly positive values irrespective of season, which clearly indicates the lack of convection that is consistent with the underprediction of rainfall in most of the cases (Figure 8). The simulated large positive LI values indicating a lack of convection during the non-monsoon season at 1730 UTC.
clearly explain the severe rainfall underestimation (a large positive bias for non-monsoon cases in Figure 4). Note that most of the rainfall activity during the non-monsoon season occurs during the evening hours.

The spatial distribution of the observed and model-simulated K index values is shown in Figure 9. There was a clear distinction between the observation and the model; while the observed values were mostly < 25, indicating a marginal–moderate convective potential, the simulated values were mostly > 25, indicating a moderate–severe convective potential. The simulated KI values did not show much seasonal variation when compared with the observation. The TTI (Figure 10), being an instability index that accounts for the static stability between 850 and 500 hPa and moisture at 850 hPa, would only represent those atmospheric regions, and a moderate CIN value in the lower atmosphere can cease the convection even if the TTI is large enough for the possibility of a severe thunderstorm. Hence, the exact prediction of a thunderstorm using the TTI alone is not possible as the TTI does not describe the total atmospheric conditions (Khole and Biswas, 2007). The marginal value of TTI for convection likelihood is considered as ≥ 46 (Tyagi et al., 2011). The model-simulated TTI values were higher compared with the observations. While the observed values were mostly in the range 30–40, the simulated values varied between 40 and 50, indicating the likelihood of convection (Figure 10). Though thunderstorm activities are generally expected in the evening hours, simulated TTI values were greater at 0530 UTC when compared with 1730 UTC, irrespective of the season.
CONCLUSIONS

To finetune a mesoscale model for weather forecast applications over different regions, its prediction skill needs to be tested under various severe weather conditions. In this context, the performance of the Weather Research and Forecast (WRF) model is assessed when simulating a large number of heavy rainfall events over Bangalore, a megacity in southern India, between 2012 and 2014. The model skill in simulating thermodynamic processes associated with those heavy rain events was examined by comparing the observed and simulated thermodynamic stability indices. Such an investigation gives greater insights into the forecast errors in quantitative rainfall associated with such events. The present study used high-density rain gauge observations from the Karnataka State Natural Disaster Monitoring Centre (KSNDMC) for validating rainfall and model-simulated stability indices were validated against moderate-resolution imaging spectroradiometer (MODIS) satellite observations. A total of 32 rainfall events, representing major rainfall seasons (southwest and northeast monsoons and the pre-monsoon) over the city were considered, and model skill was examined by computing various statistical measures.

Even though the WRF model could simulate a urban heavy rain event, it underestimated rainfall in most cases. It was found that the model bias and absolute error in rainfall simulation were less for events during the monsoon season (June–September) as compared with the rest of the season. Though the model-simulated mean vertical temperature (moisture) profiles were consistent with the MODIS observations, it showed a warm (moist) bias at lower levels and a cold (dry) bias at the middle and upper levels. The simulated dew point depression (the difference between temperature and dew point) was found to be relatively weaker compared with the observation; it accounts for weak convection and, thereby, the
underestimation of rainfall by the model. In general, the WRF model underestimated convective available potential energy (CAPE) and it has serious limitations at simulating a high CAPE associated with severe heavy rainfall cases, a feature constant with the underestimated rainfall simulation. Contrary to the observed negative values, a model-simulated positive lifted index (LI), particularly during the evening hours, indicating a lack of convective activity. It was noted that those indices, which are mostly derived from lower tropospheric temperature and moisture profiles, such as convective inhibition (CIN), K index (KI) and total totals index (TTI) were simulated relatively better compared with those derived from both lower and upper tropospheric temperature and moisture profiles, indicating the model’s limitations at simulating the thermodynamic structure of the middle and upper atmosphere. Overall, the analyses showed that forecast errors in rainfall were mostly related to model bias in simulating thermodynamic stability indices, which are indicators for convection in the atmosphere. It is also noted that the model has limitations at simulating the thermodynamic structure of the urban atmosphere, irrespective of the season analysed. As most of these thermodynamic indices follow a growth-and-decay cycle along with convection in the atmosphere, as a continuation, the lead–lag relationship between these indices and precipitation will be investigated in future.

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