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Evaluation of WRF model's lightning prediction capabilities for Sri Lanka during the second inter-monsoon

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सार – बिजली गिरना एक गंभीर और कष्टदायक मौसम संबंधी घटना है, जो अक्सर भीषण आंधी-तूफान के साथ होती है, जिससे मानव जीवन के लिए संभावित रूप से घातक परिणाम और महत्वपूर्ण अवसंरचना क्षेत्रों को भारी नुकसान हो सकता है। सार्वजनिक सुरक्षा, विमानन और विद्युत शक्ति क्षेत्रों के लिए एक प्रभावी तड़ित पूर्वानुमान प्रणाली विकसित करना अत्यंत महत्वपूर्ण है। इस अध्ययन का उद्देश्य श्रीलंका में दूसरे अंतर-मानसून के दौरान बिजली गिरने की भविष्यवाणी करने में डब्ल्यूआरएफ-आधारित लाइटनिंग पोटेंशियल इंडेक्स (एलपीआई), के-इंडेक्स और कन्वेक्टिव अवेलेबल पोटेंशियल एनर्जी (सीएपीई) की प्रयोज्यता का मूल्यांकन करना है। डब्ल्यूआरएफ-ARW मॉडल संस्करण 3.9.1 का उपयोग तीन बिजली गिरने की घटनाओं के पूर्वानुमान उत्पन्न करने के लिए किया गया था, जिसमें क्रमशः 12 किमी और 4 किमी के वियोजन वाले दो नेस्टेड डोमेन में विभिन्न भौतिक प्राचिकलन योजनाओं का उपयोग किया गया था। मॉडल द्वारा अनुकारित एलपीआई, KI और सीएपीई मानों का आकलन अर्थ नेटवर्क्स ग्लोबल लाइटनिंग नेटवर्क (ईएनजीएलएन) डेटासेट का उपयोग करके किया गया था।

परिणामों से पता चला कि अनुकारित बिजली गिरने की घटनाओं का स्थानिक वितरण, जमीनी स्तर पर प्राप्त बिजली गिरने के आंकड़ों से काफी हद तक मेल खाता है। तीनों मामलों में एलपीआई सूचकांक और प्रति घंटा सीजी फ्लैश दरों के बीच उच्च सहसंबंध, के-सूचकांक के साथ मध्यम सहसंबंध और सीएपीई के साथ निम्न सहसंबंध पाया गया। इन निष्कर्षों से पता चलता है कि डब्ल्यूआरएफ मॉडल, विशेष रूप से एलपीआई और के-सूचकांक का उपयोग करते हुए, श्रीलंका में बिजली गिरने की घटनाओं को प्रभावी ढंग से पकड़ने में सक्षम है। इसलिए, इसमें बिजली गिरने की आशंका वाले क्षेत्रों की भविष्यवाणी करने के लिए व्यावहारिक उपयोग की क्षमता है।

ABSTRACT. Lightning is a grievous and oppressive weather phenomenon often accompanied by severe thunderstorms, leading to potentially lethal consequences for human life and significant damage to critical infrastructure sectors. Developing an effective lightning prediction system is crucial for public safety, aviation, and electrical power sectors. This study aims to evaluate the applicability of the WRF-based Lightning Potential Index (LPI), K-index, and Convective Available Potential Energy (CAPE) in predicting lightning during the second inter-monsoon over Sri Lanka. The WRF-ARW model version 3.9.1 was employed to produce predictions for three lightning events, utilizing various physical parameterization schemes across two nested domains with resolutions of 12 km and 4 km, respectively. The model-simulated LPI, KI, and CAPE values were assessed using the Earth Networks Global Lightning Network (ENGLN) dataset.

Results indicated that the spatial distribution of the simulated lightning events closely aligned with ground-based lightning data. There was a high correlation between the LPI index and hourly CG flash rates across the three cases, a medium correlation with the K-Index, and a low correlation with CAPE. These findings suggest that the WRF model, particularly using LPI and K-Index, is effective in capturing lightning events in Sri Lanka. Therefore, it holds potential for operational use in predicting lightning-prone regions.

Key words – Lightning prediction; LPI; K-Index; CAPE; Sri Lanka; WRF model.

1. Introduction

To address this need, this study evaluates the potential of the WRF-based LPI, K-index, and CAPE in forecasting lightning during the second inter-monsoon over Sri Lanka. Lightning is a significant and hazardous weather phenomenon often associated with severe thunderstorms, posing lethal risks to human life and

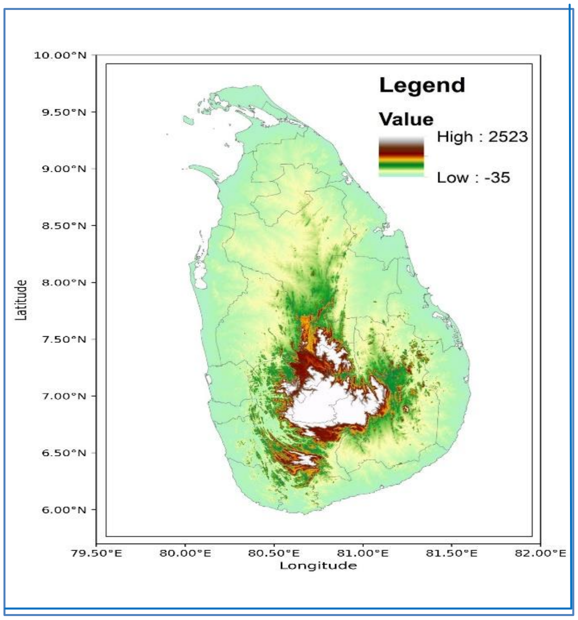


Fig. 1. Topographical elevation of Sri Lanka

causing substantial damage to critical infrastructure. Due to its direct and indirect impacts as a natural hazard, lightning forecasting has become crucial for the prevention and mitigation of these events. The severity of lightning impacts is contingent upon our understanding of its characteristics, the efficacy of forecasting methods, and the implementation of precautionary measures.

Quantitative analyses of natural hazards indicate that lightning-related fatalities occupy a notable position among weather-related deaths. Predicting thunderstorms, characterized by their temporal and spatial variability (Perler & Marchand, 2009), remains one of the most challenging tasks in meteorology. The inherent chaotic nature of the atmosphere complicates the prediction of such mesoscale phenomena compared to larger-scale weather systems (Elmore, Stensrud, & Crawford, 2002).

While numerous studies have explored lightning prediction globally, research specific to Sri Lanka remains sparse. Establishing a reliable lightning forecasting system in Sri Lanka is imperative. Enhanced forecasting accuracy is vital for the effective planning and management of climate-sensitive sectors, including agriculture, construction, electrical power, and aviation. Between 2010 and 2023, the Department of Meteorology in Sri Lanka reported 294 lightning-related fatalities, predominantly affecting the agricultural workforce.

Thus, there is a pressing need for an effective and reliable lightning prediction system to safeguard vulnerable sectors such as agriculture, construction, electrical power, and aviation. The frequent occurrence of lightning events has rendered it one of the most formidable natural hazards, resulting in numerous casualties and significant damage. Developing a robust lightning prediction system is essential for enhancing public safety and protecting critical infrastructure sectors.

In the following sections, the study area, model configuration, selected lightning events, and evaluation methods are presented, followed by a detailed discussion of the results and implications for operational forecasting.

2. Data and methodology

2.1. *Lightning data*

In this research, data collected from ten (10) ground-based Earth Networks Global Lightning Network (ENGLN) sensors stationed throughout Sri Lanka were used to compare with the model's Lightning Potential Index (LPI) predictions and to assess the model's accuracy.

The Earth Networks Global Lightning Network (ENGLN) operates with over 1,500 wideband sensors (1 Hz to 12 MHz) distributed across more than 40 countries worldwide. These sensors are designed to detect and record electromagnetic pulses generated by lightning, which propagate in all directions. Each ENGLN sensor captures pulse waveforms and transmits this data to a central processing server.

The captured waveform data, such as, signal amplitude, shape and arrival time, are utilized to determine various parameters of lightning occurrences. These parameters include the event type (intra-cloud, IC or cloud-to-ground, CG), polarity, peak current, and the precise location of the lightning event, including latitude, longitude, and height.

2.2. *Study area*

Sri Lanka is an island located in the northern part of the Indian Ocean, within the tropical region, bounded by latitudes 5° 55’ to 9° 51’ N and longitudes 79° 42’ to 81° 53’ E. The central portion of the country features a complex upland region with elevations reaching approximately 2500 meters (Fig. 1). This area includes a diverse topographical profile, characterized by peaks, basins, valleys, and plateaus. The remainder of the country is predominantly flat, with isolated mountains interspersed throughout the landscape.

