

Enhancing Thunderstorm Potential Area Detection over Northeast India Using INSAT series of Data: A Deep Learning Approach

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Case Report

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Enhancing Thunderstorm Potential Area Detection over Northeast India
Using INSAT series of Data: A Deep Learning Approach

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ABSTRACT

Accurate and timely detection of thunderstorms remains a significant challenge in operational meteorology, particularly during the early stages of convective development when visual signatures are subtle and short-lived. This study presents GeoConvNet, a deep learning-based framework for pixel-wise segmentation of convective cloud structures using multi-spectral INSAT-3D/3DR satellite observations. The model utilizes thermal infrared and water vapor channels to capture cloud-top thermodynamic characteristics and classifies pixels into four categories: no convection, moist convection, deep moist convection, and very deep moist convection. GeoConvNet was trained on over 65,000 annotated image tiles derived from INSAT data (April–June 2021), with the dataset divided into training (70%), validation (15%), and test (15%) subsets. Model performance was evaluated using an independent test dataset and further assessed across ten pre-monsoon thunderstorm events spanning 2018–2024 over Northeast India. A physically consistent validation framework was adopted using GPM IMERG rainfall as a proxy and lightning observations as an indicator of convective intensity, incorporating spatial tolerance (buffer distances up to 20 km) and terrain-based filtering using digital elevation data to account for cloud–rain displacement and orographic effects. Results demonstrate that deep convective classes (deep moist and very deep moist clouds) provide a reliable proxy for rainfall-producing systems and exhibit strong correspondence with lightning occurrence, achieving Critical Success Index (CSI) values in the range of ~ 0.4 – 0.6 under optimal configurations. Incorporating spatial buffering improves agreement with rainfall observations by accounting for cloud–rain displacement. Reduced skill over Himalayan regions reflects terrain-induced effects, the dominance of non-precipitating cloud systems and limitations of satellite-based rainfall data, while terrain-based filtering substantially enhances performance, demonstrating strong potential for operational thunderstorm monitoring.

Key words: Deep Learning, INSAT-3D/3DR, Thunderstorm, Convective cloud, Terrain

1. Introduction

Thunderstorms are rapidly evolving mesoscale convective systems (MCSs) capable of producing severe weather phenomena such as intense lightning, heavy rainfall, strong winds, and hail. These systems manifest in various structural forms, including supercells, squall lines, and multicell clusters (Houze Jr, 2004). Deep moist convection typically develops under conditions of sufficient atmospheric moisture, instability, and lifting mechanisms that enable air parcels to reach the level of free convection (Doswell III et al., 1996; Johns and Doswell III, 1992). Despite advances in Numerical Weather Prediction (NWP), forecasting thunderstorms at short lead times remains challenging due to model spin-up limitations and uncertainties in representing small-scale convective processes (Ma et al., 2020; Short and Petch, 2022).

Satellite observations provide a valuable alternative for monitoring convective activity, particularly through thermal infrared (IR) and water vapor (WV) channels, which capture cloud-top temperature and moisture characteristics. These properties are strongly linked to cloud depth and convective intensity (Adler and Mack, 1986; Schmetz et al., 2002). Several studies have used satellite-derived brightness temperature and brightness temperature differences (BTD) to identify convective features, including overshooting tops associated with strong updrafts (Bedka et al., 2010; Mikuš and Mahović, 2013; Sun et al., 2024). Such threshold-based approaches, while effective in identifying intense convection, often struggle under complex cloud conditions, particularly in the presence of cirrus contamination or evolving convective systems.

To address these limitations, multi-channel satellite-based frameworks have been developed to improve convective detection. For example, Silva Neto et al. (2016) proposed a layered approach that combines IR–WV brightness temperature differences (BTD) with tropopause temperature from NWP models, enabling improved identification of vertically extensive convective systems. While satellite observations are typically available at high temporal resolution (e.g., every 15 minutes), the corresponding NWP-based tropopause temperature fields may not always be available at comparable temporal frequency or latency, which can limit their operational applicability.

Similarly, Lima et al. (2019) introduced a dynamic thresholding strategy in which a reference surface brightness temperature (BT_s) is computed for each pixel and local time as the maximum TIR1 brightness temperature observed over the preceding 30 days, assuming at least one clear-

sky instance. Although this approach accounts for temporal variability, it may introduce uncertainties under persistently cloudy conditions or rapidly evolving environments. Furthermore, the requirement of continuous historical satellite data and the associated computational overhead for maintaining pixel-wise temporal records may constrain its operational uses.

In recent years, deep learning (DL) techniques have emerged as powerful tools for analyzing large volumes of satellite data and capturing complex nonlinear relationships in atmospheric processes. Convolutional neural networks have been successfully applied to satellite image analysis and short-term forecasting (Gong et al., 2022; Ionescu et al., 2021). Despite these advances, relatively limited work has focused on pixel-wise segmentation of convective cloud structures using geostationary satellite data, particularly in regions with complex terrain.

The North Eastern Region (NER) of India presents a unique challenge for convective storm detection due to its complex topography, including the Himalayan foothills and varied microclimatic zones. These conditions promote frequent thunderstorm activity but also introduce significant uncertainties in both cloud detection and rainfall estimation (Das and Hazra, 2019). In particular, discrepancies between cloud-top signatures and surface rainfall, especially over mountainous regions, complicate the validation of satellite-based convective detection methods.

In this study, we present GeoConvNet, a deep learning-based framework for pixel-wise segmentation of convective cloud structures using multi-spectral INSAT-3D/3DR observations. The model classifies cloud pixels into distinct convective categories based on their spectral signatures. A key challenge in evaluating such models arises from the inherent mismatch between cloud-top signals and surface rainfall, particularly over complex terrain such as the NER. Orographic influences, vertical decoupling of cloud systems, and advection-driven displacement between cloud and precipitation fields often introduce spatial inconsistencies, making direct pixel-to-pixel validation unreliable. To ensure a more physically consistent evaluation, the framework uses the latest GPM IMERG Version 07 rainfall product, which incorporates improved retrieval algorithms, enhanced calibration, and generally better representation of precipitation across diverse terrains compared to earlier versions (Batista et al., 2025). However, despite these advancements, satellite-based precipitation estimates continue to face challenges over steep and complex terrain, particularly in capturing intense precipitation associated with strong orographic uplift (Li et al., 2025). Consequently, the proposed validation strategy incorporates spatial tolerance to account for cloud–rain

displacement, along with terrain-based filtering using digital elevation data, enabling a more robust and physically meaningful assessment of convective cloud detection over mountainous regions.

2. Data Utilization

a. Satellite Data

The launch of INSAT-3D by ISRO in 2013 marked a major milestone in India's meteorological satellite program, introducing atmospheric sounding capabilities for the first time. This advancement was further continued with the subsequent launches of INSAT-3DR by ISRO in 2016. All three platforms carry three primary payloads: the Meteorological payload (MET), the Data Relay Transponder (DRT), and the Satellite Aided Search and Rescue (SAS&R) system. The MET payload features an advanced imager that captures Earth's surface and atmospheric conditions across six spectral bands, one in the visible range and five in the infrared domain. These include bands for shortwave infrared (SWIR), mid-wave infrared (MIR), water vapor (WV), and two separate thermal infrared (TIR) channels (TIR-1 and TIR-2).

