



Simulation of location-specific severe thunderstorm events using high-resolution land data assimilation

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1 **Simulation of location-specific severe thunderstorm events using high resolution land**
2 **data assimilation**

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24 **Abstract**

25 In this study, the impact of different land initial conditions on the simulation of thunderstorms
26 and monsoon depressions is investigated using the Weather Research and Forecasting (WRF)
27 model. A control run (CNTL) and a simulation with an improved land state (soil moisture and
28 temperature) using the High Resolution Land Data Assimilation System (HRLDAS,
29 experiment name: EHRLDAS) are compared for three different rainfall cases in order to
30 examine the robustness of the assimilation system. The study comprises two thunderstorm
31 cases (one in the pre-monsoon and one during the monsoon) and one monsoon depression case
32 that occurred during the Interaction of Convective Organisation, Atmosphere, Surface and Sea
33 (INCOMPASS) field campaign of the 2016 Indian monsoon. EHRLDAS is shown to yield
34 improvements in the representation of location-specific rainfall, particularly over land. Further,
35 it is found that surface fluxes as well as convective indices are better captured for the pre-
36 monsoon thunderstorm case in EHRLDAS. By analysing components of the vorticity tendency
37 equation, it is found that the vertical advection term is the major contributor towards the
38 positive vorticity tendency in EHRLDAS compared to CNTL, hence improving localised
39 convection and consequently facilitating rainfall. Significant improvements in the simulation
40 of the pre-monsoon thunderstorm are noted, as seen using Automatic Weather Station (AWS)
41 validation, whereas improvements in the monsoon depression are minimal. Further, it is found
42 that vertical advection (moisture flux convergence) is the major driver modulating the
43 convective circulation in localised thunderstorm (monsoon depression) cases and these
44 dynamics are better represented by EHRLDAS compared to CNTL. These findings underline
45 the importance of accurate and high resolution land-state conditions in model initial conditions
46 for forecasting severe weather systems, particularly the simulation of localised thunderstorms
47 over India.

48

49 **1. Introduction**

50 The eastern part of India is vulnerable to the landfall of intense tropical storms and
51 thunderstorms, which affect lives, livelihood and property in the region. The state of Odisha,
52 located on the east coast of India is highly susceptible to natural disasters arising from
53 thunderstorms (lightning), intense rainfall events from synoptic-scale monsoon low pressure
54 systems (or monsoon depressions), and cyclones (Das, 2017; Mohapatra & Mohanty, 2005;
55 Dube & Rao, 2005). The large number of deaths in recent years (the second highest in the
56 country) has led to Odisha being named the “lightning graveyard” of the country. However,
57 only a limited range of studies has been targeted at this region to address the problem.
58 Furthermore, the genesis of localised convection and associated rainfall have several
59 limitations in Weather Research and Forecasting (WRF) (Alvarez et al., 2018). The analysis
60 shows that the underestimation by the model is probably due to inability of model to generate
61 convection, apparently related to processes of larger scale and limitations on describing
62 mesoscale processes that leads to vertical movements capable of producing extreme rainfall.
63 Apart from many other factors, accurate information of the initial state of land and atmospheric
64 conditions plays a major role in rainfall prediction at the numerical weather prediction (NWP)
65 scale. Numerous studies (Osuri et al., 2017; Pielke et al., 2007; Rajesh et al., 2016) have shown
66 that improvement in short-range prediction of boundary layer development, cloud fields and
67 precipitation may rely on detailed representation of land surface physics and accurate
68 initialization of the land state (i.e. soil moisture, soil temperature, vegetation and land use/land
69 cover). The role of patterns of soil moisture and soil temperature in deep convective
70 development and thermodynamic structure of the atmosphere has also been recognised (Taylor
71 et al., 2012), including specifically for northern India (Barton et al., 2019). Baisya (2017)
72 demonstrated that there is strong influence of land surface conditions on precipitation
73 characteristics of monsoon depressions in term of spatial distribution and intensity of rainfall.

74 Further, they have demonstrated that initial soil moisture condition and soil moisture
75 availability have strong influence on the rainfall spatial distribution and intensity respectively,
76 over the east coast of India.

77 One of the key roles of soil moisture is to partition the available surface energy into latent and
78 sensible heat fluxes, among which latent heat flux is directly proportional to
79 evapotranspiration, since it is the sum of transpiration, soil evaporation and canopy evaporation
80 (Lawrence et al. 2007; Yuan et al. 2017). These three components of evapotranspiration are
81 calculated within the land surface scheme, thus stressing the role of land-atmosphere
82 interaction in numerical weather prediction models. Taylor et al., 2012 suggested that semi-
83 arid regions have more relation between soil moisture and associated precipitation and this
84 mechanism is modulated by any changes in surface fluxes of moisture and heat (latent and
85 sensible). Past studies have suggested that localised Convective Available Potential Energy
86 (CAPE), high surface temperature and elevated moisture content (upper troposphere) are
87 important ingredients to fuel to the eventual development of deep cumulus convective clouds
88 and rainfall (Murugavel et al., 2014; Price et al., 2010).

89 Monsoon depressions are synoptic-scale systems which form over the Bay of Bengal and move
90 in a westward/north-westward direction and often make their entrance to central India through
91 Odisha, thereby causing heavy rainfall there. It is found that moisture flux convergence is the
92 main source of moisture for such systems, while local evaporation is of lesser importance
93 (Rajesh et al., 2017; Hunt & Turner, 2017). Rajesh et al., (2017) have already demonstrated
94 improvements in the prediction of rainfall and other convective parameters for monsoon
95 depressions using high resolution land data assimilation techniques.