Lightning occurrences in Sri Lanka exhibit distinct peaks during the inter-monsoon seasons (March & April and October & November). During these periods,

Fig. 2. Nested domains of the WRF model with resolutions of 12 km and 4 km (*Source: Author's research)*

TABLE 1

Model and Nested Domain Configurations

Configuration	Outer Domain	Inner Domain
WRF version	3.9.1	
Grid Points (x, y)	92 x103	102 x 144
Horizontal Resolution	12km	4km
Model Top	Top 50hPa	
Time Step	60 seconds	20 seconds
Microphysics	WSM - 6/WDM- 6/THOM/MORISSON	
Lightning option	LPI (3)	
Surface layer	MMS Similarity Scheme	
Land surface	Unified Noah Land Surface Model	
Land use and topography data	modis_30s+5m	modis_30s+2m
Cumulus	BMJ/Grell 3D	BMJ/Grell 3D/NA
Initial boundary condition	Global Forecasting System (GFS) Model Forecast Fields (27km resolution, NCEP)	

Source: Author's research

particularly in the afternoon and evening, the atmospheric conditions are highly conducive to the development of convective clouds, specifically cumulonimbus clouds, across much of Sri Lanka. These convective systems are responsible for the increased lightning activity observed during these transitional monsoonal phases. To simulate lightning-relevant atmospheric variables over this complex terrain, the Weather Research and Forecasting (WRF) model was configured as described below.

TABLE 2

Selected Lightning Incidents in 2018 during the Second Inter-Monsoon (SIM)

Incident	Date	Climate Season
1	22.10.2018	SIM
2	17.11.2018	SIM
3	23.11.2018	SIM

Data provided by the Department of Meteorology, Sri Lanka

2.3. *Method and materials*

In this study, the Weather Research and Forecasting (WRF) model was employed to produce various predictions for selected lightning events, utilizing different physical parameterization schemes. The model configuration comprised two nested domains with resolutions of 12 km and 4 km, as illustrated in Fig. 2, incorporating 92 x 103 & 102 x 144 grid points, respectively.

To investigate the sensitivity of the microphysics processes within the model, four different microphysics schemes were employed, each incorporating six types of hydrometeors. The schemes used in this research included WRF Single-Moment 6-class (WSM6), WRF Double-Moment 6-class (WDM6), Thompson & Morrison 2-Moment. These schemes were selected to simulate lightning events in Sri Lanka and assess their impact on the accuracy & reliability of lightning predictions. Table 1. Details of the WRF model the two nested domain configurations.

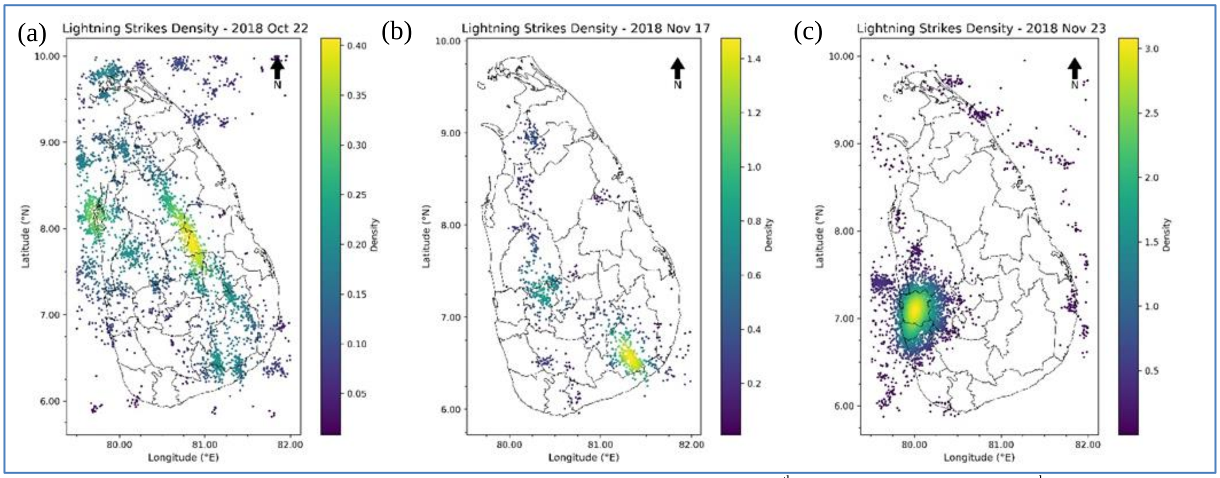
2.4. *Selection events*

Thunderstorms and lightning are prevalent weather phenomena in Sri Lanka, particularly during the inter-monsoon seasons. These events are crucial in the dry zones of the country, where they serve as a vital water source for extensive agricultural lands. For this study, three significant lightning events occurring within the second inter-monsoon period of 2018 were selected for analysis. The spatial distribution of cloud-to-ground lightning flashes for these events is illustrated in Fig. 3, while the details of the selected events are summarized in Table 2.

2.5. *Lightning detecting parameters*

2.5.1. Lightning potential index (LPI)

Yair *et al*. (2008) introduced the Lightning Potential Index (LPI) as a parameter for predicting lightning, which has since been incorporated into the Weather Research and Forecasting (WRF) model. The LPI is defined as the volumetric integral of the total mass flux of ice and liquid water within the "charging zone" of a developing thunderstorm cloud, specifically



Figs. 3.(a-c). (a) CG lightning flash density recorded on 22nd October 2018, (b) on 17th November and (c) on 23rd November in 2018 (*Source: Data provided by Earth Networks, Inc., an AEM company and Created by author using Python*)

within the temperature range of 0 °C to -20 °C. This index reflects the potential for electrical charge separation in the thundercloud's charging zone, driven by the non-inductive ice graupel mechanism.

The LPI is calculated using the model's simulated vertical wind component at the grid scale, along with the mass ratios of cloud ice, liquid water, graupel, and snow. It changes over time, as it is derived from the model's dynamical and microphysical fields at each time step and across every grid point within the domain.

For the LPI to be significant at a particular grid point, the following conditions must be met: The LPI value will only be non-zero if a majority of cells within a five-grid radius of that point exhibit a vertical velocity greater than 0.5 m/s, indicating the thunderstorm is in its growth phase.

Mathematically, the LPI can be expressed as:

$$LPI = \frac{1}{v}\iiint \in w2 \; dx \; dy \; dz \qquad (1)$$

where LPI is the Lightning Potential Index, $\in$ is the scaling factor based on cloud ice and liquid content, w is the vertical velocity (m/s) and V is the volume of the cloud layer between 0 °C & -20 °C.

This includes the model's mass mixing ratios for liquid water, snow (qs), graupel (qg), and cloud ice (qi). Additionally, ε is a dimensionless parameter that takes a value between 0 and 1, defined as:

$$\in = \frac{2\sqrt{QiQl}}{Qi + Ql} \qquad (2)$$

where Qi represents the total mass ratio of liquid water in kilograms per kilogram (kg/kg),
Qi denotes the ice fractional mixing ratio, in kilograms per kilogram (kg/kg).

$$Qi = qg\left[\frac{\sqrt{qs\,qg}}{\sqrt{qs+qg}} + \frac{\sqrt{qi\,qg}}{\sqrt{qi+qg}}\right] \qquad (3)$$

Here, qs is Snow mixing ratio,
Qg is Graupel mixing ratio and
Qi is Cloud ice mixing ratio

In this context, ε acts as a scaling factor for the cloud updraft and reaches its maximum value when the mixing ratios of supercooled liquid water (Ql) and ice species (Qi) are equal. Qi also achieves its maximum when the mass mixing ratios of ice, snow, and graupel are balanced. This indicates that effective charge separation necessitates the synergistic interaction of all these components within the charging zone, as evidenced by numerous experiments summarized by Deierling & Petersen, 2008.

2.5.2. *Convective available potential energy (CAPE)*

Convective Available Potential Energy (CAPE) is a key variable used to identify areas with a high potential for thunderstorms. CAPE measures the amount of energy available to an air parcel to rise and reach the level of free convection in the atmosphere. Higher CAPE values indicate a greater likelihood that an air parcel can be lifted to this level, leading to the development of convective weather systems.

The CAPE values can range from 0 to 4000 J/kg, with different ranges indicating the stability of the atmosphere. CAPE values between 0-1000 J/kg indicate a

TABLE 3

Model Forecast and Observation Contingency

		Observed		
		Yes	No	
Forecast	Yes	Hits	False alarm	Forecast yes
	No	Misses	Correct non-events	Forecast no
		Obs. yes	Obs. No	Sum total

Source: Statistical Methods in the Atmospheric Sciences (D.S. Wilks)

stable atmosphere, while values between 1000-2500 J/kg suggest a moderately unstable atmosphere with potential for severe weather, particularly if factors like orographic lifting or solar heating add energy to the developing system. Values exceeding 2500 J/kg denote an extremely unstable atmosphere, highly favorable for heavy thunderstorms.

2.5.3. Whiting index (K-Index)

The Whiting Index, or K-Index, is another measure of atmospheric instability, useful for predicting thunderstorms. It is defined as:

$$\text{K-Index} = (T_{850}-T_{500}) + T_{D850}-(T_{700}-T_{D700}) \quad (4)$$

here, T850, T700, and T500 are the temperatures at the 850 hPa, 700 hPa, and 500 hPa pressure levels, respectively, while TD850 and TD700 are the dew point temperatures at the 850 hPa and 700 hPa pressure levels, respectively. According to Tajbakhsh *et al*. (2012), the probability of thunderstorms occurring is 50% when the K-Index value exceeds 26 °C.

