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Atmospheric Stability Index Threshold for Very Heavy Rainfall Events in Indonesia

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ABSTRACT
Indonesia's maritime tropical climate exhibits high atmospheric variability often triggering extreme rainfall that disrupts flight and increases hydrometeorological disaster risks. This study investigates threshold values of atmospheric stability indices —Lifted Index (LI), K-Index (KI), and Precipitable Water (PW)— as predictors of very heavy rainfall events (>100 mm/day). Daily rainfall data from six meteorological stations (Medan, Padang, Tangerang, Surabaya, Merauke, Kupang) across Indonesia for 1993-2024 was analysed for very high rainfall events. We used the receiver operating characteristic area under the curve (ROC AUC) method to quantify the indices' ability to characterize and distinguish very heavy and non-very heavy rainfall, objectively identifying the optimal threshold. The results show spatially varying thresholds reflecting dominant local atmospheric factors, with KI dominant in Kupang, while LI and PW in Merauke. This suggests that the optimal threshold value is a region specific, emphasizing a local calibration. further, the findings are crucial for enhancing prediction accuracy and extreme weather warnings at airports.

KEYWORDS
precipitable water, K-Index, lifted index, local calibration, optimal threshold

1. INTRODUCTION

Extreme weather is a major challenge in aviation operations nationally and globally. This weather does not only impacts flight safety but also causes operational disruptions such as delays, diversions, flight cancellations, and significant economic losses (Bombelli and Sallan, 2023; Budnukaeku and C., 2022). Approximately 58% of aviation accidents in Indonesia are related to extreme weather conditions (Pramono et al., 2020). Characteristics of the tropical maritime atmosphere is very dynamics leading to a high weather variability. This dynamics condition that may lead to aviation disruption requires scientific tool for better understanding and prediction of atmospheric condition supporting safety flight.

Atmospheric stability indices, such as the Lifted Index (LI), K-Index (KI), and Precipitable Water (PW), have long been used as indicators of the potential for convective cloud formation, thunderstorms, and extreme rainfall in various climate zones (Ashidi et al., 2024; DeRubertis, 2006; Fernando et al., 2021; Jayakrishnan and Babu, 2014; Marinaki et al., 2006; Matthew et al., 2021). Studies have shown that these indices are effective in predicting convection and heavy rainfall events, along with the increasing trend of atmospheric instability (DeRubertis, 2006; Marinaki et al., 2006; Rahiman et al., 2017). Also, LI and KI have been shown to accurately detect thunderstorms and extreme rainfall in Sri Lanka and Nigeria, (Ashidi et al., 2024; Fernando et al., 2021; Matthew et al., 2021). However, most previous approaches and parameters are localized and may not be appropriate for the characteristics of Indonesia's tropical-maritime atmosphere.

Research on the threshold of atmospheric stability in Indonesia is still very limited, both in terms of multi-station data and the direct relationship between KI, LI, and PW and extremely heavy rainfall events (Prima et al., 2023). Local studies, such as in Padang have only identified specific index thresholds for thunderstorms events, and have not been cross-regional or multidecade (Ari Nuryadi et al., 2025). A deeper understanding on atmospheric parameters and very high rainfall events is needed to strengthen the national hydro-meteorological disaster early warning system.

The use of evaluation methods such as ROC-AUC has been proven to be effective in assessing the optimal parameter thresholds for separating extreme and normal weather conditions (Dwiyanti and Prianto, 2023). The use of ROC-AUC has been widely applied, such as reported by ECMWF and the UK Met Office (ECMWF, 2019; UK Met Office, 2024). In Indonesia, the application of ROC-AUC has also been carried out to distinguish between extreme and normal weather conditions (Dwiyanti and Prianto, 2023; Hapsari and Pandya Wisesa, 2025).

This objectives of study are: (i) to elucidate the significant relationships between atmospheric stability indices and the occurrence of very heavy rainfall events, and (ii) to establish new region-specific threshold values that enhance the detection and characterization of such events across diverse climatic conditions. We test the thresholds for KI, LI, and PW based on the analysis of observational data from six meteorological stations in Indonesia over two decades. The findings are expected to contribute on the strengthening the early warning system and managing extreme rainfall disaster risks in Indonesia.