96 The major problem limiting the accurate initiation of a model is the scarcity of high spatial
97 resolution observations of the land surface over the model domain. This scarcity of high
98 resolution land surface observations can be overcome by combining satellite observations with

99 high resolution land-surface models. In this context, High Resolution Land Data Assimilation
100 System (HRLDAS) is a land data assimilation system based on the Noah Land Surface Model,
101 and is a modelling interface in conjunction with WRF. Its dynamical framework calculates
102 temporal changes in surface energy fluxes such as sensible, latent, ground heat fluxes, net
103 radiation, soil moisture and temperature, soil water content and surface runoff etc., in offline
104 mode (Rajesh et al., 2016 & 2017). Various assimilation studies have proved that imposing
105 different soil moisture conditions can modulate the surface temperature forecast (due to
106 localised interactions between the land surface and overlying atmosphere), but among non-
107 local factors, the horizontal transport of moisture is the dominant parameter impacting the
108 model's predicted rainfall. Eltahir (1998) demonstrated that wet soil moisture would enhance
109 the moist static energy in elevated boundary layer and would be associated with more rainfall.
110 Previous studies have suggested that co-varying patterns of temperature and rainfall indicate
111 strong coupling of the land and atmosphere and implying the need to improve the initial land
112 state to simulate heavy rainfall events (Koster et al., 2005). In addition, assimilation of high
113 resolution satellite data has also been shown to have a positive influence on the dynamic and
114 thermodynamic features of monsoon depressions along with the spatial distribution of the
115 simulated precipitation over India (Kumar et al., 2014). Despite the positive impacts of various
116 data assimilation methods on the prediction skill of forecast rainfall for short-range forecasts
117 (Bohra et al., 2006; Routray et al., 2008), there is a scarcity of this kind of study examining the
118 impact of land surface assimilation on the prediction skill of NWP models for India, especially
119 for improving the forecast of localised heavy rainfall events.

120 Thus, this manuscript is targeted at addressing this problem particularly over the state of Odisha
121 (east coast India) with the aim to evaluate the influence of improved land surface assimilation
122 on the prediction skill of localised rainfall and to understand associated feedback mechanisms.
123 The method followed is to test the implementation of the HRLDAS scheme in the Weather

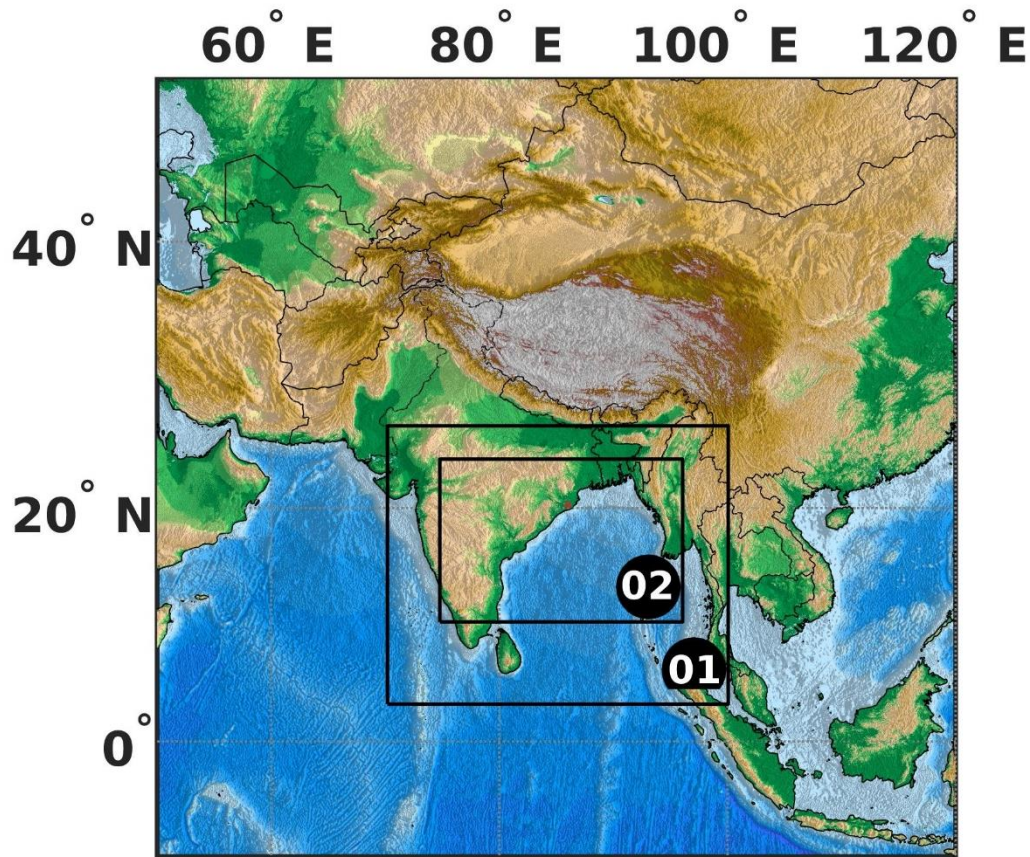
124 Research Forecast (WRF) model. This study focuses on the INCOMPASS objective to capture
125 the key surface-atmosphere feedback processes in models, and to evaluate the performance of
126 data assimilation techniques on monsoon rainfall.

127 The paper is structured as follows: in Section 2, the model and the experiment design is
128 discussed, while Section 3 illustrates the results. All the results discussed in Section 3 belong
129 to an inner model domain at simulated at 3 km resolution. Finally, conclusions and discussions
130 arising from this study are presented in Section 4.

131 **2. Model, Experiment Design and Data**

132 **2.1 The WRF model**

133 The Advanced Weather Research Forecast (WRF-ARW) model version 3.7.1 developed by the
134 National Center for Atmospheric Research (NCAR) and National Center for Environmental
135 Prediction (NCEP) in collaboration with universities is used in this study. The WRF-ARW
136 model is a limited area, non-hydrostatic primitive equation model with multiple options for
137 various physical parameterization schemes (Skamarock et al., 2008). Two nested domains with
138 grid resolutions of 9 and 3 km with 35 vertical sigma levels and a model top at 50 hPa are
139 considered for this study. The initial and lateral boundary conditions are provided from the
140 National Centre for Environment Protection (NCEP)-Final (FNL) operational global analysis
141 ($1^\circ \times 1^\circ$) grid at a 6-hourly interval. The physics components include the Noah Scheme for land
142 surface processes (Tewari et al. 2004), Rapid Radiative Transfer Model for General Circulation
143 Models (RRTMG) longwave and shortwave radiative transfer scheme (Iacono et al. 2008),
144 MM5 similarity theory for calculating surface heat and moisture fluxes, WRF Double Moment
145 6-class scheme for resolving clouds, and Yonsei University Scheme (YSU) for planetary
146 boundary layer parameterization (Jiménez et al., 2012; Lim and Hong, 2010; Hong et al., 2006).
147 The Kain-Fritsch scheme (Kain, 2003) was used for cumulus convection for the outer domain
148 (9 km) while the inner domain is explicitly resolved.