Table 1. Spectral Bands and Spatial Resolution of INSAT-3D Imager

Spectral Band	Wavelength (μm)	Ground Resolution (km)
VIS	0.55–0.75	1
SWIR	1.55–1.70	1
MIR	3.80–4.00	4
WV	6.50–7.10	8
TIR-1	10.3–11.3	4
TIR-2	11.5–12.5	4

Table 1 presents the spectral characteristics of the imager. This study used INSAT Imager data from spectral bands namely: WV, TIR1 and TIR2 and were obtained from MOSDAC (<http://www.mosdac.gov.in>) in HDF5 format for Imager.

c. Data for validation

1) LIGHTNING DATA

Lightning data used in the study is taken from the Indian Lightning Location Network (ILLN), primarily operated by the Indian Institute of Tropical Meteorology (IITM), Pune. It was initiated in 2018 using sensors provided by Earth Networks, USA, which now has expanded to include over 86 sensors across India. Several validation studies have affirmed the reliability of ILLN's lightning data by comparing it against independent observations, including electric field mills, the ISS Lightning Imaging Sensor (LIS), dual-frequency radar reflectivity from the Global Precipitation Measurement mission, and ground-based radar systems (Biswasharma et al., 2025). Over Northeast India (NEI), the system provides a minimum location accuracy of approximately 300 meters for CG lightning events. The network's detection efficiency (DE) is estimated at $90 \pm 5\%$ for CG flashes and $50 \pm 5\%$ for IC flashes (Mudiar et al., 2021). Srivastava et al. (2024) further evaluated the network using optical measurements from standard-speed cameras and reported a DE of 78.9% over Lucknow and Shillong.

2) GPM IMERG PRODUCT

The Integrated Multi-satellite Retrievals for GPM (IMERG V07) is an advanced precipitation estimation algorithm developed under NASA's Global Precipitation Measurement (GPM) mission. In this study the final IMERG product has been used. The final product incorporates monthly rain gauge data for enhanced accuracy. IMERG outputs are provided at fine spatial ($0.1^\circ \times 0.1^\circ$) and temporal (30-minute) resolution, making them highly suitable for monitoring rainfall events.

3) Elevation Data

The terrain data used in this study is derived from the Shuttle Radar Topography Mission (SRTM) Global 1 arc-second dataset (SRTMGL1 v003), providing near-global elevation information at approximately 30 m spatial resolution (NASA JPL, 2013).

3. Methodology

a) Deep learning-based convective cloud detection (GeoConvNet)

A modified U-Net architecture, referred to as GeoConvNet, was developed for pixel-wise segmentation of convective cloud structures from multi-spectral INSAT imagery. The GeoConvNet model follows a modified U-Net framework with an encoder–decoder structure and skip connections to preserve spatial and contextual information (Fig. 1). The bottleneck layer consists of high-level feature representations with dropout regularization to prevent overfitting. The decoder progressively reconstructs spatial resolution using transposed convolutions and feature concatenation. A final 1×1 convolution with softmax activation produces four output classes corresponding to different convective cloud categories.

To address class imbalance, class weights were computed based on pixel frequency distributions in the training dataset. The model was trained using the Adam optimizer with a learning rate of 1×10^{-4} , a batch size of 4, and 50 training epochs. Input images were normalized, and ground-truth masks were encoded for multi-class segmentation. Model performance during training was monitored using loss and accuracy metrics for both training and validation datasets.

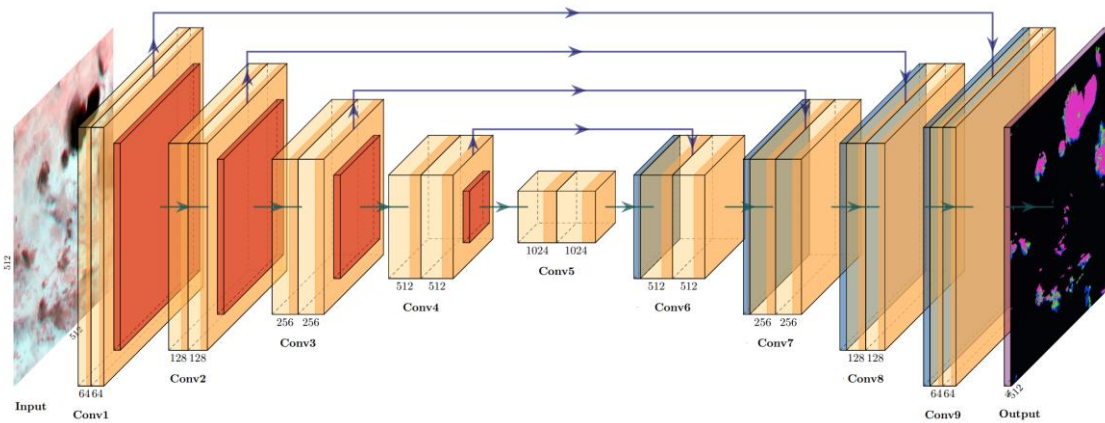


Fig. 1. Schematic diagram of GeoConvNet architecture used in this work.

b) Data preprocessing

INSAT HDF5 data were converted to GeoTIFF format, and the spectral bands (TIR1, TIR2, and WV) were extracted and stacked to form three-channel inputs. Training labels were generated using a thresholding approach derived from established brightness temperature (BT) and brightness temperature difference (BTD) criteria (Lima et al., 2019; Silva Neto et al.,

2016). Since the focus is on cold cloud tops, cloud pixels were initially identified using a fixed threshold applied to the TIR1 brightness temperature, with pixels colder than 233 K classified as cloud. Subsequently, convective cloud detection was refined using spectral tests involving TIR1 and water vapor (WV) channels. Specifically, cold cloud-top temperatures ($TIR1 < 233$ K) and positive WV–TIR1 differences were used to identify deep convective clouds, while stronger thresholds (e.g., $WV - TIR1 > 4$ K) were employed to detect intense convection associated with overshooting tops. The labeling scheme classifies each pixel into four categories: no cloud (NC, Class 0), moist convection (MC, Class 1), deep moist convection (DMC, Class 2), and very deep moist convection (VDMC, Class 3). The threshold-based method was used only for initial label generation, while the model learns generalized spatial features beyond these predefined criteria. The GeoConvNet model subsequently learns spatial, contextual, and multi-spectral features from the data, enabling it to generalize beyond the predefined threshold rules. The dataset was tiled into 512×512 patches, yielding approximately 65,000 samples, which were divided into training (70%), validation (15%), and test (15%) subsets.

c) Postprocessing and operational implementation

A Python-based graphical interface was developed to facilitate operational use of the GeoConvNet model. The system enables conversion of INSAT data, spatial sub setting, and generation of convective cloud outputs for visualization in GIS platforms.

d) Validation framework

A physically consistent validation framework was adopted using lightning and GPM IMERG rainfall as a proxy for convective activity. To account for spatial displacement between cloud-top signatures and surface rainfall, buffer distances of up to 20 km were applied. Additionally, terrain-based filtering using digital elevation data was incorporated to reduce spurious cloud–rain mismatches over mountainous regions. Performance was evaluated using standard metrics including Probability of Detection (POD), False Alarm Ratio (FAR) and Critical Success Index (CSI).

4. Study Area and Case Studies

4.1 Study Area

The North Eastern Region (NER) of India is one of the most active zones for pre-monsoon thunderstorm activity, frequently experiencing mesoscale convective systems associated with intense rainfall, lightning, and strong winds casualties (Bhardwaj et al., 2017; Manohar and Kesarkar, 2005; Tyagi, 2007). The region is characterized by highly complex topography, including the eastern Himalayan foothills, plateau regions, and low-lying alluvial valleys. These terrain features play a crucial role in modulating convective processes through orographic lifting, localized moisture convergence, and thermodynamic variability. Such complexity introduces significant challenges for satellite-based convective cloud detection. Owing to these factors, the NER provides an ideal testbed for evaluating the robustness and physical consistency of deep learning based convective cloud classification frameworks. A terrain map of NER, India is shown in Fig. 2.