Once the relevant atmospheric indices were generated by the WRF simulations, the model output was evaluated against observed lightning data using standard verification metrics.

2.6. *Data analysis methods*

To quantify the correct negatives, false alarms, hits, and misses, a contingency table (Table 3) is utilized for model predictions. In this approach, each grid point where a lightning event occurs is treated as an individual lightning event.

2.6.1. *Probability of detection (Hit Rates) (POD)*

The POD considers only the occurrence events, providing the ratio of observed lightning events that were correctly forecasted by the model. The hit rate value ranges from 0 to 1, with a perfect score being 1.

2.6.2. *Threat score (TS)*

The Threat Score (or critical success index) is a standard verification method sensitive to both missed events and false alarms. It is a good general score for evaluating or comparing model forecasts, focusing only on important forecasts while neglecting correct rejections. The threat score value ranges from 0 to 1, with a perfect score being 1.

2.6.3. *Correlation (r)*

The Pearson correlation coefficient measures the strength of a linear relationship between two variables, with values ranging from -1 to 1.

2.6.4. *Combined score for lightning prediction*

A combined skill score integrates the POD, TS, and correlation coefficient to summarize the results and better understand the model's overall forecasting capability. This score is implemented by averaging these individual scores.

Based on the definitions in sections 3.5.1, 3.5.2, and 3.5.3, the ranges for TS and POD lie between 0 and 1. In contrast, the correlation coefficient ranges from -1 to 1, as defined. To ensure all scores are on the same scale, normalize the correlation coefficient (r) to a range of 0 to 1. Because, r is between -1 and 1, r can be normalized as follows:

$$r\ norm\ = \frac{r+1}{2} \quad (5)$$

where, r is Pearson correlation coefficient

Compute the combined score as the average of the three normalized scores:

$$Combined\ Score\ = \frac{POD\ +\ TS\ +\ r\ norm}{3} \quad (6)$$

where, POD is Probability of Detection, TS is Threat Score and R norm is normalized Pearson correlation coefficient.

The table 4 presents the combined score used to assess model performance. This skill score serves as a measure of overall model effectiveness and helps identify the optimal model configurations. By considering Probability of Detection (POD), Threat Score (TS), and Pearson Correlation (r), the combined score provides a comprehensive measure of the model's capability in forecasting lightning events, allowing for a more informed selection of optimal model setups.

TABLE 4

Summary of combined score

Parameter	Evaluation Method	Value range	Perfect score
Overall performance of lightning prediction	Combined score	0~1	1

Source: Author's research

2.7. *Experiment design*

Model simulations for this experiment were conducted over a 24-hour period, from 0000 UTC to 0000 UTC the following day. The objective of these simulations was to forecast the Lightning Potential Index (LPI) to assess variations in cloud-to-ground lightning flashes based on different microphysical and cumulus parameterizations. The WRF-ARW model simulations were initiated at 0000 UTC on the specified date, using GFS model data at a 0.25-degree resolution to establish the lateral boundary and initial conditions.

2.7.1. *Sensitivity of physical parameterization*

Eighteen (18) simulations were carried out to predict the values for LPI, CAPE and K-Index to evaluate the physical parameterization for testing lightning prediction. The model configuration is shown in Table 5. The microphysical and cumulus parameterizations were used to investigate the sensitivity of WSM6, WDM6, and Thompson microphysics with Betts-Miller-Janjic, Grell-3, and explicit cumulus parameterization.

The following section presents the model simulation results and evaluates the performance of LPI, K-Index, and CAPE in predicting lightning events.

3. Results & discussion

This chapter presents the results of Lightning Potential Index (LPI), K-Index, and CAPE values obtained from the model simulations using the previously outlined methodology. The evaluation of model-simulated LPI, CAPE, and K-Index from different microphysical and cumulus parameterizations is presented, examining their effect on the predictability of these indices for three significant lightning events. The results are analyzed to understand how different physical parameterizations impact the forecast accuracy of LPI, CAPE, and K-Index, and their correlation with observed cloud-to-ground lightning flashes. This analysis helps in identifying the most reliable configurations for operational lightning prediction over Sri Lanka during the second inter-monsoon season.

TABLE 5

Summary of experiments

Simulation	Microphysics Domain		Cumulus Physics Domain	
	01	02	01	02
01	WSM6	WSM6	BMJ	BMJ
02	WSM6	WSM6	BMJ	No Cumulus Physics
03	WDM6	WDM6	BMJ	BMJ
04	WDM6	WDM6	BMJ	No Cumulus Physics
05	THOMPSON	THOMPSON	BMJ	No Cumulus Physics
06	THOMPSON	THOMPSON	Grell3D	No Cumulus Physics

Source: Created by Author

The performance of these indices is validated against ground-based observations to determine the effectiveness of the WRF model configurations in predicting lightning events. The results highlight the strengths and weaknesses of each parameterization scheme, providing insights for improving lightning prediction capabilities in future studies.

3.1. *Results*

3.1.1. *Effects of physical parameterization on the lightning potential index (LPI)*

LPI measures the potential for charge generation and separation within convective thunderstorms, which can lead to lightning. In this study, the hourly area-averaged LPI values predicted by the model were compared with the hourly rates of cloud-to-ground lightning flashes to assess the model's performance. This comparison aims to assess how well the LPI can represent the actual frequency of lightning events, providing insights into the accuracy of lightning prediction based on LPI values.

As shown in Fig. 4, the Pearson correlation coefficients between hourly lightning flash rates and the model-generated hourly average LPI values. The correlation coefficients range from -0.17 to 0.85 across the simulations, while the 4th simulation demonstrating values between 0.74 and 0.85.

It's essential to understand that the correlation coefficient does not directly measure accuracy; rather, it indicates how well the variance in observations is accounted for by the forecast. Among the simulations, the 4th simulation shows the strongest linear relationship between LPI and lightning flash rates.

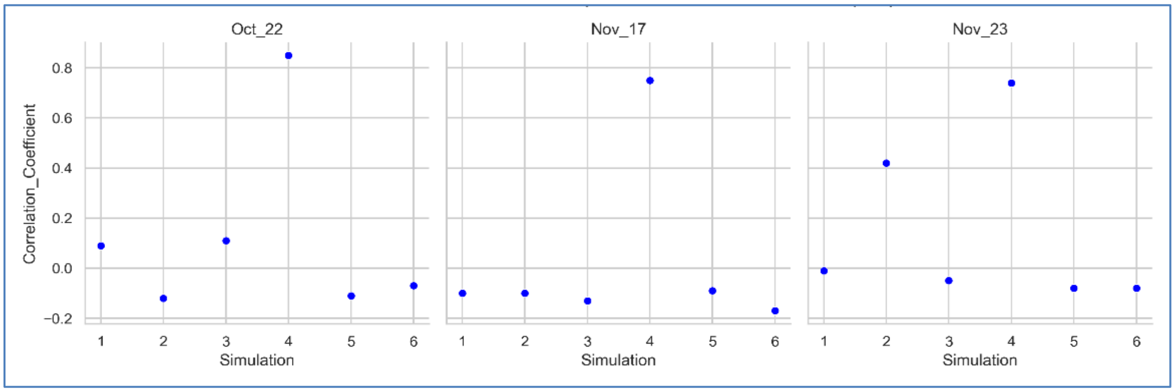


Fig. 4. Pearson Correlation Coefficient (r) Between Hourly Lightning Flash Rate and Hourly Average LPI (*Source: Created by Author*)

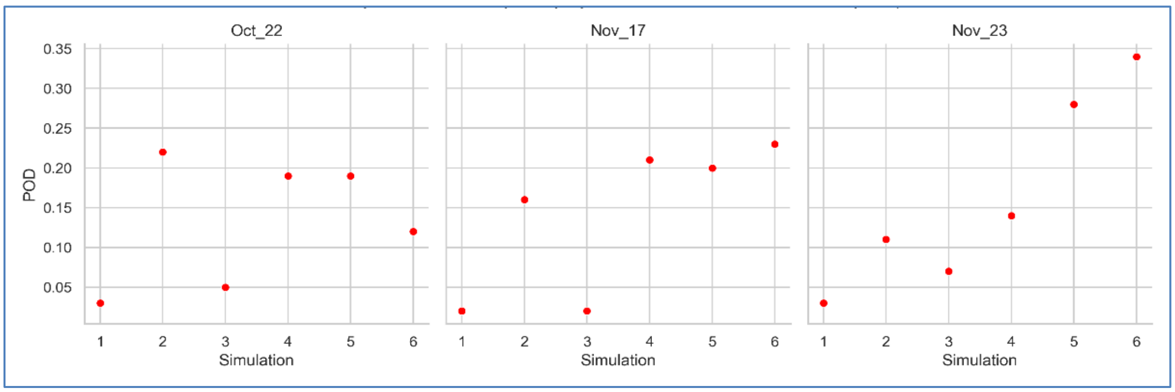


Fig. 5. Probability of Detection (POD) Between Hourly Lightning Occurrence and Hourly Average LPI (*Source: Created by Author*)

In terms of microphysics schemes, the WDM6 scheme shows a more pronounced linear relationship with lightning flash rates compared to other schemes. However, the strength of this relationship is also influenced by the cumulus physics scheme. Analysis indicates that the Betts-Miller-Janjic (BMJ) scheme provides more significant values for the linear relationship compared to other cumulus physics schemes.