150

151 **Figure 1.** The nested outer (01) and inner (02) WRF domains are shown within the wider South
 152 Asia region. The red circle on the map shows the location of Argul on the map (85.70°E,
 153 20.17°N).

154 2.2 Experiment design

155 HRLDAS is an uncoupled land-surface model which runs offline to evolve the land surface
 156 parameters constrained by forcing data from the surface and the above atmosphere (Rajesh et
 157 al. 2016 & 2017; Chen et al., 2007; Nayak et al., 2018). The forcing data used in this experiment
 158 is taken from the Global Land Data Assimilation System (GLDAS) at 0.25° grid and European
 159 Centre for Medium Range Weather Forecasting Interim reanalysis data (ERA-Interim) at 0.75°
 160 grid resolution (bilinear interpolated to 0.25°). Surface parameters such as precipitation,
 161 shortwave and longwave radiation, air temperature, specific humidity and surface pressure are

162 taken from Global Land Data Assimilation System (GLDAS) datasets, while u and v
 163 components of wind at 10 m are obtained from ERA-Interim (Dee et al., 2011) to be used as
 164 forcing data. The HRLDAS model is first integrated from January 2006 to July 2017 to evolve
 165 land surface parameters over the Indian region. The output land state from HRLDAS is
 166 assimilated into the WRF model initial conditions. Readers are referred to Rajesh et al. (2016,
 167 2017) for a detailed methodology of HRLDAS.

168 Both CNTL and EHRLDAS experiments are forced with FNL initial and lateral boundary
 169 conditions except that EHRLDAS is additionally being forced by the land state (i.e. soil
 170 moisture and soil temperature) obtained from the HRLDAS. In Table 1, we illustrate three
 171 different rainfall events occurring over the Argul location associated with different weather
 172 systems. Case 1 is a pre-monsoon isolated thunderstorm event, Case 2 is thunderstorm event
 173 during the monsoon, while Case 3 is a thunderstorm embedded within a synoptic-scale
 174 monsoon depression that occurred in July of 2016. The idea behind considering three rainfall
 175 events associated with different weather events is to examine the robustness of HRLDAS in
 176 predicting a range of events with heterogeneous origins and different rainfall mechanisms.

177 **Table 1.** The three cases taken in this study detailing duration and simulation period of the
 178 experiment.

S. No.	Duration (Hours of Prediction)	Experiments
Case 1	0000 UTC 6 – 0000 UTC 7 March 2017 (24 hr)	i) CNTL ii) EHRLDAS
Case 2	0000 UTC 30 June – 0000 UTC 1 July 2017 (24 hr)	
Case 3	0000 UTC 26 June – 0000 UTC 29 June 2016 (72 hr)	

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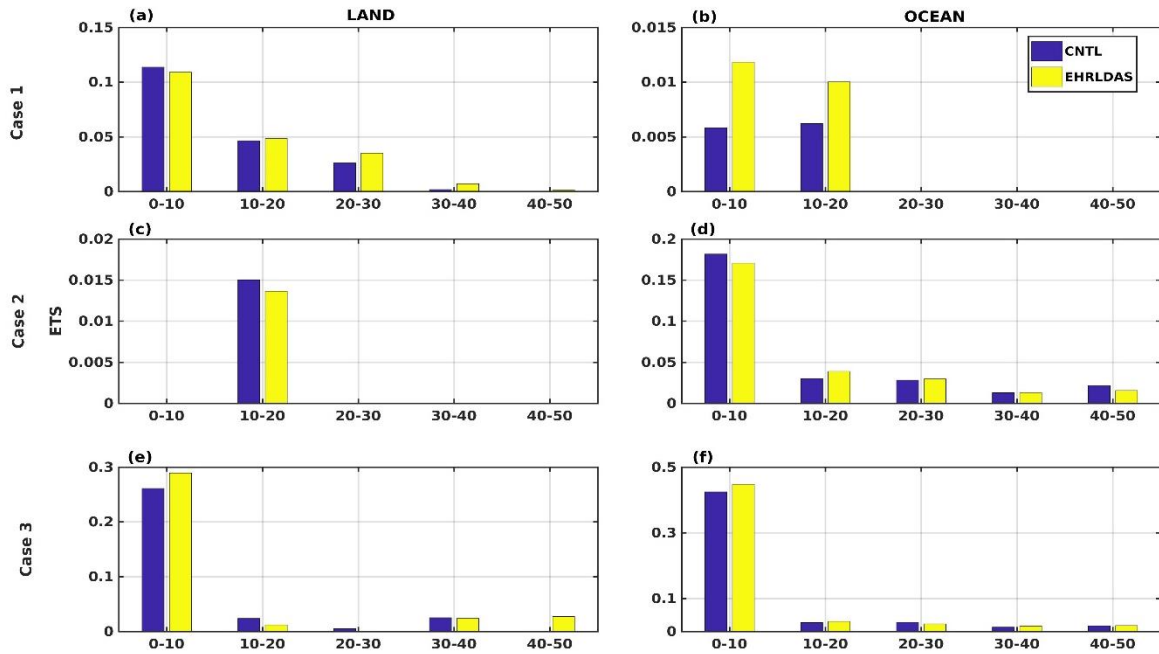
182 **2.3 Validation data**

183 For validation, surface parameters including rainfall are obtained from an Automatic Weather
184 Station (AWS) installed at Argul (85.680 °E, 20.170 °N). Further, Global Precipitation
185 Measurement (GPM) IMERG satellite rainfall data (Huffman, et al., 2014) is used to validate
186 the spatial distribution of rainfall at 0.25° resolution at half-hourly intervals. In addition,
187 ECMWF Fifth Generation Reanalysis (ERA5) hourly data (Copernicus, 2017) is also used to
188 validate the model-simulated dynamical and thermodynamic parameters.