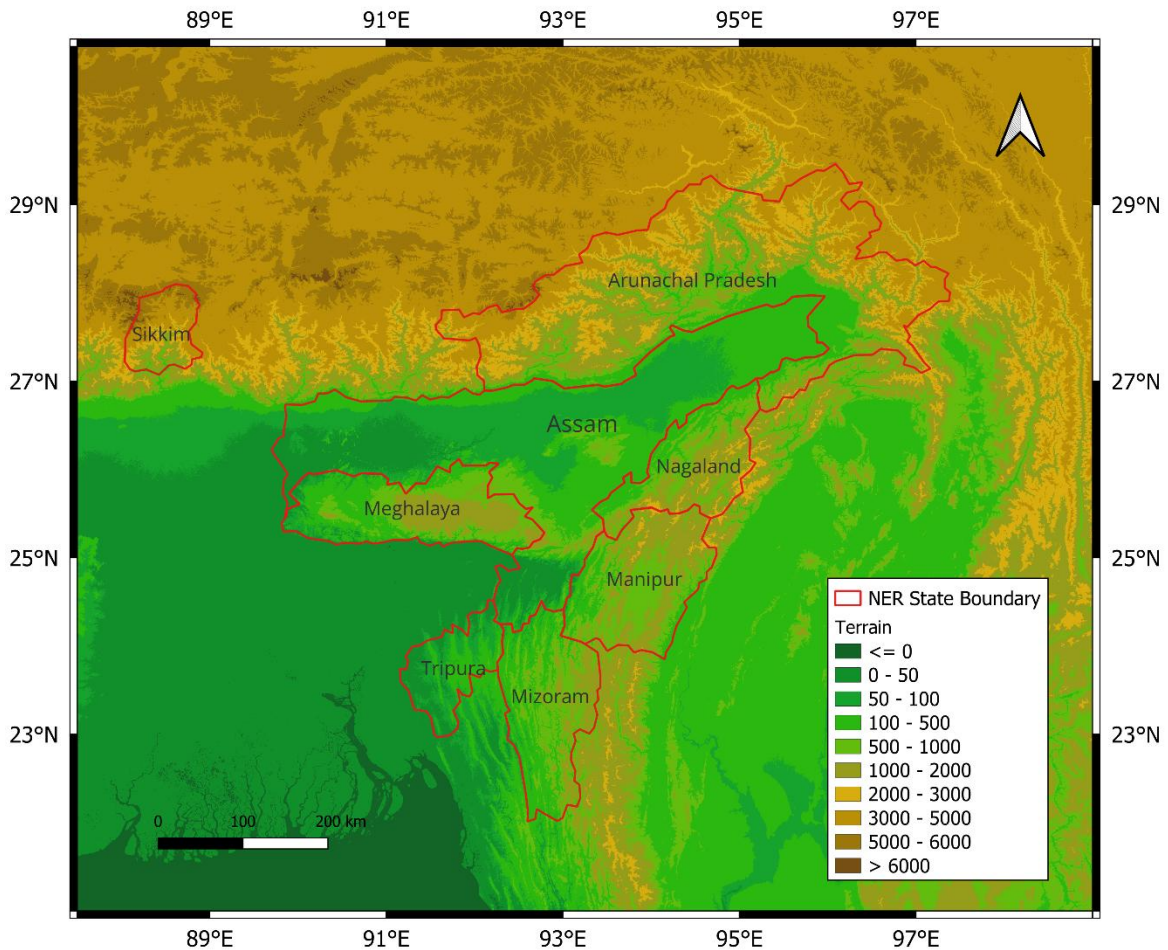


Fig. 2. Terrain map of NER States of India and its surrounding

4.2 Case Study Selection

To evaluate the performance of the proposed GeoConvNet framework, three representative thunderstorm events were selected (Table 2), encompassing a range of convective intensities, spatial organization, and societal impacts. These cases were chosen to assess the model's capability to detect both isolated and organized convective systems. The inclusion of both low-impact and high-impact events enables evaluation of the model's sensitivity to varying convective intensities and its relevance for operational applications.

Table 2. Three representative thunderstorm events

S. No.	Date of Occurrence	Location	Remarks
1	07 May 2021	South Garo Hills, Meghalaya (25.4°N, 90.3°E)	a localized convective event with limited reported damage
2	12 May 2021	Nagaon District, Assam (26.27°N, 92.78°E)	a high-impact convective event associated with intense lightning activity caused death of 18 elephants
3	16–18 June 2024	Meghalaya (East Khasi Hills, West Garo Hills, East Jaintia Hills, North Garo Hills)	a multi-day, spatially extensive convective system leading to widespread disruption

In addition to the primary case studies, ten additional thunderstorm events spanning the period 2018–2024 were analyzed (Table 3) to investigate the influence of terrain and storm structure on model performance. This extended dataset allows for a more comprehensive assessment of model robustness under varying meteorological conditions and topographic influences. In particular, it facilitates systematic analysis of terrain-dependent performance variations and provides insight into how different storm morphologies, such as compact convective cores versus extensive cloud shields affect the correspondence between cloud classification and rainfall observations.

Table 3. Extended Event Set for Terrain and Structural Analysis

S. No.	Date of Occurrence	Location	Remarks
1	09 May 2018	Karbi-Anglong, Kokrajhar	Strong wind and rain affected the normal life with 2 people dead
2	10 – 11 May 2018	Tripura	Heavy rains accompanied by thunderstorms claiming human lives and causing severe damages to property
3	01 June 2019	West Tripura and Sepahijala districts, Tripura	Heavy rainfall accompanied by storm uprooting trees, disrupting power supply

			and leaving many low-lying areas inundated.
4	15 April 2019	Manipur	Massive thunderstorm hits Manipur, leaves entire state without power, 3 people dead and over 50 injured
5	16 April 2019	Changlang and Longding, Arunachal Pradesh	Widespread disruption
6	09 April 2020	Jorhat, Assam	Widespread disruption
7	30 March 2021	Dhalai district, Tripura	Houses were damaged while many trees and electric poles were uprooted
8	9 June 2022	East Garo Hills, South Garo Hills, South West Garo Hills, South West Khasi Hills (Meghalaya)	Heavy rainfall event causing flood, landslide etc.
9	22 April 2023	Several parts of NER	Multi-location evolving event
10	31 March 2024	Guwahati, Manipur	Widespread disruption

5. Result and Discussion

The performance of the deep learning-based cloud classification model is first evaluated through spatial validation (Fig. 3a-d), which provides an intuitive assessment of its ability to capture the structure and intensity of convective cloud systems. A representative example demonstrates strong agreement between the predicted cloud classes and the reference labels, with the model accurately reproducing the morphology and spatial extent of convective regions.

The corresponding error map indicates that misclassifications are sparse and primarily confined to cloud boundaries and small fragmented regions, suggesting that the model performs reliably in identifying core convective structures while exhibiting minor uncertainty in transitional zones. The training and validation loss and accuracy curves further confirm stable model convergence and good generalization, with no significant evidence of overfitting (Fig. 3e-f).

A more detailed statistical evaluation based on the confusion matrix (Supplementary Fig. S1) supports these observations. Although high accuracy values are obtained, accuracy alone does not fully capture model performance due to class imbalance. The confusion matrix reveals that most misclassifications occur between adjacent cloud classes, particularly between deep moist and very deep moist clouds, reflecting the inherent difficulty in distinguishing cloud intensity levels from satellite observations. Minimal confusion between background and convective

cloud classes indicates robust cloud detection capability, although a slight tendency to overestimate cloud presence is observed.