2. MATERIALS AND METHODS

2.1 Study Area and Data

The rainfall data were obtained from several meteorological stations distributed across various regions of Indonesia; (1) Medan, North Sumatra (96035), (2) Padang, West Sumatra (96163), (3) Cengkareng, Banten (96749), (4) Surabaya, East Java (96935), (5) Merauke, Papua (97980), and (6) Kupang, East Nusa Tenggara (97372). The data is for 1993 to 2024 (Table 1).

The selection of the stations reflects a broad geographic coverage spanning from western to eastern Indonesia (Figure 1), and ensures an extensive historical dataset in the last two decades. Therefore, the dataset represents atmospheric characteristics across diverse climatic and geographic zones.

A 6-hour observed rainfall data were obtained from the University of Wyoming database and filtered for 00 UTC to serve as initial predictors for evaluating the stability indices in predicting the occurrence of very heavy rainfall.

2.2 Data analysis

2.2.1 Index of atmospheric stability

The atmospheric instability is a key characteristic that describes the behavior of air masses as they move vertically within the atmospheric column. Previous studies (Alves et al., 2020; Huntrieser et al., 1997) have demonstrated that variations in atmospheric stability indices influence the intensity of heavy rainfall and reflect significant differences driven by local atmospheric conditions. In this study, atmospheric stability is characterized using three instability indices, namely the Lifted Index (LI), K-Index (KI), and Precipitable Water (PW).

a. Lifted Index (LI)

The Lifted Index (LI) is the value obtained from the difference between the air temperature and the air parcel temperature at the 500 mb layer (Galway, 1956), as in Equation (1).

$$LI = T500 - Tp500' \qquad (1)$$

Where: T500 = air temperature in the 500 mb layer (K), Tgp = air parcel temperature in the 500 mb layer (K)

b. K-Index (KI)

The K-Index is an indicator of the potential for storms due to convective movement, calculated based on the temperature values at the 850, 700, and 500 mb layers, along with the dew point temperatures at the 850 and 700 mb layers. Its value is formulated in the Equation (2):

$$KI = T850 - T500 + Td850 - (T700 - Td700) \qquad (2)$$

Where: T= temperature (℃), Td= dew point temperature (℃).

c. Precipitable Water (PW)

Precipitable Water (PW) is a measure of the total amount of water vapor in the atmosphere in the vertical direction, between the Earth's surface and the top of the atmosphere (or between two specified levels). PW is determined from the mass of water vapor in the troposphere and deposited on the Earth's surface.

The mass of water vapor is determined by the dew point (saturation mixing ratio) of the air integrated above the troposphere. Higher dew points result in higher PW values, especially if the relatively high dew point extends through a significant vertical depth. The scale below provides an indication of the water vapor content of the troposphere through PW (Skew T).

Figure 1. Location of meteorological stations across Indonesia

2.2.2 Relationship between stability index and very heavy rainfall

The relationship data for each pair of variables were visualized using boxplot, a statistical method widely used in meteorological research to describe variability, detect outliers, and analyze the distribution of rainfall data and model prediction results (Taiyab et al., 2024). This relationship analysis includes three main parts:

- The correlation between KI (K Index) and rainfall intensity. It is to assess how the atmospheric temperature lapse rate influences rainfall intensity.
- The correlation between LI (Lifting Index) and rainfall intensity. It is to evaluate how temperature differences at the 500 mb level, influences rainfall intensity.
- The correlation between PW (Precipitable Water) and rainfall. It is to determine the role of total atmospheric moisture in enhancing heavy rainfall events.

2.2.3 Determining the maximum threshold

The determination of the threshold for daily atmospheric lability parameters in this study was carried out quantitatively using a statistical approach based on the Receiver Operating Characteristic (ROC) curve, which has been recommended by the World Meteorological Organization (WMO) and is widely applied in extreme weather forecast verification studies (Mason and Graham, 2002; Wilks, 2006).

Daily observation data from 6 stations in Indonesia for the period 1993–2018 were used as the basis for the analysis, including the K Index (KI), Lifted Index (LI), and Precipitable Water (PW) parameters, which have gone through a cleaning and transformation process using R software Core Team, 2023. Rainfall intensities are categorized into four levels: light (1–5 mm/hour or 5–20 mm/day), moderate (5–10 mm/hour or 20–50 mm/day), heavy (10–20 mm/hour or 50–100 mm/day), and very heavy (>20 mm/hour or >100 mm/day) (Kiyotoka Mori et al., 2003).