While correlation provides insight into linear relationships, it does not reflect detection accuracy. Therefore, Probability of Detection (POD) is examined next.

3.1.1.1. *Probability of detection (POD)*

Each graph demonstrates the Probability of Detection (POD) for various model simulations. However, none of the simulations show substantial POD values for all events.

In Fig. 5, high values of POD suggest that the model successfully predicts lightning occurrences, whereas low POD values indicate a failure to predict lightning events. Generally, except for a few cases, most events are associated with low POD scores, reflecting challenges in accurately forecasting lightning occurrences across the simulations.

In summary, the POD helps assess how effectively the LPI model predicts actual lightning events. If the POD values are high, it indicates that the model's LPI predictions are successfully detecting most of the lightning occurrences. Conversely, low POD values suggest that the model's predictions are missing a significant number of actual lightning events.

In addition to POD, the Threat Score (TS) offers a complementary view of the model’s ability to identify true positives while penalizing false alarms.

3.1.1.2. *Threat score (TS)*

The Threat Score (TS) for the hourly lightning flash rate and the model-generated hourly average LPI is shown in Fig. 6. Each graph in this figure displays the TS values corresponding to various model simulations. The TS values plotted on the vertical axis range between 0 and 0.09, indicating generally low scores across all simulations for each event. The highest TS is observed with the 6th combination for the event on 23rd November. In this analysis, only the available observed lightning

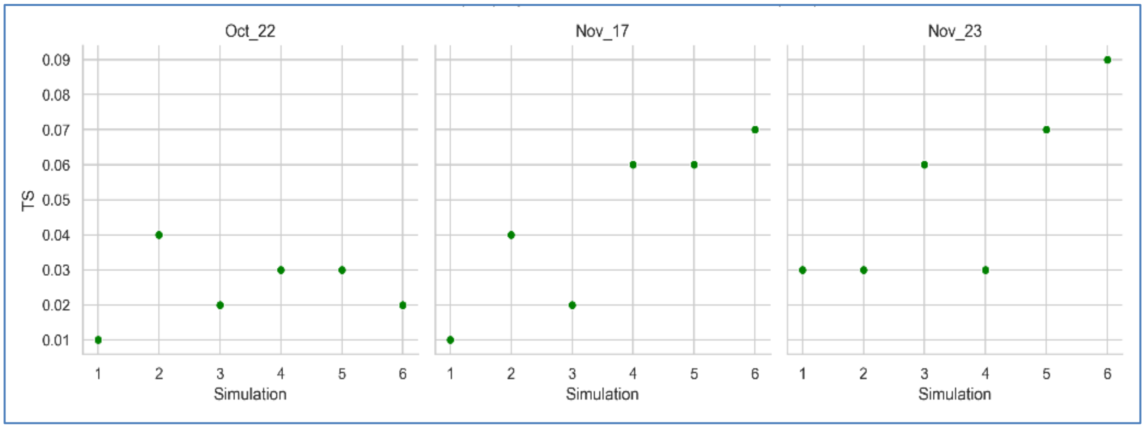


Fig. 6. Threat Score (TS) Between Hourly Lightning Occurrence and Hourly Average LPI (Source: Created by Author)

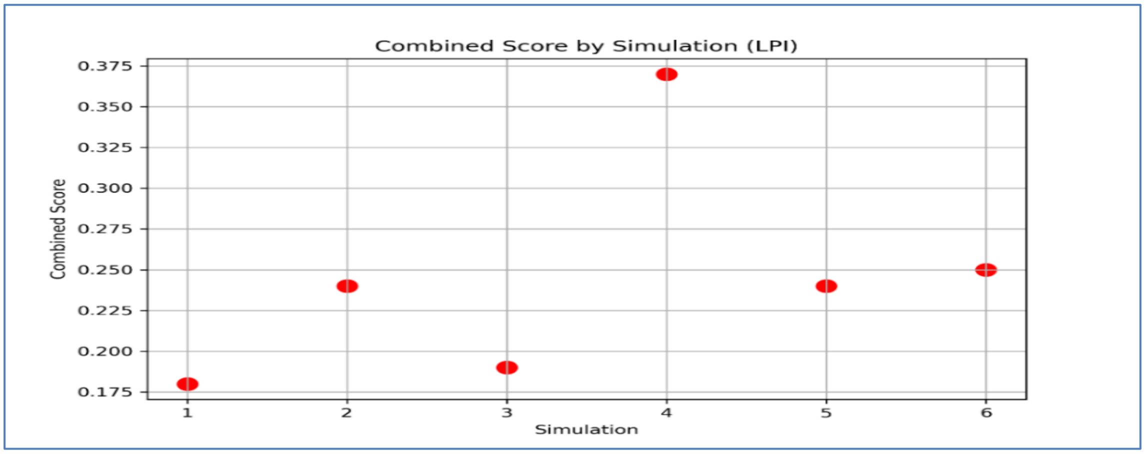


Fig. 7. Combined Score between Hourly Lightning Occurrence and Hourly Average LPI (*Source: Created by Author*)

events were considered, with correct negatives excluded. The low TS values reflect the fact that observed lightning occurrences are localized and not uniformly distributed across the country. Consequently, many of the model forecasts resulted in negative corrections due to the specific and limited areas of observed lightning. These negative corrections, which arise from areas where lightning was not observed, are excluded in this analysis, leading to the overall low TS values.

3.1.1.3. *Combined score*

The combined score reflects the overall performance of the model in predicting lightning using the LPI. This score facilitates the comparison and selection of the most appropriate physical parameterization. As shown in Fig. 7, the fourth simulation is the most effective for predicting lightning with the LPI. This simulation incorporates WDM6 microphysics and BMJ cumulus physics, while excluding cumulus physics for the fine domain.

3.1.2. *Effects of physical parameterization on the K-index*

K-Index gives a sense of atmospheric instability, making it useful for identifying the potential for thunderstorms and lightning.

3.1.2.1. *Correlation*

As shown in Fig. 8, the correlation coefficient between the hourly lightning flash rate and the hourly average K-Index (KI) produced by the model. The correlation coefficients range continuously from -0.35 to 0.58, with the highest value observed in the fourth simulation across all events. This coefficient reflects the strength of the linear relationship between the K-Index and the hourly flash rate. It is clearly demonstrating a moderate to nearly moderate linear relationship between the K-Index and the hourly flash rate, though no strong linear relationship is observed in any simulation. Among these model simulations, the 4th simulation exhibits a

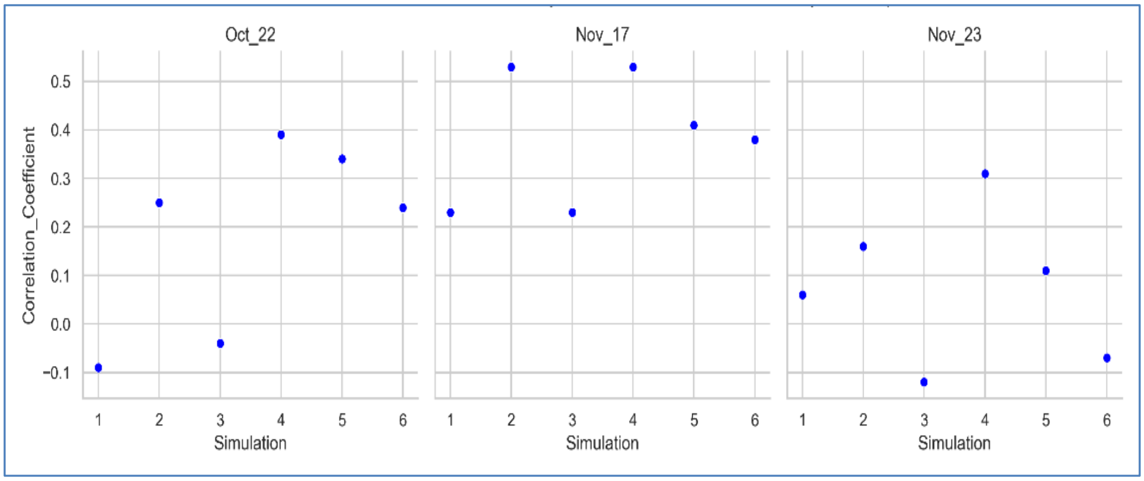


Fig. 8. Pearson Correlation Coefficient (r) Between Hourly Lightning Flash Rate and Hourly Average K-Index