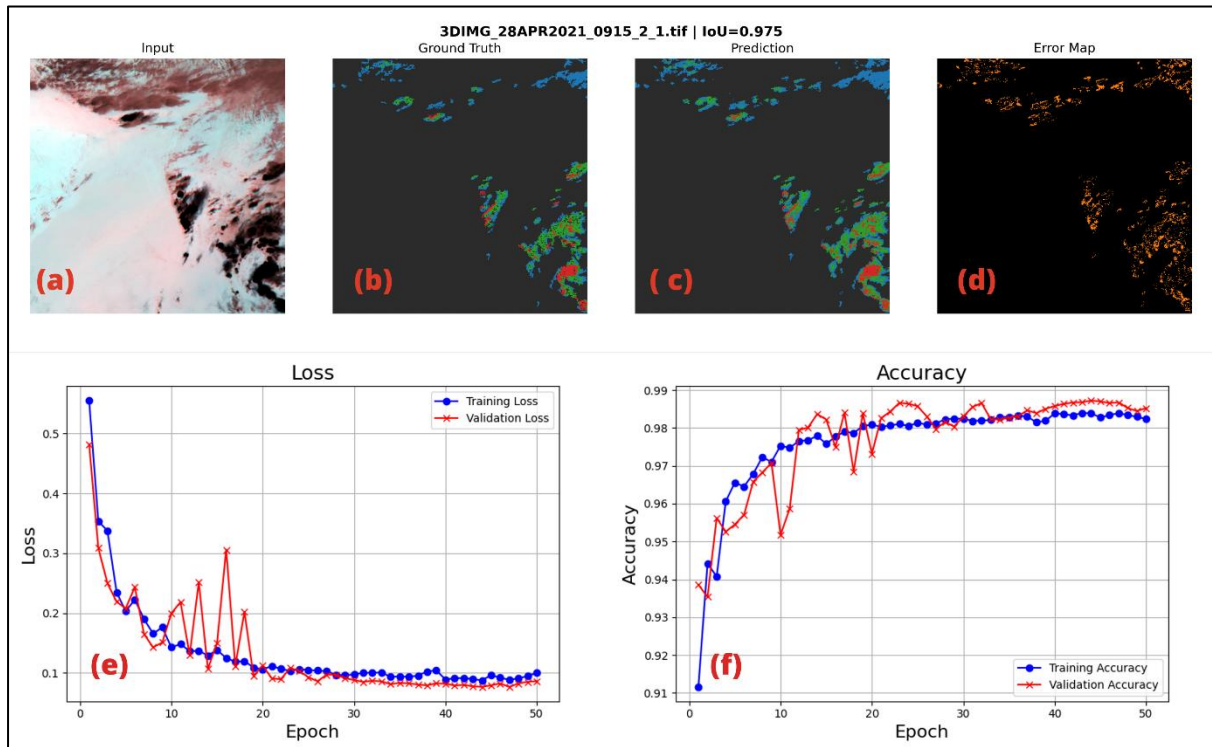


Fig. 3. Spatial validation and training diagnostics of GeoConvNet model. Panels (a–d) illustrate the input image, ground truth, predicted cloud classes, and error map for a representative case (IoU = 0.975). Panels (e–f) present the evolution of training and validation loss and accuracy.

5.1 Physical consistency of cloud classification

The evaluation of GeoConvNet-derived cloud classes using lightning observations provides an independent assessment of their physical relevance to convective processes. Lightning activity is a well-established proxy for deep convection, as it is closely associated with strong updrafts, mixed-phase microphysics, and charge separation processes within cumulonimbus clouds (Cecil et al., 2005; Nesbitt, 2002; Zipser, 1994).

The left panels of Figure 4 illustrate the absolute lightning counts associated with each cloud class, reflecting the overall magnitude of storm activity. In contrast, the right panels of Figure 4 present lightning density normalized by cloud area (per 1000 pixels), which provides a measure of convective intensity independent of cloud extent. This distinction is important, as large systems may exhibit high lightning counts due to their spatial coverage, while more compact systems can show higher lightning density, indicating stronger localized convection.

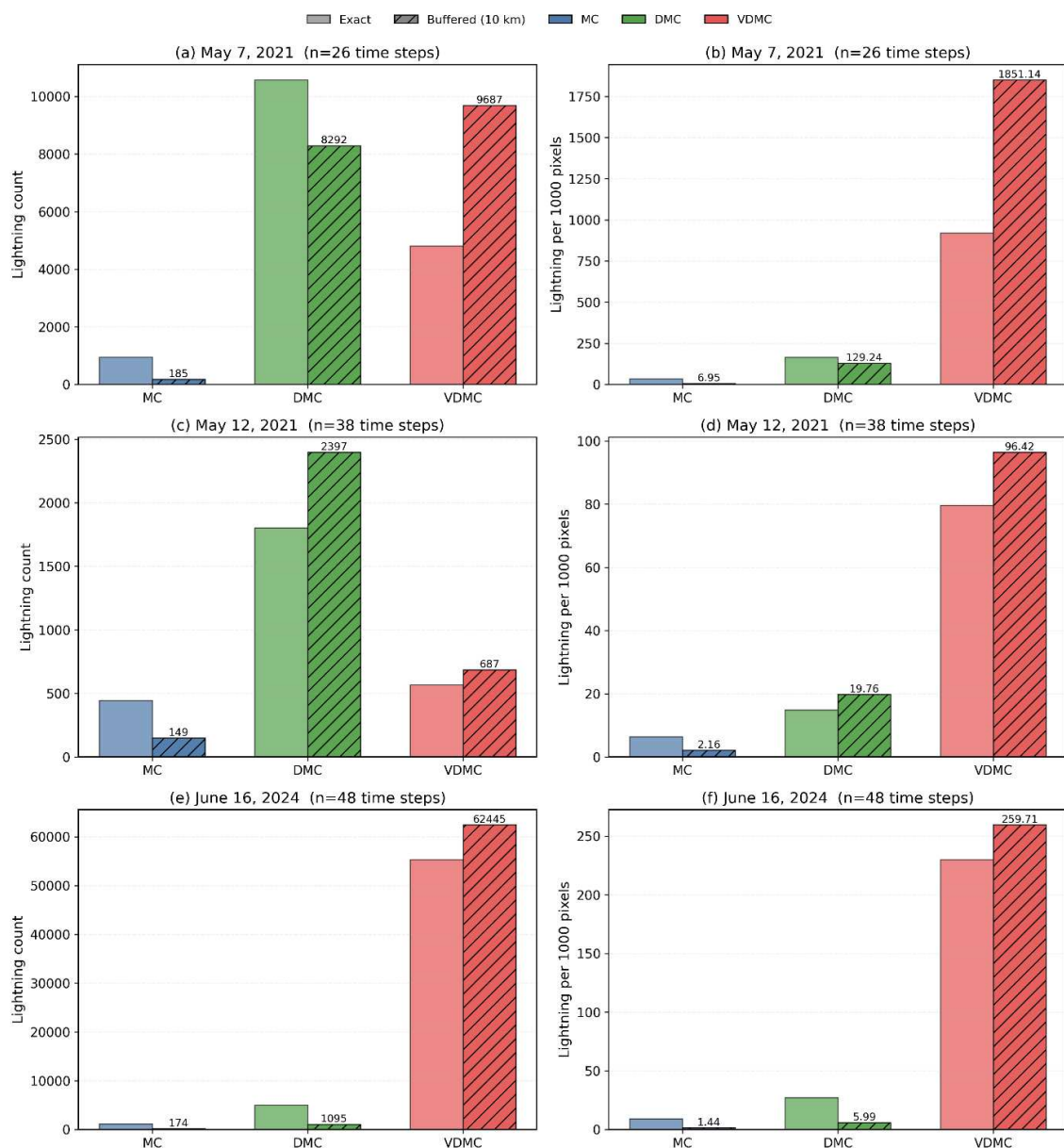


Fig. 4. Lightning validation of GeoConvNet cloud classes for three thunderstorm cases

The analysis further highlights the distinct roles of DMC and VDMC in convective systems. While both classes are associated with convective activity, VDMC consistently exhibits the highest lightning counts and densities, indicating its association with mature deep convective cores where electrification processes are most active. In contrast, DMC shows moderate lightning activity, suggesting its role as a transitional stage representing developing or weakening convection. This systematic increase in lightning activity from MC to DMC to VDMC reflects the progressive intensification of convective processes, with VDMC capturing the most electrically active regions of the storm. This hierarchical distribution is consistent across all three case studies (Table 2), indicating that the classification scheme effectively

captures the intensity spectrum of convective systems. This agreement confirms that the GeoConvNet classification is not merely a radiometric segmentation of satellite imagery but is physically meaningful in representing convective intensity. In particular, the strong association between DMC/VDMC and lightning supports the interpretation that deep moist cloud regions correspond to convective cores characterized by vigorous updrafts and active electrification. Similar relationships between cold cloud tops, deep convection, and lightning activity have been documented in previous studies (Petersen and Rutledge, 1998; Price and Rind, 1992).