189 **3. Results and Discussions**

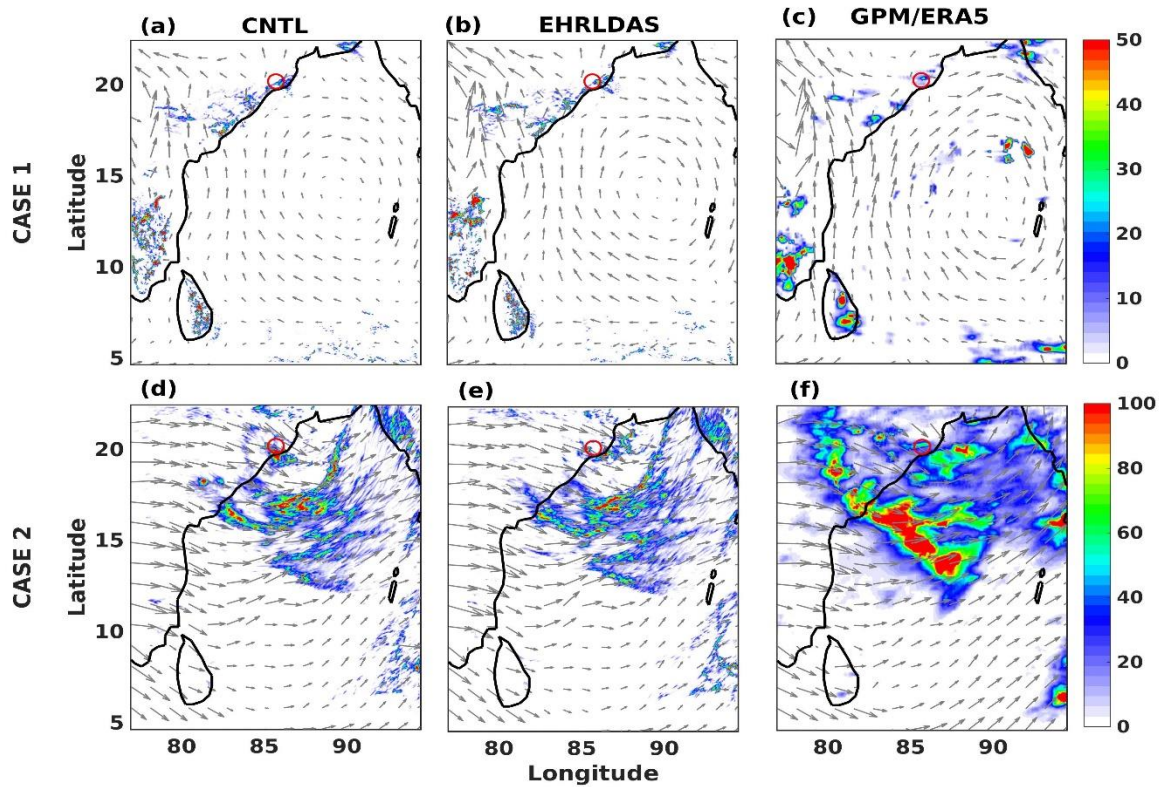
190 **3.1 Rainfall**

191 Figure 2(a-f) shows the Equitable Threat Score (ETS) which measures the fraction of observed
192 and/or forecast events that were correctly predicted for all three cases over land and ocean
193 separately. Except for the lowest rainfall threshold (0 - 10 mm), ETS scores are below 0.2 for
194 all simulated cases. Usually in monsoon depression, the rainfall is scattered throughout the
195 domain, but the thunderstorm are isolated and covered a small portion of the domain giving
196 such a low skill score. Among these three cases, EHRLDAS experiments show better rainfall
197 prediction skill. The pre-monsoon thundershower case has the lowest skill compared to the
198 other two monsoonal cases. For Case 1, EHRLDAS improves rainfall prediction over the land
199 as well as ocean particularly for lower rainfall thresholds (i.e. up to 30 mm), however, the skill
200 over land is poor for Case 2. In Case 3 (monsoon depression), EHRLDAS shows a higher peak
201 for the lowest rainfall threshold (0-10 mm), but the skill remains poor both over ocean and land
202 for higher rainfall thresholds (Figure 2 e, f). This is because the simulations for Case 3 could
203 not capture the pockets of intense rainfall as shown in supplementary Figure S1. We therefore
204 highlight that EHRLDAS has outperformed CNTL in rainfall prediction skill except for Case
205 2.



206

207 **Figure 2.** Equitable Treat Score (ETS) for three cases (a-b) Case 1: 6 March 2017, (c-d) Case 2:
 208 30 June 2017 and (e-f) Case 3: 28 June 2016 for land (left column) and sea grid points (right
 209 column) respectively. Thresholds 0-10 mm ($0 < \text{rainfall} \leq 10$), 10-20 mm includes ($10 < \text{rainfall}$
 210 ≤ 20) and same for other thresholds. ETS is calculated for the 3km inner domain and TRMM
 211 data is remapped to the model forecast.



212

213 **Figure 3(a-f).** Day-1 accumulated rainfall (mm) for the first two thunderstorm cases along with
 214 wind at 850 hPa i.e. (a, b, c) for Case 1 and (d, e, f) for Case 2 in model CNTL experiment,
 215 EHRLDAS experiment and GPM/ERA5 observations for the inner model domain,
 216 respectively. The circle marked in the figure represents the location of Argul.

217 Figure 3 shows the 24-hour accumulated rainfall for Case 1 and Case 2 along with GPM-
 218 IMERG satellite observations, in each case overlaid with 850 hPa winds from the model or
 219 ERA5 as appropriate. An anticyclonic flow is seen over the central Bay of Bengal with strong
 220 winds near the east coast of India; these features are well replicated by all experiments. There
 221 is not much rainfall for Case 1 over the ocean but isolated pockets of convection and rainfall
 222 are noted over the land. Further, intense precipitation pockets seen over the east coast and
 223 southern peninsular regions of India have been well reproduced in the EHRLDAS experiment.
 224 In addition, it is noted that wind speed at 850hPa, particularly of the southerly winds, has
 225 increased in EHRLDAS compared to CNTL (Figure 3 b, c), becoming more realistic. The

226 spatial distribution of rainfall for Case 2 is shown in Figure 3(e, f, g, h), where CNTL and
227 EHRLDAS are found to feature similar distributions. But interestingly, EHRLDAS produces
228 a better rainfall distribution over land including over the Argul location (circled). The spatial
229 distribution of rainfall up to Day 3 is shown in Supplementary Figure S1. It is found that the
230 centre of the low is located over the North Bay of Bengal, which propagates north-westward.
231 In general it is clearly evident that EHRLDAS is able to replicate the observed rainfall
232 distribution pattern reasonably well, particularly over the land region even for the isolated pre-
233 monsoon thunderstorm (Case 1).