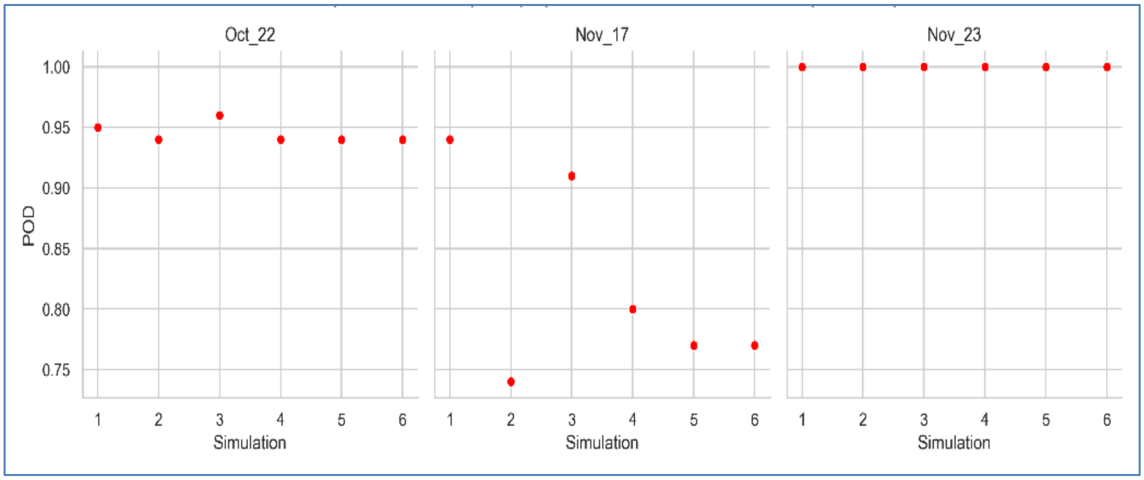


Fig. 9. Proportion of Detection (POD) Between Hourly Lightning Occurrence and Hourly Average K-Index

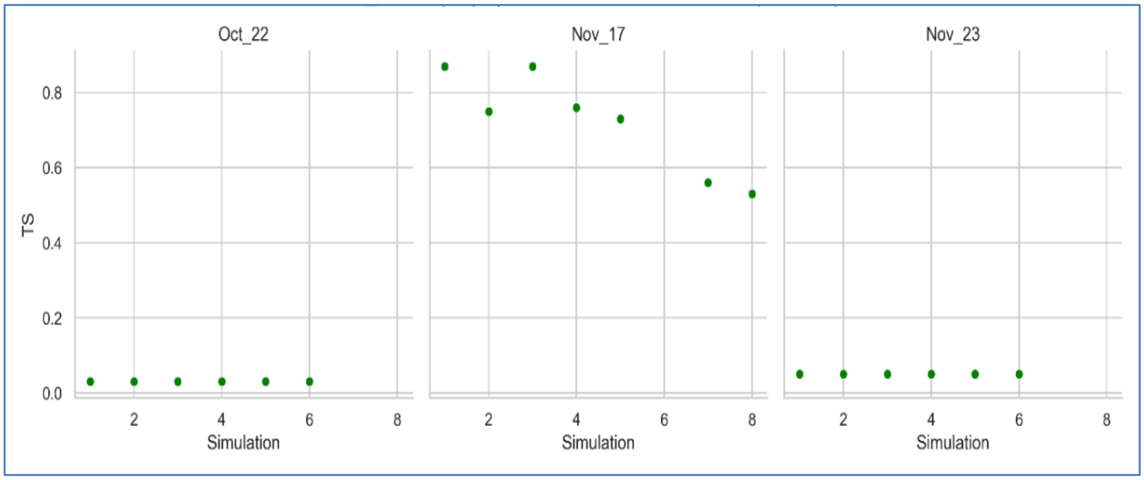


Fig. 10. Threat Score (TS) Between Hourly Lightning Occurrence and Hourly Average K-Index

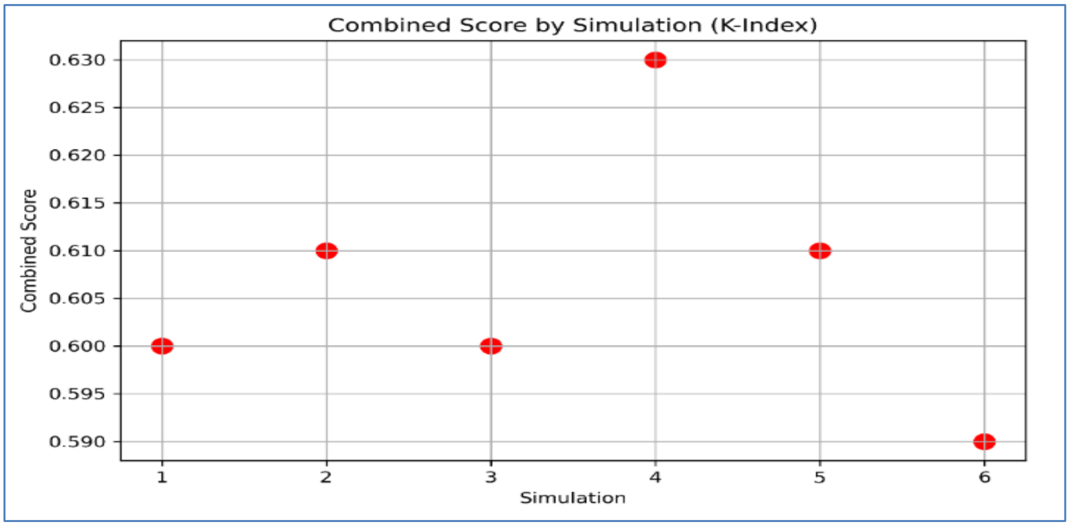


Fig. 11. Combined Score between Hourly Lightning Occurrence and Hourly Average K-Index

moderate to nearly moderate uphill linear relationship for all events, but it is not significantly different from other model simulations. The WDM6 and WSM6 microphysics schemes show a moderate to nearly moderate linear relationship for almost all events, whereas the Thompson and Morrison microphysics schemes only show this relationship for a few experiments and a low linear relationship for others. The strength of the linear relationship also depends on the cumulus physics scheme, with BMJ showing significant values for a linear relationship compared to other cumulus physics.

3.1.2.2. *Probability of detection (POD)*

The Probability of Detection (POD) for the hourly lightning flash rate and model-generated hourly average KI values greater than 31 is displayed in Fig. 9. All simulations show significant POD values for every event. Sturtevant (1995) revealed that severe thunderstorms can be expected when the K-Index exceeds 31.

3.1.2.3. *Threat score (TS)*

The Threat Score (TS), indicated by the position of blue triangle shapes, ranges from 0 to 0.87, as shown in Fig. 10. Every simulation shows significantly low TS values for every event except the 17th November event.

The values for the Threat Score (TS) on the vertical axis range from 0 to 0.8. Each simulation displays notably low TS values for most events, with the exception of the event on 17th November. This analysis considers only the available observed events while disregarding correct negatives.

3.1.2.4. *Combined core*

The combined score reflects the overall performance of the model in predicting lightning using the K-Index, facilitating the comparison and selection of the most appropriate physical parameterization (see Fig. 11). The continuous values of the combined score range between 0.59 and 0.63. All three events show the moderate combined score for the 4th simulation, though the values are not significantly high. This graph clearly indicates that the fourth simulation is the most effective for predicting lightning using the K-Index.

A high-pressure system generally indicates a stable atmosphere with a low chance of thunderstorms, whereas a low-pressure system indicates an unstable atmosphere with a higher chance of thunderstorms. According to the definition of the K-Index, the first and second terms are related to the lapse rate and the moisture content between the 850 hPa and 700 hPa pressure levels, providing a measure of atmospheric instability. Unlike the LPI, the K-Index is based on thermodynamic instability parameters and is not reliant on microphysics, allowing most microphysics schemes to be used for calculating K-Index values.