While lightning provides validation of convective intensity, rainfall remains the primary variable of interest for disaster management. Therefore, the cloud classification is further evaluated against GPM IMERG rainfall. Spatial validation of the deep learning-based cloud classification is carried out using three representative thunderstorm events (Table 2), where observed storm locations and impacts are documented. For the event on 7 May 2021 over South Garo Hills, Meghalaya, the model successfully captures a well-defined convective cluster, which aligns closely with both GPM-derived rainfall and observed lightning activity (Fig. 5 First row). In the 12 May 2021 event over Nagaon district, Assam, the model identifies organized convective cloud regions corresponding to lightning activity associated with a severe incident that resulted in the death of 18 elephants, highlighting its capability to detect high-impact localized convection (Fig. 5 Second row). The multi-day event of 16–18 June 2024 across Meghalaya, which caused landslides and widespread disruption, is characterized by an extensive cloud shield with embedded convective cores (Fig. 5 Third row). The model effectively delineates these convective regions, with strong agreement between very deep moist cloud areas, rainfall distribution, and lightning occurrence. These results demonstrate that the model effectively captures the spatial structure and intensity of convective systems, with errors primarily occurring in transitional or stratiform regions.

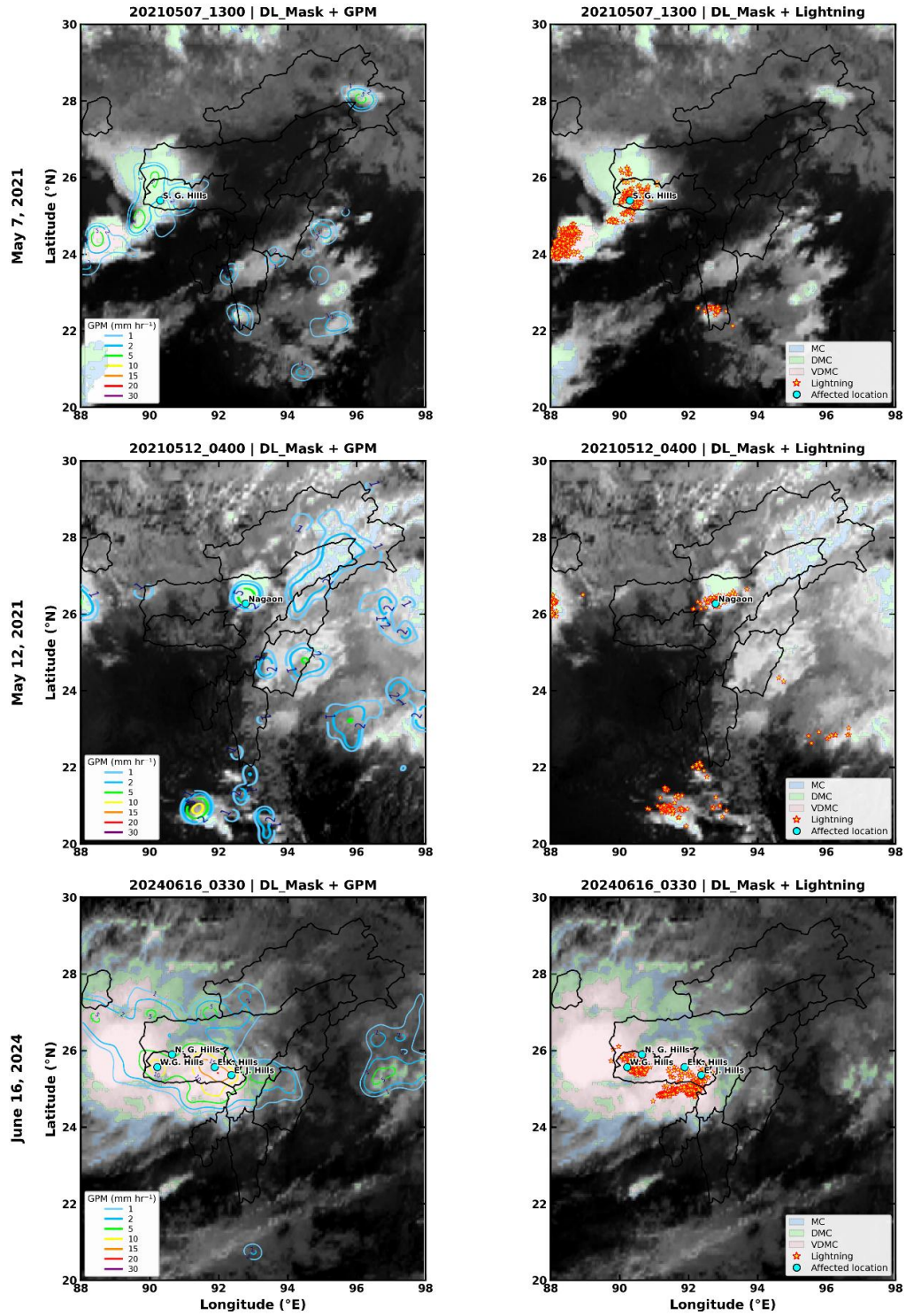


Fig. 5. GeoConvNet Convective cloud mask comparison with GPM IMERG rainfall (Contours ranging from 1mm to 30 mm) and lightning flashes (red star) for three thunderstorm cases

5.2 Cloud–rainfall relationship and inherent spatial decoupling

Figure 6 presents the variation of CSI across three thunderstorm cases as a function of cloud class selection, rainfall threshold, and spatial buffering. A consistent increase in CSI is

observed with increasing buffer distance, indicating the presence of spatial displacement between convective cloud signatures and observed rainfall. This behavior is often interpreted as a spatial mismatch; however, such an interpretation is overly simplistic. Instead, the observed displacement between cloud-top features and surface rainfall is physically expected due to the internal structure and dynamics of convective systems.

Deep convective systems are characterized by a spatial separation between updraft and downdraft regions. The strongest updrafts, associated with cold cloud tops (VDMC), are not necessarily collocated with peak surface rainfall, which often occurs in adjacent downdraft regions (Houze Jr, 2004). Furthermore, mesoscale convective systems (MCSs) exhibit a distinct organization consisting of a convective core and an extensive stratiform precipitation region (Houze R. A., 1997). The stratiform region can extend tens to hundreds of kilometers away from the convective core, resulting in rainfall that is spatially displaced from the coldest cloud tops. In addition, anvil spreading and upper-level divergence led to the horizontal expansion of high-level clouds, further decoupling cloud-top signatures from precipitation. Hydrometeors formed in the convective core may also be advected by environmental winds as they fall, causing additional displacement between the cloud and rainfall locations (Nesbitt et al., 2000). Therefore, the improvement in CSI with increasing buffer distance should not be interpreted as a correction of model error but rather as a representation of the inherent spatial separation between cloud-top signatures and surface precipitation processes.