234 Further location-specific validation of model results is carried out at a station observation
235 location i.e. Argul. Figure 4 (a, b) shows the hourly rain rate from the inner domain for Case 1
236 and Case 2 (for Case 3 AWS data was not available). The nearest four grid points to the Argul
237 location in model inner domain are used to linearly interpolate model output and then validated
238 against AWS observations. The observed event durations are marked by the dashed red vertical
239 lines in Figure 4. The improvement in the EHRLDAS simulation can be seen in Supplementary
240 Table 2, showing Pearson Correlation Coefficient (PCC) and Root Mean Square Error (RMSE)
241 calculated over the inner domain for the thunderstorm cases (i.e. Case 1 & 2). It is clearly seen
242 that the EHRLDAS simulations have higher correlation coefficients than CNTL for all surface
243 parameters (rain rate, 2-metre relative humidity, 10 metre wind speed and 2 metre temperature).
244 It is seen that for Case 1, all experiments are able to correctly capture the location as well as
245 timing when compared to observations. The rainfall intensity of the thunderstorm episode was
246 not correctly captured by either experiment, although EHRLDAS is closest to observed values.

247 In Case 2, the EHRLDAS captured the event but with a delay of four hours, whereas CNTL
248 failed to detect the event over the observation location. Figure 3 (c, d) shows the 10 m wind
249 speed for these two cases. In Case 1, all experiments underestimated the wind speed prior to
250 the event, however the EHRLDAS-simulated time series is closest to observations.

251 In general, it is noted that for Case 2, the experiments are not coherent with observations but
 252 feature a time lag of approximately four hours, and the wind speed is over-predicted. Further,
 253 on examining the temperature and relative humidity (Figure 3 e-h), it is noted that EHRLDAS
 254 predictions are closest to observed values. In more detail, it is clear that surface air temperature
 255 from EHRLDAS closely follows that from observations with a 2-hour time lag. In order to
 256 confirm the better performance of EHRLDAS over CNTL, we have examined its moisture
 257 transport and vertical velocity characteristics over the location compared to ERA5
 258 (Supplementary Figure S2). We found that there is a better resemblance between ERA5 and
 259 EHRLDAS compared to CNTL. In general the overestimation in CNTL simulation has been
 260 reduced in EHRLDAS.

261 **Table 2.** Correlation coefficient and Root Mean Square Error for convective Indices (CAPE (J
 262 kg⁻¹), CIN (J kg⁻¹), KI (°C), TTI (°C)) for first two thunderstorm cases with respect to ERA5
 263 data and surface parameters (rain rate (mm hr⁻¹), 2m temperature (°C), 2m relative humidity
 264 (%)) and 10m wind speed (m s⁻¹) with respect to AWS station at Argul.

	Convective Indices(ERA5)					Surface parameters (AWS)			
PCC		CAP E	CIN	KI	TTI	Rain Rate	Rel. Hum.	10m Wind	2m Temp
Case 1	CNTL	0.7	-0.03	0.57	0.22	0.88	0.88	0.66	0.84
	EHRLDAS	0.8	0.26	0.63	0.45	0.99	0.90	0.73	0.95
Case 2	CNTL	-0.58	0.26	0.57	0.03	-0.07	0.70	-0.02	0.65
	EHRLDAS	-0.31	0.59	0.58	-0.02	-0.08	0.72	0.09	0.78
RMSE		CAP E	CIN	KI	TTI	Rain Rate	Rel. Hum.	10m wind	2m Temp
Case 1	CNTL	872	201.5	2.62	2.92	4.91	12	3.1	2.04

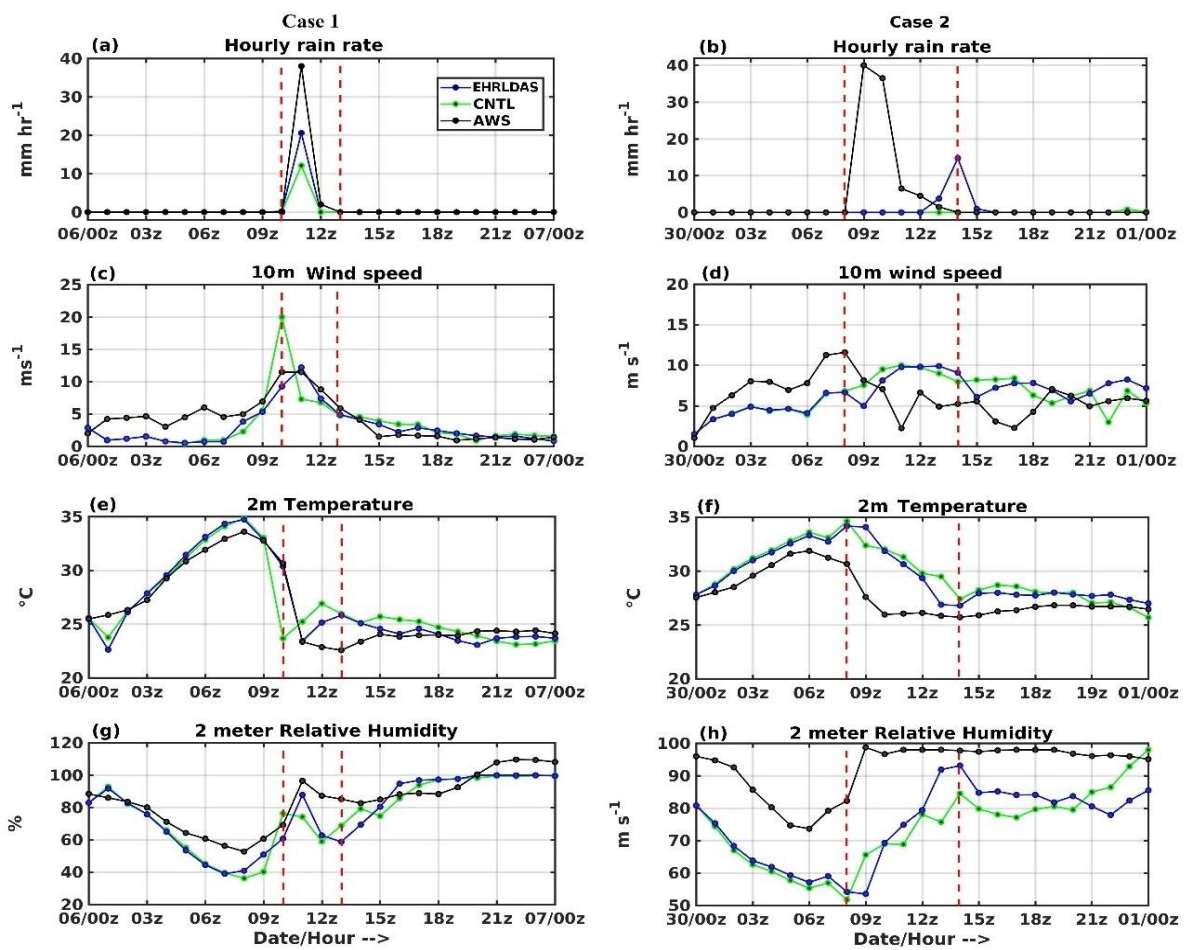
	EHRLDAS	705	203.2	3.54	2.53	3.51	11.24	2.48	1.24
Case 2	CNTL	751	66.1	0.96	6	11.94	20.42	3.41	3.15
	EHRLDAS	661	53.7	1.33	6.14	11.34	19.4	3.48	2.77