The combined score results show that all the selected microphysics and cumulus physics schemes have a similar capability to capture lightning, with WDM6 being the best microphysics option among them. Both WDM6 and WSM6 microphysics schemes can represent moist convection in 3D platforms and demonstrate a moderate and nearly moderate linear relationship for almost all events compared to other microphysics schemes. Based on

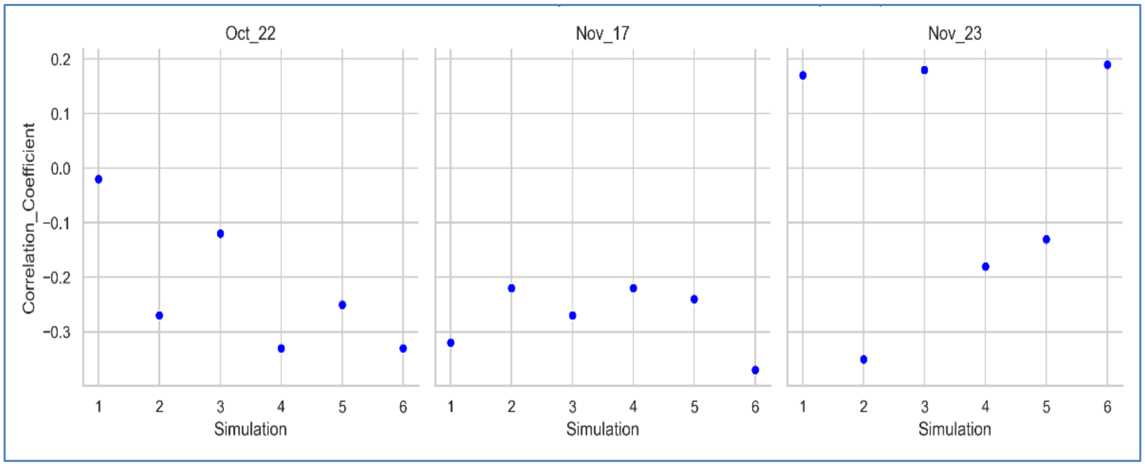


Fig. 12. Pearson Correlation Coefficient (r) between Hourly Lightning Occurrence and Hourly Average CAPE

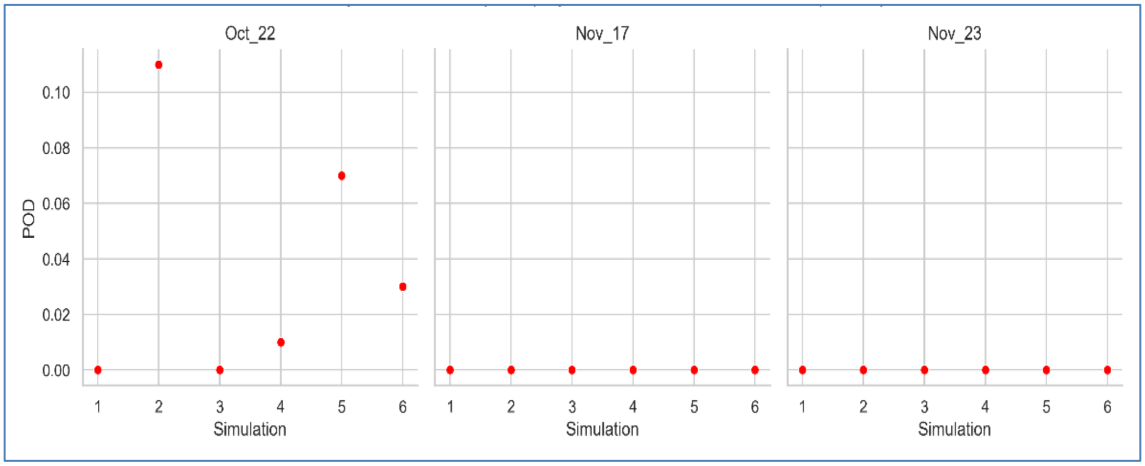


Fig. 13. Proportion of Detection (POD) between Hourly Lightning Occurrence and Hourly Average CAPE

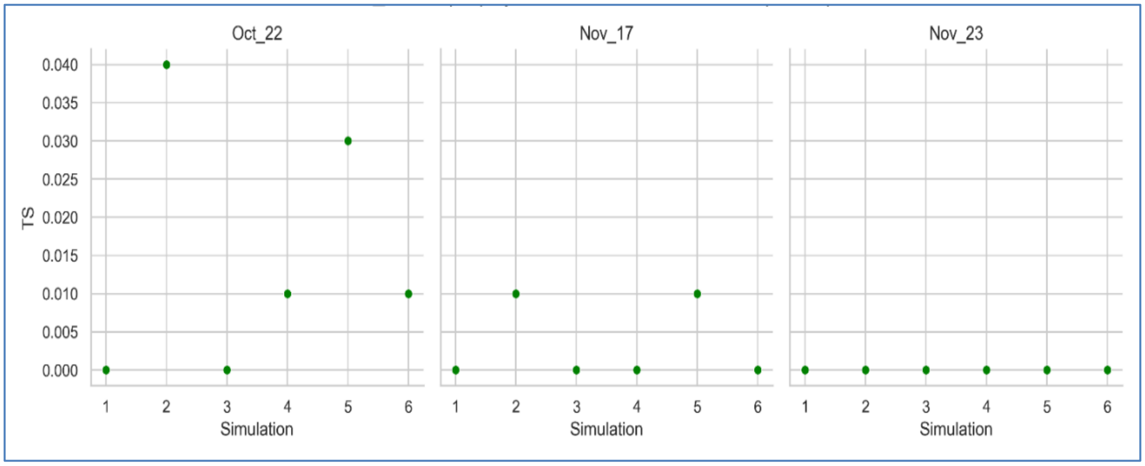


Fig. 14. Threat Score (TS) between Hourly Lightning Occurrence and Hourly Average CAPE

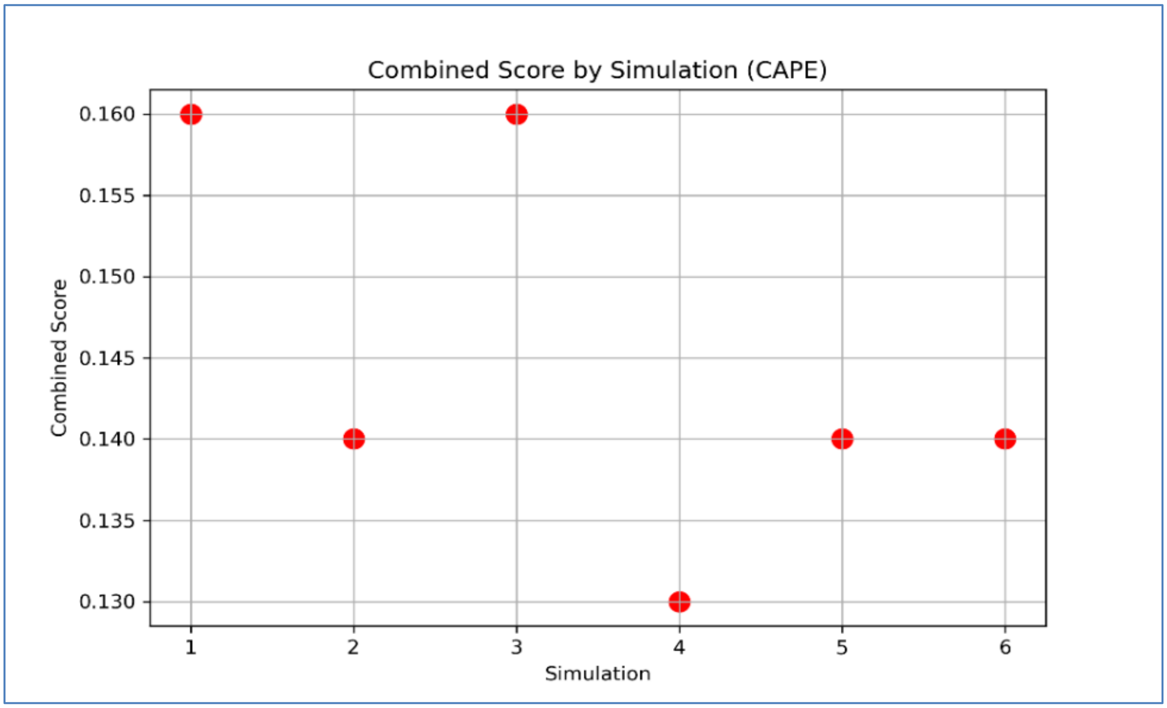


Fig. 15. Combined Score between Hourly Lightning Occurrence and Hourly Average CAPE

the analysis of the Pearson correlation coefficient, the BMJ scheme demonstrates stronger values for a linear relationship compared to other cumulus physics schemes.

Overall, it is clear that the K-Index is a good indicator for predicting lightning occurrence and detecting potential areas for thunderstorms. A previous study by Millangoda *et al*. (2018) also revealed that the K-Index can be used to predict lightning in Sri Lanka.

3.1.3. *Effects of physical parameterization on the CAPE*

3.1.3.1. *Correlation*

Fig. 12 shows the correlation coefficient between the hourly lightning flash rate and the hourly average model-generated CAPE, represented by the position of blue dotted shapes. The continuous values of the correlation coefficient range from -0.37 to 0.19. Except for the maximum correlation coefficient (r) value, all other values are significantly low and negative.

Here, the correlation coefficient indicates the strength of the linear relationship between CAPE and the hourly flash rate. Fig. 12 clearly shows a weak negative relationship between CAPE and the hourly flash rate, except for a few events that have positive linear relationships. Among these events, Only November 23 event has a low positive linear relationship for only three experiments, but no strong linear relationship is observed for any simulations.

According to the definition of CAPE, it represents the energy and fuel available to a developing thunderstorm, implying that there should be a positive correlation coefficient between CAPE and the hourly flash rate. However, for the domain of this experiment, a positive linear relationship is not observed.

3.1.3.2. *Probability of detection (POD)*

Fig. 13 displays the Probability of Detection (POD) for the hourly lightning flash rate and the model-generated hourly average CAPE values greater than 2500. The continuous POD values range from 0 to 0.11. All simulations show very low POD values for every event.