The results indicate that the optimal combination of cloud classes depends on the dominant precipitation regime. For events with widespread or stratiform-dominated rainfall, the inclusion of all cloud classes (1, 2, and 3) yields higher CSI values, as it captures both deep convective cores and the surrounding weaker or non-precipitating cloud regions. This is evident in the May 7 and May 12, 2021 cases, where the combined use of all classes provides the best agreement with rainfall observations. In contrast, for events characterized by more intense and organized convection, the contribution of deeper convective clouds becomes more significant. This is reflected in the June 16, 2024 case, where the combination of deep and very deep moist clouds (classes 2 and 3) achieves CSI values higher than those obtained using all classes. This suggests that during strongly convective events, rainfall is more closely associated with the core convective regions, whereas in stratiform or mixed regimes, broader cloud structures contribute substantially to precipitation.

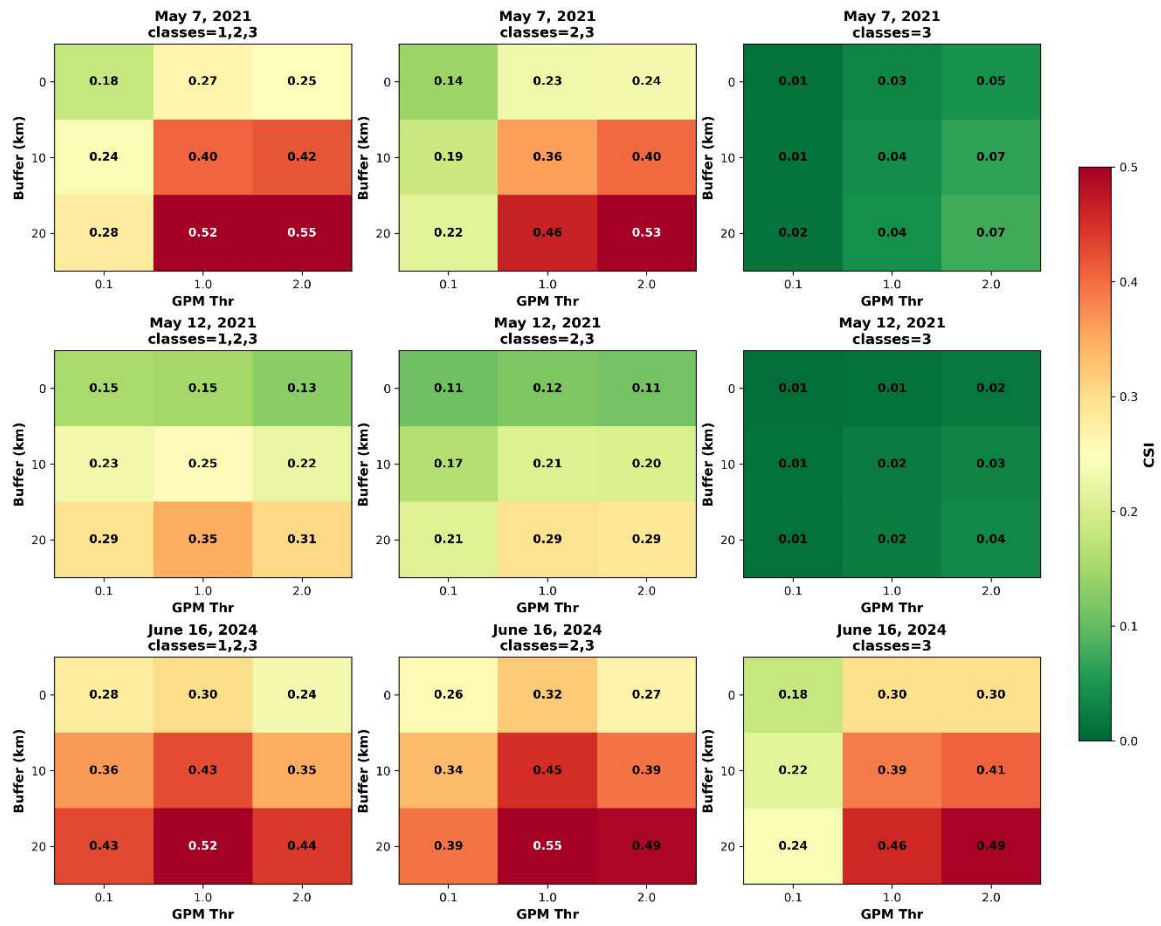


Fig. 6. CSI heatmaps across the three thunderstorm cases (Table 2) as a function of cloud class selection (1,2,3), rainfall threshold, and spatial buffering

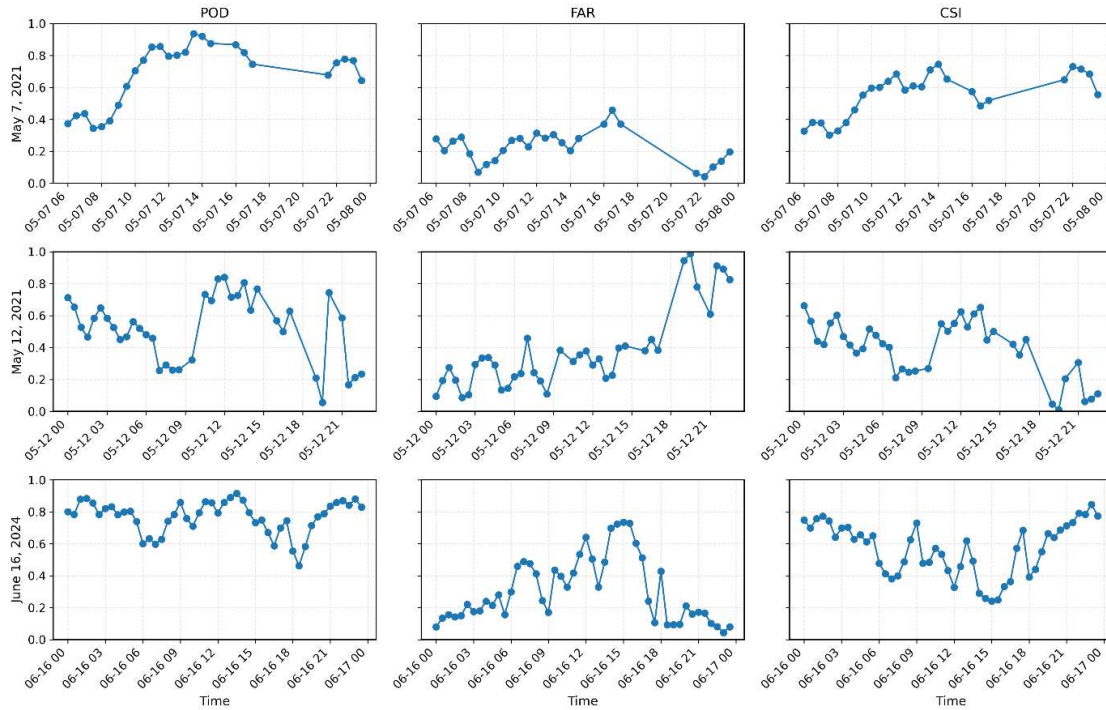


Fig. 7. Time Series of POD, FAR, and CSI across three thunderstorm events with buffer of 20 km

Temporal analysis of framework metrics further highlights the event-to-event variability in model performance (Fig. 7). For the May 7, 2021 case, the progressive increase in probability of detection (POD), coupled with relatively low false alarm ratio (FAR), results in a steady improvement in CSI, indicating strong correspondence between detected convective clouds and observed rainfall during organized storm phases. In contrast, the May 12, 2021 event exhibits highly variable POD and a marked increase in FAR, particularly during later stages, leading to a substantial reduction in CSI. This behavior suggests the presence of weaker or stratiform-dominated precipitation, where cloud-top signatures do not consistently translate into surface rainfall, resulting in both missed detections and increased false alarms. The June 16, 2024 event demonstrates consistently high POD throughout the storm lifecycle, with moderate but fluctuating FAR, leading to relatively stable and higher CSI values. This indicates sustained deep convection where cloud-top characteristics provide a reliable proxy for rainfall, despite some overestimation during certain phases. Overall, periods of high CSI are associated with well-organized convective systems characterized by high POD and controlled FAR, whereas reduced skill is observed during transitional phases such as storm initiation, decay, or stratiform dominance, where both missed detections and false alarms increase. This highlights the dynamic nature of convective systems and the limitations of static cloud-based indicators in capturing all phases of storm evolution.