The ROC method is used to evaluate the ability of each parameter to distinguish between days with and without very heavy rainfall events. The ROC curve is created by plotting the True Positive Rate (TPR, sensitivity) against the False Positive Rate (FPR, 1-specificity) at various threshold values. The optimal threshold value is determined using the Youden method, namely by finding the maximum value of the Youden statistic (J), which is formulated as J = Sensitivity + Specificity − 1 or mathematically, as in Equation (3)

$$J = \frac{TP}{TP+TN} + \frac{TP}{TN+FP} - 1, \quad (3)$$

Where TP, TN, FP, and FN are the number of true positives, true negatives, false positives, and false negatives, respectively. The threshold value that maximizes J is chosen as the optimal threshold. In addition, the Area Under Curve (AUC) value is calculated to measure the overall discrimination performance of the parameters, where an AUC close to 1 indicates excellent predictive ability.

2.2.4 Evaluation and threshold testing

The evaluation of the index in detecting very heavy rainfall events was carried out by applying threshold values obtained from ROC analysis to daily observational data from multiple stations for 2019–2024 period. We evaluated the index using the Confusion Matrix to calculate metrics such as accuracy, sensitivity, and specificity for very heavy rainfall events (CH > 100 mm).

Table 1. Details of meteorological stations used in this study, including station name, WMO ID, geographic coordinates, available rainfall data period to analyzed.

Location	ID WMO	ICAO	Coordinate (lat, long)
Medan Meteorological Station, North Sumatra.	96035	WIMM	-3.65, 98.88
Padang Meteorological Station, West Sumatra	96163	WIEE	-0.79,100.29
Tangerang Meteorological Station, Banten.	96749	WIII	-6.12,106.65
Surabaya Meteorological Station, East Java.	96935	WARR	-7.38,112.78
Merauke Meteorological Station, Papua	97980	WAKK	-8.52,140.41
Kupang Meteorological Station, East Nusa Tenggara	97372	WATT	-10.17,123.67

The Confusion Matrix is used to assess the level of agreement between prediction and observations. This matrix consists of four main components: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN), which describe the classification pattern of the model. Based on this matrix, several evaluation metrics such as accuracy, precision, recall, and F1-score are calculated to provide a comprehensive assessment (Equations 4-8).

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (4)$$

$$\text{Precition} = \frac{\text{TP}}{\text{TP+FP}} \quad (5)$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}} \quad (6)$$

$$\text{Spesifity} = \frac{\text{TN}}{\text{TN+FP}} \quad (7)$$

$$\text{F1} - \text{Score} = 2\text{x}\frac{\text{Precition x Sensitivity}}{\text{Precition+Sensitivity}} \quad (8)$$

3. RESULTS AND DISCUSSIONS

The K-Index (KI) values showed a significant increase in very heavy rainfall conditions compared to the non-very heavy rainfall category at almost all stations (Figure 2). For example, at Surabaya, Medan, and Padang stations, the K-Index (KI) values during heavy rainfall ranged from 33 to 40. Conversely, during non-very heavy rainfall conditions, KI value is smaller ranging from 20-30 with wider variations. This indicates a more unstable atmosphere during very heavy rainfall, thus contributing to the potential for convective cloud formation.

LI values varied across stations during very heavy rain from -4 to around -1, and its value increased for not very heavy rain (-1 to +2). This indicates more positive LI during non-heavy rain, whereas LI drops more negative during heavy rainfall. This trend indicates that the air is experiencing greater instability during very heavy rain, which is consistent with the lower (negative) LI value strengthening the potential for convection.

For Precipitable Water (PW) variable, the value during very heavy rain appears to be much higher with a range of approximately 55-65 mm, compared to when it is not very heavy rain which has a range of between 40-55 mm. This confirms the positive relationship between the total availability of water vapor in the atmosphere and extreme rainfall events, where a large supply of water vapor supports the development of high-density rain clouds.

At Kupang station, the median and range values for KI and PW are consistently lower than those at other stations, both in the light (< 100 mm) and very heavy (≥ 100 mm). KI in Kupang is generally in the range of 20-25 with a smaller range, while PW is around 30-40 mm, much lower than in areas such as Medan or Padang. This condition indicates lability and limited water vapor content due to the dominance of the East Monsoon winds that bring dry air masses, topography and geographic location that receive less water vapor supply from the sea, and high atmospheric stability (Deshafa, 2025; Permana et al., 2016; Gradiyanto, 2025).