265

266 From these results, we find clear evidence that between the two thunderstorms (pre-monsoon

267 and mature monsoon cases), the pre-monsoon (Case 1) is well predicted by both models with

268 EHRLDAS performing better across a range of fields than CNTL.



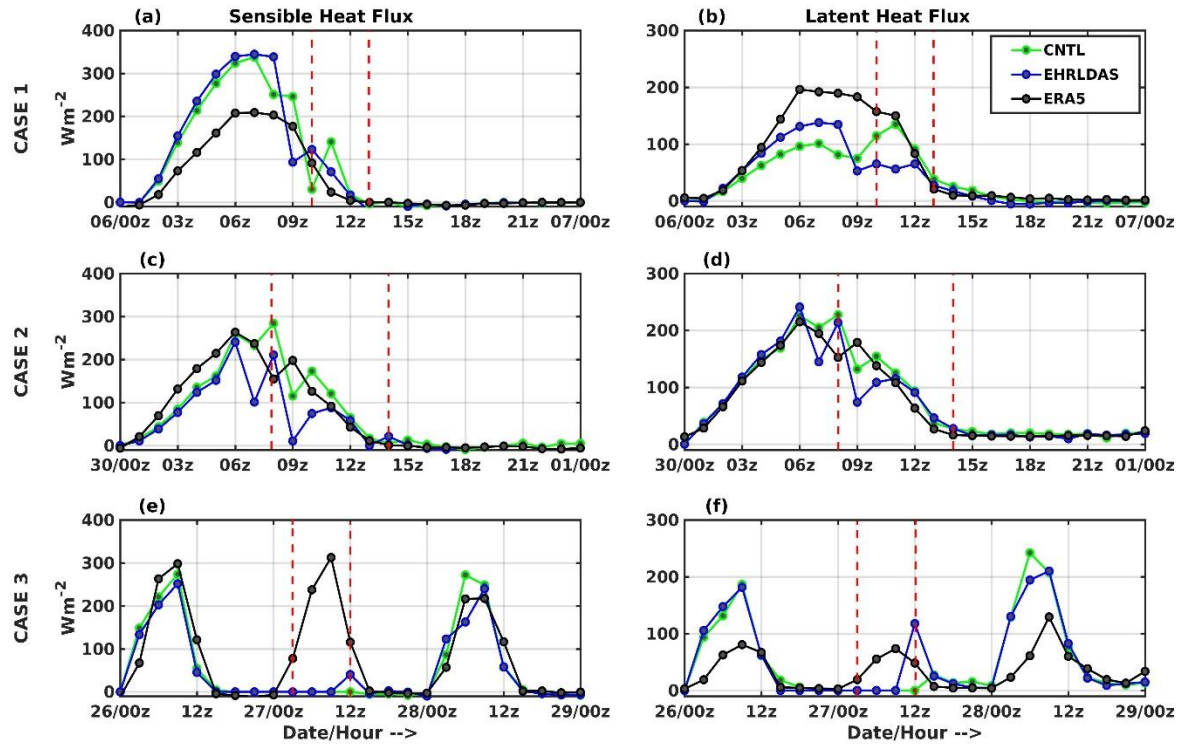
269

270 **Figure 4.** Time series of surface parameters (rain rate (mm hr^{-1}), 10m wind speed (m s^{-1}), 2

271 metre temperature ($^{\circ}\text{C}$) and 2 metre relative humidity (%)) for the two thunderstorm cases i.e.

272 (a, c, e, and g) for Case 1 and (b, d, f, h) for Case 2 from CNTL, EHRLDAS and AWS data.

273 Vertical red lines representing the event duration over Argul (85.70°E , 20.17°N).



274

275 **Figure 5** Time series of sensible heat flux (W m^{-2}) and latent heat flux (W m^{-2}) over Argul
 276 (85.70°E , 20.17°N) for all three cases i.e. (a, b) for Case 1, (c, d) for Case 2 and (e, f) for
 277 Case3 from CNTL, EHRLDAS (calculated from the nearest four grid points linearly
 278 interpolated over Argul location) and AWS data.