5.3 Terrain and Storm-Structure Dependence on Model Performance

a. Physical interpretation of terrain effects

To isolate the effect of terrain, model performance was further analyzed across discrete elevation bands (Fig. 8) across 10 additional thunderstorm events (Table 3). The model exhibits relatively stable and consistent performance over low to mid-elevation regions (0–1000 m), with median CSI values around 0.45–0.48 and limited variability. However, a gradual decline in performance is observed with increasing elevation, particularly beyond 1000 m. The degradation becomes more pronounced over the 2000–3000 m band, where both the median CSI decreases significantly and the spread increases, indicating higher variability and reduced reliability. Over very high elevations (>3000 m), the model performance drops sharply, with most CSI values concentrated below 0.2. This behavior suggests that the model is optimized for detecting deep convective cores but struggles to capture precipitation associated with stratiform or terrain-modulated cloud systems, which are more prevalent in high-altitude

regions. The increasing spread in CSI values with elevation further indicates that model performance becomes highly event-dependent in complex terrain.

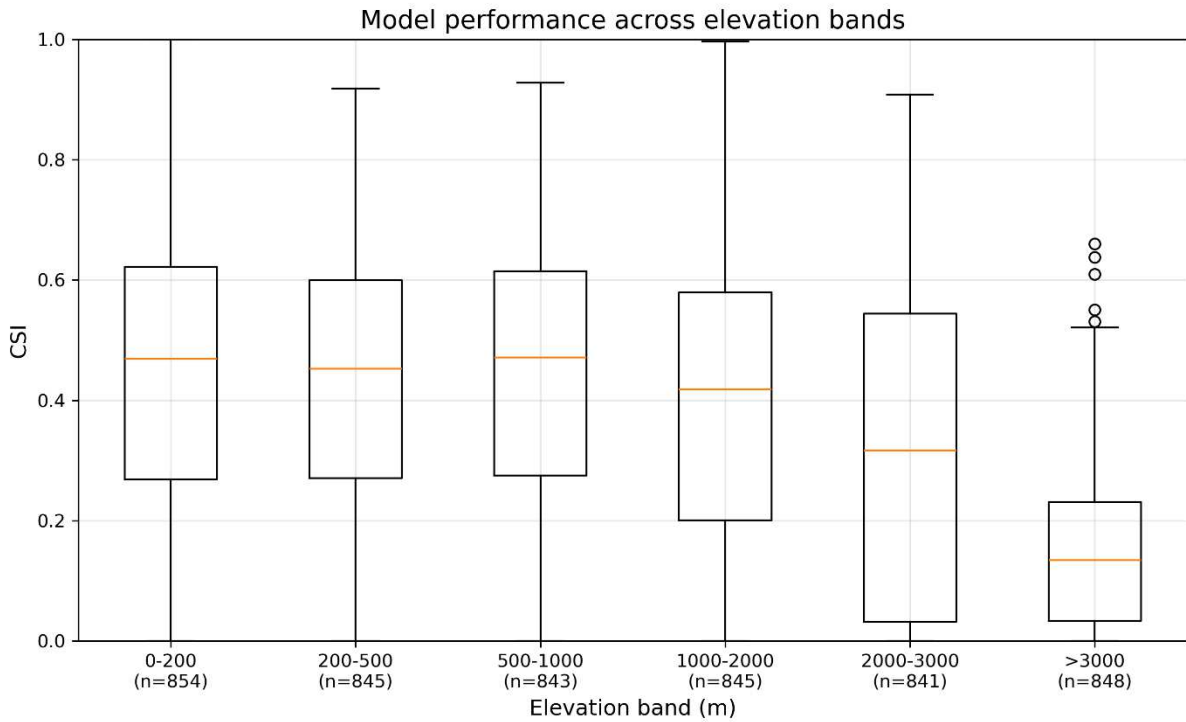


Fig. 8. GeoConvNet Model performance based on CSI values across elevation band for 10 thunderstorm events

The observed degradation in model performance with increasing elevation can be attributed to several physical and observational factors. Over low elevations, deep convective systems dominate, where strong vertical cloud development is closely associated with significant precipitation. In such cases, cloud-top characteristics provide a reliable proxy for rainfall, resulting in higher CSI values. In mountainous regions, particularly in the northeastern Himalayas, cold cloud tops do not always correspond to surface rainfall. Orographic lifting can produce extensive cloud cover without significant precipitation, while shallow convection and non-precipitating clouds may also contribute to cold cloud-top signatures. Additionally, precipitation processes in complex terrain are influenced by microphysical and dynamical factors that may not be directly captured by cloud-top temperature alone (Houze, 2012).

b. Temporal variability of model skill

To further strengthen the validation, the temporal evolution of model performance across the 10 thunderstorm events (Table 3) is examined using framewise skill scores (POD, FAR, and CSI) (Fig. 9). The results show substantial variability in model performance across different

events and time steps. While many events exhibit high probability of detection ($POD > 0.6$) and moderate CSI values (~ 0.4 – 0.7), there are several instances where CSI drops sharply, often accompanied by reduced POD and increased FAR.