Our spatial analysis (Figure 3) show variations in the value of KI threshold. The highest KI threshold value was found at Kupang Station, while the lowest was recorded at Merauke Station. This spatial variation reflects differences in atmospheric characteristics influenced by regional factors such as humidity, vertical temperature, and the influence of atmospheric circulation and local topography in each observation area.

Eastern Indonesia, such as Kupang, exhibits a higher KI threshold than the western region. This is influenced by the Australian monsoon cycle, which brings dry air masses to the eastern region, while the western region is more influenced by the Asian monsoon, which brings high humidity, especially during the rainy season. Another factor influencing this spatial difference is sea surface temperature, which plays a role in providing water vapor for convection processes, particularly in areas bordering the Pacific and Indian Oceans (Fibriantika and Mayangwulan, 2020).

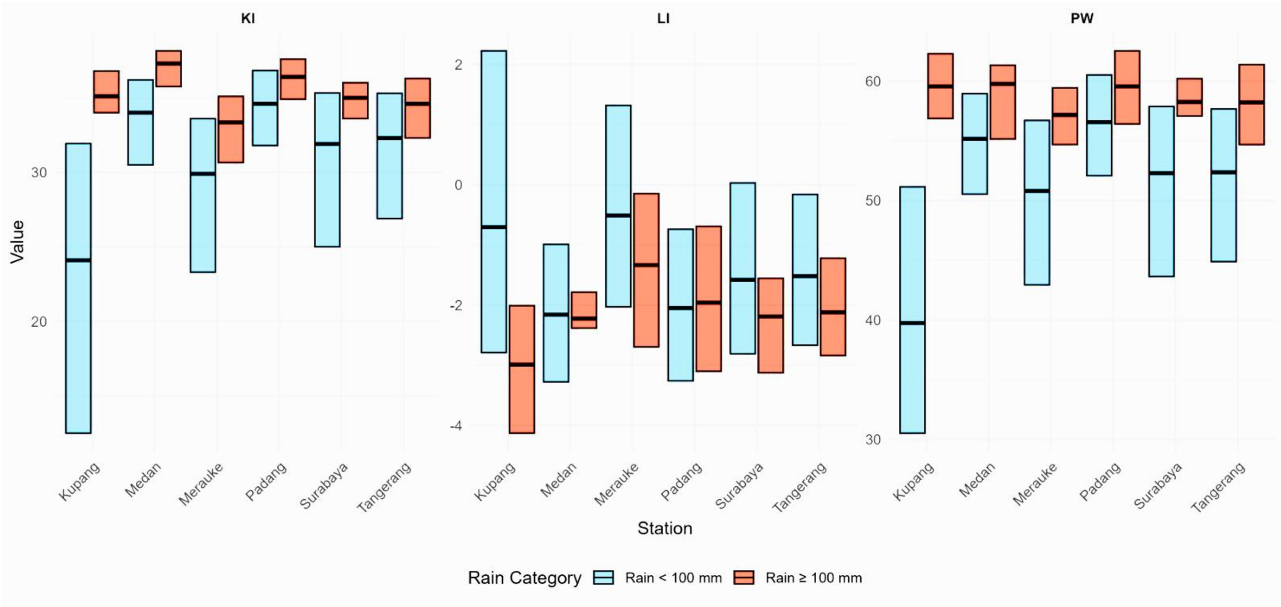

Figure 2. Boxplot of the distribution of stability index (KI, LI, and PW) for very heavy rainfall for the period 1993 – 2024, observations at 00 UTC.

In terms of index performance, the AUC values at each station also show significant variation. For example, at Surabaya and Merauke Stations, high AUC values indicate more accurate predictions of convective events during the rainy season. This indicates that KI tend to show the best predictive performance when the atmosphere is humid and unstable (wet season), and decline in the dry season when the air is more stable.

Based on the ROC model performance measured by AUC, Surabaya (0.76) showed the best ability, followed by Merauke (0.7) and Kupang (0.67). This value indicates that the model in these locations has a fairly good ability to distinguish stable and unstable data. On the other hand, the Medan and Padang areas recorded an AUC of 0.50, which is statistically equivalent to a random guess. This suggests KI model has absolutely no predictive value at Medan and Padang stations.