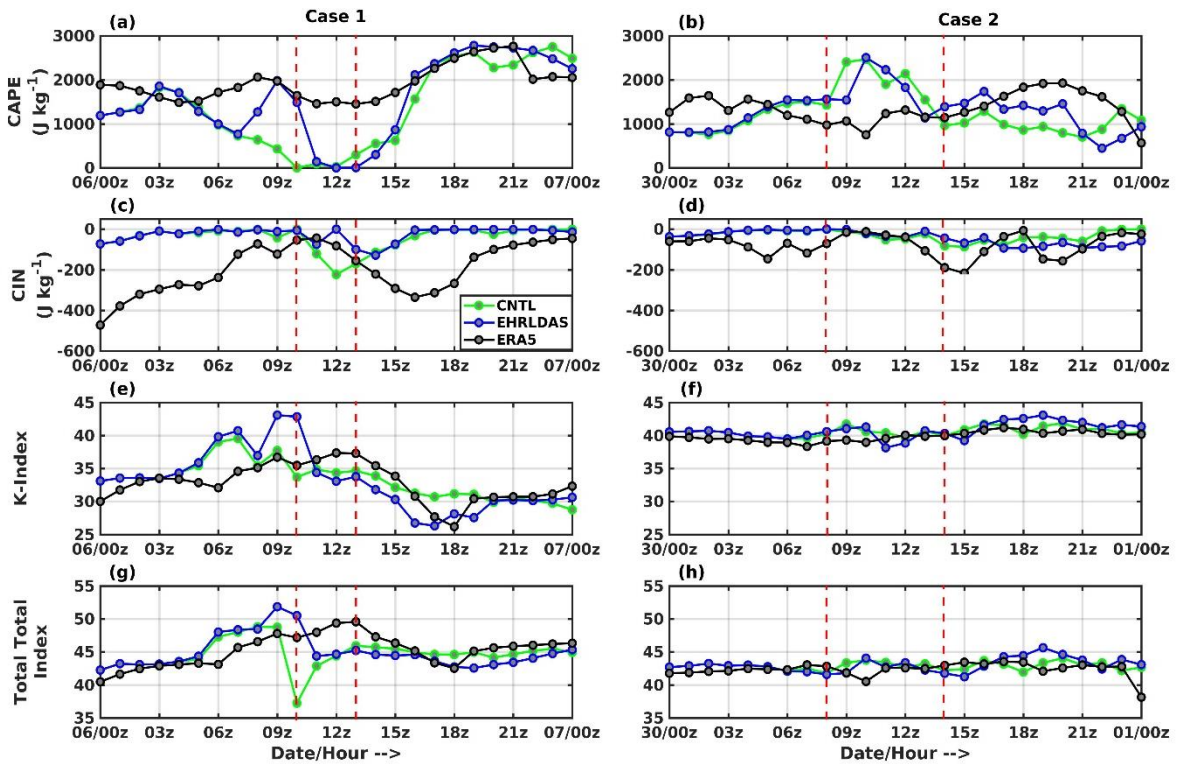
279 3.2 Surface Fluxes and Thermal Indices

280 In order to understand exchanges of heat and moisture between the land and atmosphere and
 281 how they may change with the improved surface initialisation, time series of surface latent
 282 (LHF) and sensible heat flux (SHF) over the Argul location are shown in Figure 5. Considering
 283 the sensitivity of land surface towards different initial conditions, surface fluxes are analysed
 284 here and validated against hourly ERA5 surface fluxes (considering reanalysis data as
 285 benchmark, and ERA5 data is remapped to the model grids). A sudden decrease in SHF is
 286 shown in all experiments two hours prior to the rainfall peak (Figure 5a, b). This reduction may
 287 be attributed to an increase of cloud cover leading to reduction of the shortwave radiation and

288 surface temperature resulting in reduced SHF. However, the overestimation (underestimation)
289 of SHF (LHF) with respect to ERA5 is seen for both experiments for Case 1. Most interestingly,
290 LHF patterns simulated by EHRLDAS are closer to ERA5, suggesting the impact of improved
291 land state initialisation (soil moisture and temperature) over the location. It is noteworthy to
292 mention that EHRLDAS is able to improve the simulation of this aspect compared to CNTL.
293 Figure 5 (e, f) shows the time series of fluxes for the 72-hour simulation period for Case 3, in
294 which it is interesting to note that the model simulations are able to accurately replicate the
295 surface fluxes for the daytime duration, while EHRLDAS is better at simulating their diurnal
296 changes. However, we note that for 27 June, both the simulations failed to replicate the diurnal
297 changes in SHF, and the LHF is better represented by EHRLDAS compared to CNTL.

298 Along with the surface fluxes, convective indices associated with thunderstorms are also
299 computed and shown in Figure 6 for the first two cases. The major indices such as Convective
300 Available Potential Energy (CAPE), Convective Inhibition (CIN), Total Totals Index (TTI)
301 and K-index (KI) (Williams and Renno', 1993; Miller, 1972; George, 1960) are validated over
302 Argul. The EHRLDAS experiment nicely accumulates CAPE before the occurrence of the
303 thunderstorm for both cases, whereas CNTL failed in this respect (Figure 6a). The enhanced
304 magnitude of CAPE seen in Figure 6b is associated with additional LHF into the boundary
305 layer for Case 2; the magnitude of CAPE is very close to that of ERA5, suggesting the robust
306 impact of EHRLDAS (Figure 5a). Further, two more convective indices i.e. TTI and KI are
307 also plotted for these cases in Figure 6 (e, f, g and h). The higher value of KI indicates the
308 occurrence of intense rainfall, when there is abundant moisture through the mid-levels (850 –
309 500 hPa), as well as a strong lapse rate. In contrast, TTI takes into account both the static
310 stability and the 850 hPa moisture which is very high in case of monsoon depressions. In
311 general it is clearly evident that EHRLDAS is better able to reproduce the actual instability (in
312 terms of magnitude and pattern in ERA5) compared to CTRL. More precisely, a value above

313 the threshold of 30 for KI and 44 for TTI (George, 1960; Miller, 1967) indicates an unstable
 314 atmosphere as seen in EHRLDAS (Figure 6e, g). In Case 2, the thermal indices have shown
 315 higher values than threshold for the entire simulation (may be due to higher moisture
 316 convergence in lower atmosphere during monsoon depression situation and reduced lapse rate)
 317 , suggesting the inability of convective indices to indicate any significant changes in synoptic-
 318 scale systems.. During the pre-monsoon season, a high value of the KI indicates favourable
 319 conditions for thunderstorms, but high values of KI associated with a synoptic low-pressure
 320 system or monsoon depression do not mean conditions for thunderstorm as seen in Figure 6(h).
 321 The pre-monsoon season is associated with drier troposphere as compared to monsoon
 322 depression cases, thus localised effect of convection can bring a variation in KI index but due
 323 to high moisture content during monsoon depression it fails to indicate any variation in time
 324 series.



325

326 **Figure 6.** Thunderstorm indices (CAPE, CIN, TTI and KI) for the first two cases i.e. Case 1
 327 (a, c, e, g) and for Case 2 (b, d, f, h) over the Argul location. (Nearest four grid points are used
 328 from inner domain to linearly interpolate over Argul and ERA5 data is remapped to model
 329 grid).

330 **3.3 Vorticity**

331 The convective indices and point-location validation of surface parameters might not
 332 comprehensively help in evaluating the impact of EHRLDAS on the monsoon depression
 333 (synoptic-scale system). Thus relative vorticity and its components are critically examined over
 334 the inner study domain for the 850 hPa pressure level. In this analysis, the vorticity tendency
 335 (Dodla and Ratna, 2010) is computed for the whole domain, then the grid points exceeding the
 336 95th percentile of rainfall (i.e., heavy rainfall) are considered for discussion.