Low POD scores indicate a failure in predicting lightning occurrences. This indicates that generally, predicting the occurrence of lightning was not successful in this experiment.

3.1.3.3. *Threat score*

The Threat Score values, represented by the positions of the green triangular shapes, range from 0 to 0.04 as shown in Fig. 14. Each simulation exhibits nearly zero TS values for all events.

3.1.3.4. *Combined score*

The combined score reflects the overall performance of the model in predicting lightning using CAPE. It is valuable for comparing and selecting the most appropriate physical parameterization. The continuous values of the combined score ranged from 0.13 to 0.16 , as shown in Fig. 15.

CAPE can be used to understand the potential for thunderstorms and how powerful they might become if they materialize. Unlike LPI, CAPE is based on thermodynamic instability parameters rather than microphysics. Various microphysics schemes can calculate CAPE values. High CAPE values do not guarantee thunderstorms and lightning occurrences but indicate favorable environmental conditions for developing thunderstorms. CAPE for a given area is often determined from a thermodynamic or sounding diagram using dew point temperature and air temperature data, typically measured by a weather balloon. In this experiment, CAPE values were measured using model forecasted atmospheric temperature and dew point temperature.

The ability of a model to accurately calculate CAPE heavily depends on the vertical grid spacing within vital layers. The WRF model often overemphasizes dew point temperature, air temperature, and available moisture content, potentially leading to CAPE overestimation in some instances. Unfortunately, none of the physics schemes in this experiment captured significant correlation coefficients, POD, and TS values. This indicates that the WRF model's forecasted CAPE values are not suitable for identifying the potential for thunderstorms and lightning occurrences. A previous study by Millangoda *et al*. (2018) also revealed that CAPE values cannot be used to predict lightning in Sri Lanka.

3.2. *Analysis*

The results above illustrate the model’s ability to represent lightning-relevant indices. The discussion below interprets these findings in the context of operational forecasting and model sensitivity

Limitations of Case Study Scope

One of the primary limitations of this study is the small number of lightning events analyzed limited to only three cases from the second inter-monsoon season of 2018. This limited scope constrains the statistical robustness and generalizability of the findings. The selection of these specific events was based on their representativeness of typical convective activity in Sri Lanka and the availability of high-quality lightning observation data during those periods. Additionally, the high computational cost of high-resolution WRF simulations, especially when using multiple physical parameterization schemes, restricted the number of cases that could be feasibly studied. Despite this limitation, the analysis provided valuable insights into the sensitivity of lightning-related indices to different model configurations. To strengthen statistical confidence and broaden applicability, future work should expand to multi-year analysis for broader applicability.

According to the analysis of lightning prediction using LPI, K-Index, and CAPE for different physical parameterizations, it was revealed that different physical parameterizations exhibit varying skills in predicting these parameters. The summarized findings for LPI, K-Index, and CAPE are as follows:

(i) Lightning Potential Index (LPI):

The LPI provides a measure of the ability to generate and separate charges leading to lightning in convective thunderstorms.

Model simulations showed that the 4^{th} simulation had acceptable correlation coefficient values for most events, indicating a moderate linear relationship between LPI and hourly flash rate.

Among the microphysics schemes, WDM6 showed a more significant linear relationship than other schemes. The Betts-Miller-Janjic (BMJ) cumulus physics scheme demonstrated better performance in linear relationships.

(ii) *K-Index (KI):*

The K-Index gives an indication of atmospheric instability and potential for thunderstorms and lightning.

The correlation analysis showed a moderate linear relationship between K-Index and hourly flash rate in some events, with the 4^{th} simulation performing better overall.

WDM6 and WSM6 microphysics schemes exhibited better performance, with BMJ cumulus physics showing significant linear relationship values.

(iii) Convective Available Potential Energy (CAPE):

CAPE measures the energy available for thunderstorms and potential storm intensity.

The correlation between CAPE and hourly flash rate was generally weak, with few events showing positive relationships.

The analysis indicated that the WRF model often overestimates CAPE due to the model's tendency to overemphasize dew point temperature and air temperature.

None of the physical parameterizations showed significant correlation, POD, or TS values for CAPE, suggesting that CAPE is not a reliable indicator for lightning prediction in this experiment.

Overall, while LPI and K-Index demonstrated some ability to predict lightning occurrence under certain conditions, CAPE did not show reliable predictability in this study. The results highlight the importance of selecting appropriate physical parameterizations for accurate lightning prediction, with LPI and K-Index being more promising indicators than CAPE.

The Lightning Potential Index (LPI) reflects the strength of the vertical wind component within a developing thundercloud and indicates the potential for charge generation and separation based on the mass mixing ratios of ice and liquid water in the "charging zone" (0 °C to -20 °C) of the cloud. It is calculated using the simulated grid-scale vertical wind component along with model-simulated hydrometeor mass mixing ratios for liquid water, cloud ice, snow, and graupel. The WSM6 and Thompson schemes can predict six types of hydrometeors, including rainwater, water vapor, cloud ice, cloud water, snow, and graupel (Skamarock *et al*., 2008). In addition to these hydrometeors, the WDM6 scheme can predict the number concentrations for both rainwater and cloud, as well as a variable for cloud condensation nuclei (CCN) number, allowing for the examination of aerosol effects on cloud properties and precipitation methods.

Despite applying similar formulas in both microphysics schemes, the microphysical processes within WDM6 operate differently from those in WSM6 due to the predicted number concentrations of cloud water and rainwater, which directly influence the LPI value. The WSM6 microphysics scheme predicts the mass mixing ratios of six classes of hydrometeors, while the WDM6 microphysics scheme builds on the WSM6 framework and includes the same predicted water substance variables. However, as a double-moment scheme, WDM6 can predict both mass mixing ratios and number concentrations of warm-phase hydrometeor species, leading to better LPI results compared to the WSM6 scheme.

A cumulus physics scheme is essential for coarser grid sizes; however, if the horizontal grid spacing is sufficiently small (4 km x 4 km), the convection processes may be adequately resolved by the microphysics alone, potentially eliminating the need for a cumulus scheme.

Results indicate an acceptable relationship between the hourly average LPI and the hourly lightning flash rate for the fourth simulation. The ability to predict lightning is highly influenced by both microphysics and cumulus physics schemes, with the WDM6 microphysics scheme yielding the most favorable results. The BMJ cumulus physics scheme also produced acceptable outcomes, while the Grell 3D cumulus physics scheme showed the poorest performance. According to the correlation coefficient and combined score values, the fourth simulation (using WDM6 microphysics for both domains and BMJ cumulus physics for the outer domain, with no cumulus physics for the inner domain) was the best among the six simulations.

Overall, the Lightning Potential Index (LPI) serves as a valuable tool for predicting the likelihood of lightning occurrences and identifying potential areas for thunderstorms on a larger scale.

The LPI value is influenced by the vertical wind component and the mass mixing ratios of snow, cloud ice, and graupel, which are affected by the presence of Cloud Condensation Nuclei (CCN) in the atmosphere. The area around Sri Lanka has a high concentration of CCN, and only the WDM6 microphysics scheme incorporates CCN concentration, setting it apart from other microphysics schemes. This consideration of CCN concentration likely contributes to the WDM6 scheme producing better LPI values for this study domain, leading to higher combined scores in the 4^{th} simulation compared to the others.

The K-Index calculation is based solely on atmospheric temperature and dew point temperature, a simple process consistently applied across all microphysics schemes, explaining the similar K-Index values.

The K-Index showed moderate and variable correlation with lightning activity, ranging from 0.35 to 0.58. This variation reflects the complex and localized nature of convective processes during the Sri Lankan second inter-monsoon season. While the K-Index can be useful in identifying general instability, it may not fully capture the mesoscale and topographically driven convection patterns specific to the region. Therefore, caution is advised when using the K-Index as a standalone predictor for lightning in operational forecasting over Sri Lanka.

The K-Index exhibited a wide range of correlation values with lightning activity (–0.35 to 0.58), indicating inconsistent predictive skill across different events. This variability reflects the complex and localized nature of convection during Sri Lanka’s inter-monsoon season, where thermodynamic conditions alone may not fully explain lightning occurrence. These findings suggest that the K-Index has limited reliability as a standalone predictor in this regional context. Future research should consider combining the K-Index with complementary indices such as CIN, Lifted Index, or moisture flux parameters or integrating it into machine learning frameworks for more robust lightning forecasting.

All selected microphysics and cumulus physics schemes exhibited similar capabilities in capturing lightning, but WDM6 emerged as the superior option. Thus, any of these microphysics schemes can predict K-Index values, demonstrating the K-Index's utility in forecasting lightning occurrence and identifying potential thunderstorm areas. Previous research by Millangoda *et al*. (2018) supports the use of the K-Index for lightning prediction in Sri Lanka.

The combined score values for CAPE were also similar, with some negative values. The negative correlation coefficients between CAPE and hourly flash rate led to negative combined score values. CAPE, which is typically determined from thermodynamic or sounding diagrams using dew point and air temperatures, represents the energy available for an air parcel to rise to the level of free convection. Future studies should consider CAPE together with Convective Inhibition (CIN), as CIN represents the energy that prevents an air parcel from rising to the level of free convection. CAPE provides the energy for ascent, while CIN suppresses it. Thus, evaluating both variables together would provide a more comprehensive assessment of atmospheric instability.