Based on model performance (Table 2), Surabaya and Kupang is best performed in predicting atmospheric instability triggering very heavy rainfall. In contrast, the lowest performance was observed at Padang, where KI based prediction yielded only an accuracy of 0.43 and a sensitivity of zero. Such low sensitivity indicates that the model failed to identify any actual extreme rainfall events at this location. Sensitivity is a crucial metric for evaluating a model's ability to detect real events; a value of zero means that none of the observed extreme rainfall events were detected by the KI threshold. Furthermore, an accuracy below 0.5 emphasizes that the predictive capability is nearly equivalent to random guessing. These findings underscore the limited effectiveness of the KI threshold as a predictive tool for extreme rainfall in Padang and highlight the urgent need for local calibration and the integration of complementary predictors to enhance early warning system performance in this region.

Station in Medan displayed a moderate effort in balancing Sensitivity (0.5) and Specificity (0.84), although its overall discriminatory ability was very weak (AUC 0.5). Meanwhile, Merauke showed the least reliable performance, recording lowest accuracy (0.460) and lowest specificity (0.45), reflecting susceptibility to prediction errors in both classes.

Spatial maps of LI and AUC (Figure 3b) show variations in atmospheric instability for each location. The very negative LI values in Padang indicate a highly unstable atmosphere, with a high potential for heavy rainfall due to the orographic influence of the surrounding mountains, which can trigger forced air uplift (Huang et al., 2022). The Merauke and Kupang regions have high AUC values, indicating that mesoscale mechanisms such as monsoon winds and local convergence strongly support strong convection processes. Conversely, in lowland areas such as Medan and Cengkareng (Tangerang), AUC values are low due to limited air uplift due to reduced orographic effects and less dominant mesoscale processes.

This variation indicates that the LI value alone is insufficient for very-heavy rainfall prediction without considering other factors such as air humidity, topographic characteristics, mesoscale dynamics, and urbanization. Therefore, AUC maps are crucial for identifying areas requiring specific modeling and early warning approaches tailored to local and seasonal conditions (Taiyab et al., 2024).