337 Equation (vii) indicates the relative vorticity tendency.

338
$$\frac{\Delta\varepsilon}{\Delta t} = -u \frac{\Delta\varepsilon}{\Delta x} - v \frac{\Delta\varepsilon}{\Delta y} - w \frac{\Delta f}{\Delta z} + f \frac{\Delta w}{\Delta z} - w \frac{\Delta\varepsilon}{\Delta z} + \varepsilon \frac{\Delta w}{\Delta z} + \frac{\Delta u}{\Delta z} \frac{\Delta w}{\Delta y} - \frac{\Delta v}{\Delta z} \frac{\Delta w}{\Delta x} \dots\dots\dots \text{(vii)}$$

339

340 **A** **B** **D** **E** **C** **F** **G**

341 **A:** relative vorticity tendency (VORTED)

342 **B:** horizontal advection (HADV)

343 **C:** vertical advection (VADV)

344 **D:** beta term

345 **E:** stretching term 1

346 **F:** stretching term 2 (STRETCH)

347 **G:** tilting term (TILT)

348 where, ε is relative vorticity, t is time step (model output time step, hourly), f is the Coriolis
349 parameter, Δx & Δy are the horizontal grid spacing (in metres), w is vertical velocity (Pa s^{-1}),
350 u & v are zonal and meridional components of wind.

351 The values of the various terms A to G of the vorticity equation are computed for each hour for
352 the entire period of simulation. Supplementary Figures S3, S4, S5 show the time series of all
353 the components along with rainfall for the three cases. The VORTED term (vorticity tendency)
354 shows an improvement in EHRLDAS compared to CNTL for Case 1 and in general shows a
355 large dependency on vertical advection (VADV). The tilting and stretching terms are found to
356 contribute towards a negative vorticity tendency (anti-cyclonic flow), while horizontal and
357 vertical advection terms are the main contributors to a positive vorticity tendency (consistent
358 with the findings of Yoon and Huang, 2012 for the case 2 and 3. Table 3 shows the correlation
359 of various terms of the vorticity tendency with respect to rainfall. It is seen that the EHRLDAS
360 has increased (bold numbers in the table) the correlation of vertical advection with rainfall for
361 all cases. For Case 2 and Case 3, the improvement in correlation is found for two major terms,
362 i.e. the vertical advection and stretching term, suggesting an enhancement of the relative
363 vorticity in EHRLDAS compared to CNTL. Interestingly, for Case 3, there is no change in
364 correlation values as noted for Case 1 and 2. This suggests the smallest contribution from
365 stretching terms to monsoon depression rainfall that is due to the dominant influence of
366 synoptic scale circulation in the system. Further, for cases 2 and 3, EHRLDAS has reduced the
367 magnitude of overestimated contributions of relative vorticity to rainfall as simulated in CTNL
368 (Supplementary Figure S4 and S5).

369 **Table 3.** Correlation of vorticity tendency equation components with precipitation for the grid
370 points with precipitation exceeding the 95th percentile, based on hourly data from 24 hours in
371 Case 1 and Case 2 and 72 hours in Case 3. Number in bold signify the improvement in the
372 EHRLDAS simulation in VADV term.

Cases	Experiments	HAD V	VADV	TIL T	STRETC H	VORTED	VORTICIT Y
1	CNTL	0.13	0.43	-0.53	-0.34	0.48	0.01
	EHRLDAS	0.68	0.44	-0.07	-0.53	0.65	-0.61
2	CNTL	-0.71	0.27	0.63	0.17	-0.69	0.24
	EHRLDAS	-0.48	0.51	-0.02	0.45	-0.02	-0.05
3	CNTL	-0.63	0.13	-0.40	0.66	-0.57	0.59
	EHRLDAS	-0.23	0.44	-0.61	0.66	-0.02	0.09

373

374 4. Conclusions

375 This study investigates the impact of two different land states as initial conditions in the WRF
376 model for two thunderstorm cases (one in the pre-monsoon, Case 1 and one mature monsoon
377 case, Case 2) and one monsoon depression system (Case 3) over the [Indian region. For these
378 three cases, different land states are obtained from NCEP Final Operational Global Analysis,
379 FNL (CNTL) and high resolution land data assimilation system (EHRLDAS) at 9 and 3 km
380 resolutions respectively. The skill of the rainfall prediction is improved in HRLDAS,
381 particularly for the isolated pre-monsoon thunderstorm (Case 1). In general, EHRLDAS results
382 demonstrate an improved prediction of rainfall by capturing high intense rainfall pockets and
383 the associated stronger winds, particularly over the coastal region. These strong winds are
384 closer to the ERA5 re-analysis, suggesting an improved land-ocean thermal contrast in
385 EHRLDAS. In addition, the location-specific representation of thermal indices of convection
386 and surface fluxes are better represented by EHRLDAS in all cases. It is seen that EHRLDAS
387 is able to capture the localised instability conditions (thermal indices) more distinctly over
388 coastal eastern India (i.e. Argul) prior to (up to 2 hours lead time) the occurrence of rain from
389 the pre-monsoon thunderstorm compared to the other two cases (Cases 2 & 3) which are

390 embedded within the large-scale influence of the monsoon circulation. Overall, for the point-
391 location validation, EHRLDAS shows more resemblance with ERA5 in terms of fluxes, CAPE
392 and CIN for all cases compared to CNTL. Further, the components of the vorticity tendency
393 equation are computed for those grid points featuring heavy rainfall (> 95 th percentile). In
394 general, results suggest that enhancement of vertical advection primarily contributes towards
395 the positive vorticity tendency in these convective systems and particularly for the pre-
396 monsoon thundershower. Thus EHRLDAS has shown enhanced correlation of the vertical
397 advection term with precipitation for cases 1 and 2.

398 We clearly found that better land initialisation is useful for improving the representation of
399 local convective and dynamical processes, which are crucial for better prediction of rainfall
400 particularly over coastal east India. This therefore conveys the need for incorporating an
401 accurate land-surface state in the initial conditions of numerical models to improve rainfall
402 prediction skill, especially at very high resolution (3 km). Further, we highlight that EHRLDAS
403 shows better representation of convective indices of localised and synoptic-scale severe
404 weather events. Further work would be needed to perform a more comprehensive analysis of
405 pre-monsoon and monsoon storms, for example by systematically comparing day-1 forecasts
406 of all days through spring and summer seasons using this modelling framework.

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