Although CAPE is widely used as an indicator of atmospheric instability, the analysis revealed weak or negative correlations with lightning activity in this study. This highlights a key limitation of relying on CAPE alone for lightning prediction. CAPE does not account for atmospheric suppression mechanisms such as Convective Inhibition (CIN), which can prevent storm initiation even under high CAPE conditions. The omission of CIN likely affected the physical completeness of the convective assessment. Future studies should incorporate CIN alongside CAPE to better evaluate convective potential and improve lightning forecasting skill.

CAPE showed weak or negative correlations with lightning, indicating poor predictive skill and physical inconsistency. The omission of CIN, a key factor in convective suppression, limits the analysis. Including both CAPE and CIN is recommended for improved assessment.

McCaul *et al*. (2006) found that operational lightning forecast schemes based on parameters like CAPE fail to predict lightning potential areas accurately. Similarly, Millangoda *et al*. (2018) concluded that CAPE values are not effective for lightning prediction in Sri Lanka.

The study results indicate that cumulus physics has a minimal impact on LPI, CAPE, and K-Index values. Given the atmospheric conditions during the second inter-monsoon season and the geographical and topographical features of the study domain, thundershowers and lightning are localized phenomena, typically spreading over a few kilometers (2-4 km). Hence, cumulus parameterization has a limited effect on such small-scale systems but is more relevant for larger systems (greater than 10 km).

Based on the above findings and identified limitations, the study’s conclusions and recommendations for future research are outlined below.

4. Conclusions

While the findings indicate that LPI and K-Index are promising predictors of lightning activity over Sri Lanka, it is important to note that the current analysis is limited to three case studies from a single inter-monsoon season. This limitation restricts the statistical significance and operational generalizability of the results. Future research should aim to conduct a comprehensive multi-year evaluation encompassing a wider range of meteorological conditions. This would allow for more robust statistical assessments and the identification of consistent predictive patterns across seasons, thereby enhancing the operational potential of WRF-based lightning forecasting.

This study involved six model simulations using the WRF model for three selected events in Sri Lanka during the second inter-monsoon season of 2018, with the objective of determining the most effective microphysics scheme and variable for predicting lightning occurrences. Various parameters such as the Lightning Potential Index (LPI), K-Index, and CAPE, which are related to microphysics and thermodynamics were analyzed across these simulations as potential predictors of lightning events. The effectiveness of these variables in accurately forecasting lightning occurrences was evaluated.

Among the parameters examined, the LPI is most directly associated with lightning occurrences. The findings reveal that the LPI has an acceptable correlation coefficient with flash rates when using the WDM6 microphysics scheme, indicating its utility in predicting the likelihood of lightning events and identifying vulnerable areas. However, the correlation coefficient values range from 0.27 to 0.85 with WDM6, suggesting that the relationship between lightning flash rates and the LPI is contingent on atmospheric conditions. In summary, the Lightning Potential Index (LPI) is a valuable tool for forecasting the probability of lightning occurrences and identifying potential areas for thunderstorms on a larger scale. Nevertheless, further investigations are necessary to explore this parameter in greater depth.

The Lightning Potential Index (LPI) shows strong potential for operational lightning prediction when used with suitable microphysics and cumulus schemes. However, its skill varies significantly based on the chosen parameterization. For operational implementation, careful selection and validation of these schemes are essential.

The results show that every microphysics scheme produces almost similar values for the K-Index, with WDM6 producing slightly more reliable values than other schemes. The K-Index can be used to forecast lightning occurrences and identify areas with potential for thunderstorms. The K-Index demonstrated variable performance and should be used cautiously in isolation, particularly under localized inter-monsoonal conditions.

Although CAPE is theoretically expected to have a good relationship with thunderstorms, none of the physics schemes in this experiment captured significant correlation coefficients, POD, or TS values for CAPE and lightning occurrence. CAPE provides positive energy to develop thunderstorms, while CIN acts as a barrier to prevent their development. Therefore, CAPE and CIN should be considered together in future studies. CAPE alone showed limited usefulness in predicting lightning events. Including CIN and other thermodynamic parameters in future studies is recommended to enhance the physical realism and predictive skill of the model. CAPE alone is insufficient for lightning forecasting. Future studies should include CIN to improve convective diagnostics.

The results indicate that different microphysical schemes exhibit varying sensitivity in simulating lightning-related parameters. Specifically, the WDM6 scheme, when combined with the BMJ cumulus scheme, showed superior performance in predicting LPI, likely due to its ability to simulate both mass and number concentrations of hydrometeors, as well as the inclusion of cloud condensation nuclei (CCN) effects. In contrast, the Thompson and Morrison schemes underperformed, which may be attributed to their parameterization of ice-phase processes and lack of CCN interaction, which are critical for accurate charge generation in the LPI formulation. These findings highlight that model sensitivity to microphysics is not only structural but also physically tied to the processes influencing convective electrification. Prior studies (*e.g.*, Lim & Hong, 2010; Lynn *et al*., 2010) have also noted the influence of CCN and double-moment schemes on lightning prediction skill, supporting our results. Therefore, careful selection of microphysical and cumulus schemes is essential when simulating lightning in high-resolution WRF applications, particularly in CCN-rich tropical environments like Sri Lanka.

The low TS values observed are partly due to spatial mismatches between observed and model produced lightning. Future verification should explore more spatially tolerant methods to improve model evaluation.

The results of this study suggest that the WDM6 is the best microphysics scheme among the selected options, with cumulus physics schemes having minimal impact on the fine domain. The analysis revealed that the Lightning Potential Index (LPI) and K-Index are suitable for predicting the occurrence of lightning and thunderstorms. The corresponding lightning simulations produced spatial distributions aligned with ground-based lightning data. Moreover, the WRF model's ability to capture lightning using LPI and K-Index indicates its potential for operational use in predicting lightning-prone regions. While a high-resolution horizontal grid space like 1 km would offer greater accuracy, it is impractical due to the required computational power. However, using a 4 km grid space WRF model in Sri Lanka, along with LPI and K-Index values, can effectively identify potential areas for lightning occurrences. This approach will be beneficial for issuing early warnings of lightning occurrences in operational forecasting, ultimately helping to protect lives and property.

Recommendations

Within this limited time frame, I considered lightning events during 2018 with a restricted set of physical parameterization options. It would be beneficial to examine lightning events over several years with a broader range of physics options. Therefore, I suggest that more extensive studies encompassing multiple years of lightning events are needed, along with testing a wider variety of physical schemes, including land surface, boundary layer, and radiation physics, to identify the most effective combinations to predict lightning occurrences.

The thundercloud charging process remains based on hypotheses. One proposed mechanism involves collisions between ice crystals and graupel, where ice crystals acquire a positive charge and ascend within the cloud, while graupel acquires a negative charge and descends. Charge generation is influenced by the updraft within the charging zone, typically between 0 °C and -40 °C. The LPI calculation currently considers only the range from 0 °C to -20 °C, based on mid-latitude conditions. This range may vary by region. Future studies should explore adjusting the charging zone to ranges like 0 °C to -30 °C, 0 °C to -40 °C, or -10 °C to -30 °C to optimize the LPI for specific regions. This adjustment could enhance the LPI's predictive accuracy for different geographical areas.

Additionally, CAPE should be considered in conjunction with CIN in future studies, as these variables influence thunderstorm development in opposite ways. Evaluating both together could provide a better understanding of atmospheric instability. Future research incorporating different charging zones may enhance the accuracy of LPI predictions, especially in tropical regions.

The Threat Score (TS) values in this study were generally low (ranging from 0 to 0.09), indicating limited skill in accurately matching observed lightning locations. This is partly attributed to the highly localized and sparse nature of lightning events compared to the model's spatial resolution, which can lead to many missed or misplaced detections. Additionally, the TS calculation excludes correct negatives, which can further reduce the score in cases with low lightning coverage. These limitations suggest that conventional grid-point-based TS may not fully capture the model's predictive value. Future studies should consider applying spatial verification techniques such as neighborhood or fuzzy methods, which account for spatial displacement and are better suited for evaluating high-resolution lightning forecasts.

These findings have practical implications for early warning systems and model-based forecasting efforts in Sri Lanka.

Author Statement

I, J.S.D.S. Premathilake, Meteorologist, Department of Meteorology, Sri Lanka, hereby declare that the contents and views expressed in this research paper/article are solely my own and do not necessarily reflect the views of the Department of Meteorology or any other organizations to which I am affiliated.

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Author's Contribution

I, J.S.D.S. Premathilake, am the sole author of this study and am responsible for all aspects of the work, including conceptualization, methodology, data collection and analysis, visualization, writing, and final manuscript preparation.

Disclaimer: The contents and views presented in this research article/paper are the views of the authors and do not necessarily reflect the views of the organizations they belong to.

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