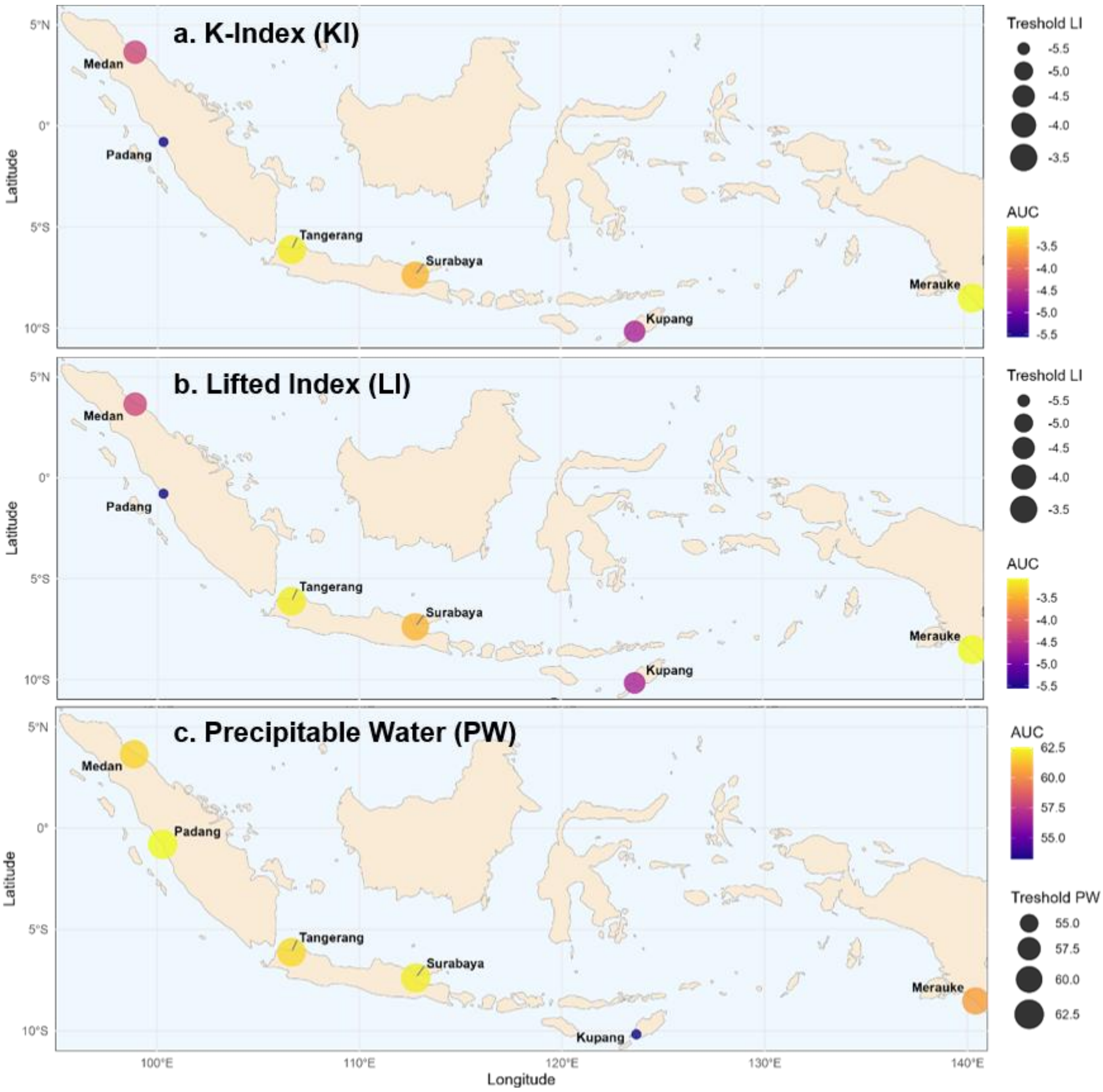

Figure 3. Spatial variation of K-Index (KI), lifted index (LI), and precipitable water (PW) thresholds based on AUC (Area Under Curve) in 6 meteorological stations in Indonesia.

International research shows that combining multiple convection indices (e.g., LI, CAPE, K-Index) can improve prediction performance compared to using a single index alone, and the best threshold should be adjusted locally for each station (Taiyab et al., 2024).

The threshold LI and AUC (Table 2) show variations across stations. The most negative LI thresholds (-5.55 in Padang) tend to be effective in detecting extreme convective rainfall with high sensitivity and accuracy. Conversely, the highest AUC value was observed in Merauke (0.69), indicating that this region exhibits good LI predictive performance in distinguishing extreme rainfall events. Another finding is that a very negative LI is strongly associated with a volatile atmosphere and heavy rainfall events, but its effectiveness depends on local conditions such as topography and humidity.

The spatial patterns of AUC and PW thresholds reflect substantial heterogeneity in the predictability and detection of extremely heavy rainfall using convective indices. A comparative analysis (Figure 3) indicates that stations in eastern Indonesia, such as Merauke and Surabaya, consistently demonstrate higher AUC values, suggesting increased reliability of extreme rainfall prediction with PW parameters, relative to stations in the western region like Padang and Medan. Further, spatial variation in PW threshold values is evident. Stations in Padang and Medan require the highest minimum atmospheric water vapor (exceeding 61 mm), while Kupang in the southeast registers the lowest threshold (~53 mm). The differences indicate that the minimum PW requirement for triggering very heavy rainfall is strongly modulated by regional atmospheric dynamics, topography, and tropical convection patterns. The Merauke station consistently exhibited the highest Area Under Curve (AUC) value of 0.84, indicating that PW-based prediction models in this region effectively distinguish between days with extreme rainfall and those without. This finding aligns with satellite observations and recent ensemble model

Table 2. Thresholds of the K Index (KI), Lifted Index (LI), and Precipitable Water (PW) for 1993–2018 and their accuracy for 2019–2024 across six locations.