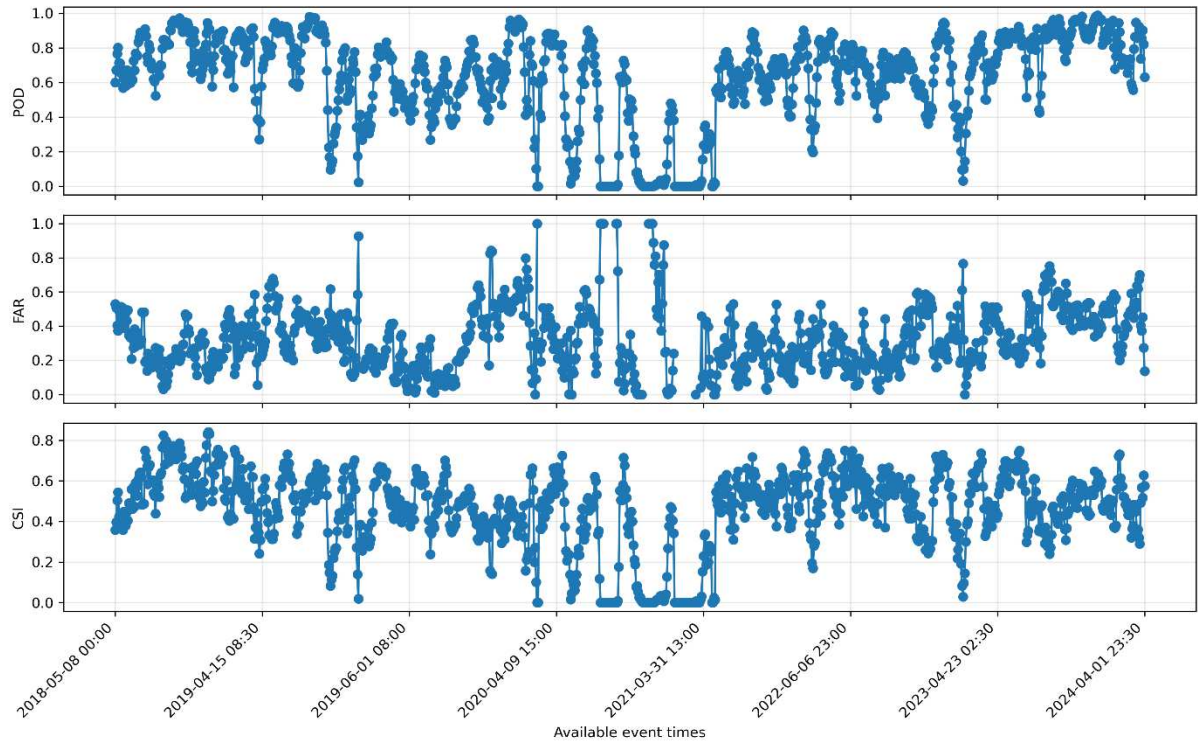


Fig. 9. Framewise variation of POD, FAR, and CSI across all 10 analyzed thunderstorm events under a fixed configuration (classes = 1,2,3; GPM threshold = 1.0 mm hr^{-1} ; buffer = 20 km; $DEM \leq 2000 \text{ m}$)

A particularly notable feature is the presence of extended periods of low CSI during specific events, most prominently in 2021. A detailed examination of individual events, particularly from 2021 (Fig. 10), reveals that storm structure plays a critical role in determining model performance. The 2021 event is characterized by a large, spatially extensive upper-level cloud shield covering much of the region, with embedded rainfall detected by GPM. However, the convective cloud mask identifies only localized regions as deep convective cores, while a substantial fraction of the raining area is associated with the surrounding non-convective cloud shield, representing stratiform or anvil cloud regions. Stratiform cloud (purple shades in Fig. 10) is represented using a proxy defined as cold, spectrally uniform cloud ($TIR1 < 250K$, $0 \leq TIR1 - TIR2 \leq 0.5$) excluding convective cores.

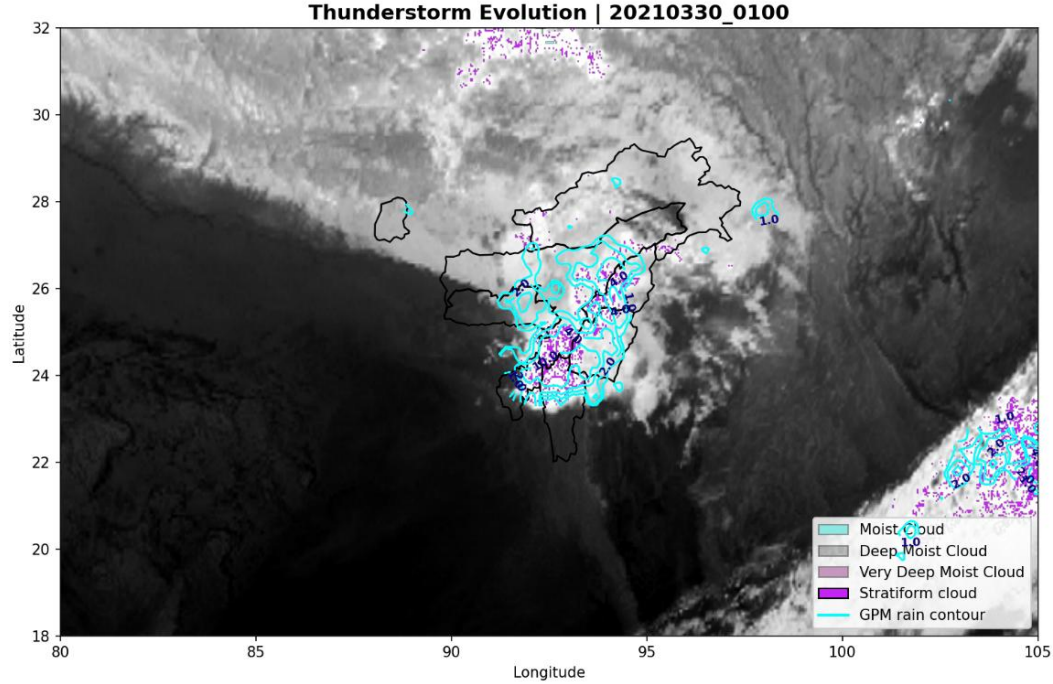


Fig. 10. Thunderstorm evolution on 30 March 2021 at 01:00 UTC. Background shows INSAT TIR1 brightness temperature. Convective clouds (MC, DMC, VDMC) are derived from the AI-based classification. Stratiform cloud is represented in purple colour and GPM rainfall is shown in cyan contours. (Animation of the Fig. 10 is given as Supplementary Fig. A1).

This results in a significant number of false negatives, leading to low CSI values across all elevation bands. The behavior indicates that the model is primarily tuned to detect deep convective cores and lacks sensitivity to widespread non-convective cloud regions that may still produce precipitation. Consequently, events dominated by extensive cloud shields, such as mesoscale convective systems with large stratiform cloud regions, are not adequately captured by the convective mask.

6. Conclusion

This study presents the development and evaluation of GeoConvNet, a deep learning-based framework for detecting and classifying convective cloud structures using multi-spectral INSAT-3D/3DR satellite observations over Northeast India. The model demonstrates strong capability in identifying deep convective cloud systems, with validation against GPM IMERG rainfall showing that deep convective classes provide a reliable proxy for precipitation-producing systems under appropriate spatial tolerance.

Independent validation using lightning observations further confirms the physical consistency of the classification, with Very Deep Moist Clouds (VDMC) exhibiting the highest lightning density, followed by Deep Moist Clouds (DMC), and minimal activity in Moist Clouds (MC).

This hierarchical relationship indicates that GeoConvNet effectively captures the intensity spectrum of convective processes.

A key outcome of this study is the identification of strong terrain dependence in model performance. Skill is highest over low to moderate elevations and decreases systematically with increasing altitude, with a pronounced degradation observed above ~2000 m and very low performance in regions exceeding 3000 m. This reduction is attributed to orographic cloud processes, cloud–rain displacement, and known limitations in satellite-based precipitation retrievals over complex terrain.

In addition to terrain effects, the analysis highlights the importance of storm structure. Events characterized by compact deep convection are well captured by the model, whereas cases dominated by widespread stratiform or weakly convective cloud systems exhibit reduced performance due to under-detection of non-convective rainfall regions. This indicates that model performance is jointly influenced by environmental conditions and cloud morphology.

Overall, the results demonstrate that GeoConvNet is effective in detecting deep convective systems and provides physically meaningful cloud classification. Although the training labels were generated using threshold-based criteria, the model learns spatial, contextual, and multi-spectral relationships beyond these predefined rules, as evidenced by its strong agreement with independent observations such as lightning activity and rainfall patterns. However, its performance is constrained over complex terrain and during events dominated by non-convective or stratiform precipitation regimes. These findings highlight the importance of incorporating stratiform cloud-type awareness and terrain-dependent strategies in future satellite-based nowcasting systems. Despite these limitations, the model shows strong potential for operational deployment when combined with physically informed validation approaches, including terrain-based filtering and spatial buffering to account for cloud–rain displacement. Such integration enables more reliable interpretation of convective signals in complex environments and enhances the practical applicability of the framework for real-time thunderstorm monitoring over data-sparse regions such as the North Eastern Region of India.

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data. The schematic diagram of GeoConvNet was generated using PlotNeuralNet, and the authors gratefully acknowledge the developers Iqbal, 2018 for making the code publicly available.

Data Availability Statement.

The model training data, outputs, and code used in this study are not presently hosted in a public repository but can be made available upon request.

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