Location	Threshold	AUC	Sensitivity Threshold	Acc. Value	Sensitivity Accuracy	Specificity
K-Index						
Medan	37.05	0.5	0.9	0.84	0.5	0.84
Padang	37.25	0.5	0.9	0.43	0	1
Tangerang	36.78	0.59	0.9	0.6	0.66	0.5
Surabaya	37.55	0.76	0.95	0.98	0	1
Merauke	35.55	0.7	0.95	0.46	0.6	0.45
Kupang	38.24	0.7	0.54	0.86	0	0.87
Lifted Index (LI)						
Medan	−4.29	0.5	0.9	0.9	0	0.9
Padang	−5.55	0.55	0.9	0.87	0	1
Tangerang	−4.22	0.55	0.9	0.53	0	1
Surabaya	−3.46	0.59	0.95	0.98	0	1
Merauke	−3.06	0.69	0.95	0.95	0	1
Kupang	−4.61	0.67	0.54	NA	0	NA
Precipitable Waater (PW)						
Medan	61.68	0.66	0.9	0.8	0	0.85
Padang	62.51	0.54	0.9	0.56	0.6	0.55
Tangerang	61.8	0.59	0.96	0.64	0.61	0.66
Surabaya	62.23	0.74	0.95	0.63	0.5	0.64
Merauke	60.44	0.84	0.95	0.49	0.83	0.48
Kupang	53.24	0.67	0.5	0.52	0.8	0.5

studies that highlight a consistent and high probability of detecting extreme rainfall in southern Papua.

The highest AUC values were observed in regions with lower PW thresholds, highlighting that the effectiveness of PW as a predictor for very-heavy rainfall is not universally applicable, but instead highly dependent on local convective complexity. The findings strengthen the hypothesis that the interplay of regional climatic regimes, convection system resilience, and local moisture variability governs rainfall extremes in Indonesia. This suggest aspatial calibration of PW thresholds in operational tropical meteorology (Roca and Fiolleau, 2020; Westra et al., 2014), and it is necessary to enhance the accuracy of early warning systems and hydrometeorological risk reduction strategies in Indonesia, supporting the development of more robust, locally optimized forecast models for ext-reme weather events.

The findings show a clear trade-off between sensitivity and specificity (Table 2). almost all stations achieve a very high threshold sensitivity (>0.90), but the specificity range is wide (0.50–0.85), reflecting the challenge in reducing the number of false positives while avoiding missed events in extreme rainfall.

Practically, the low accuracy in Merauke (0.49), despite high sensitivity and AUC, indicates potential over-prediction due to atmospheric homogeneity and the very high PW signal that does not always directly overlap with actual precipitation.

In contrast, in Surabaya and Tangerang, the model shows a more balanced performance, with relatively moderate threshold, sensitivity, and accuracy, highlighting the importance of regional calibration in PW-based early warning systems. These findings emphasize the need for integrated multi-parameter approaches and detailed spatial threshold adjustment to improve the reliability of extreme rainfall forecasts in the Indonesian archipelago.

There are several limitations to this study that should be acknowledged. The analysis primarily addresses variables linked to atmospheric stability indices, a subject that remains insufficiently explored in Indonesia. A notable constraint is the reliance on data from only six monitoring stations, which limits the ability to generalize the findings across Indonesia's highly diverse climatic and geographic regions. Future research encompassing a broader and denser network of observation stations is necessary to enhance the spatial coverage and robustness of the index assessments. Moreover, the present study does not fully account for the impact of varied climatic regimes that distinctly characterize Indonesia's maritime territory. Despite these limitations, the present findings offer a significant initial contribution to the understanding of rainfall regimes and atmospheric stability within Indonesia and provide a foundation for more detailed investigations in subsequent studies

4. CONCLUSION

This study identified and evaluated threshold values of atmospheric stability indices, namely the K-Index (KI), Lifted Index (LI), and Precipitable Water (PW), as predictors of very heavy rainfall events in Indonesia based on two decades (1993–2024) of observational data from six meteorological stations. Statistical analysis and Receiver Operating Characteristic (ROC) curve assessment revealed spatially variable optimal thresholds reflecting regional atmospheric conditions such as monsoon influence, topography, and humidity. KI thresholds ranged from 35.55 to 38.24 with maximum Area Under the Curve (AUC) up to 0.76, LI thresholds varied between -5.55 and -3.06 with AUC peak at 0.69, and PW thresholds ranged from 53.24 mm to 62.51 mm with the highest AUC reaching 0.84.

These findings emphasize the necessity of localized calibration to enhance early warning accuracy for extreme rainfall in Indonesia's tropical maritime climate. Integrating multiple stability indices have demonstrated an improved predictive performance compared to single-index models. Further, the results contribute substantially to strengthening hydro-meteorological disaster risk management through improved early warning systems.

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