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Threshold Value of Atmospheric Stability Indices During Thunderstorm Events at Minangkabau International Airport

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ABSTRACT

Thunderstorms are a significant challenge for aviation operations, especially in tropical regions such as West Sumatra. This study aims to determine threshold values for six atmospheric stability indices—Convective Available Potential Energy (CAPE), K-Index (KI), Lifted Index (LI), Showalter Index (SI), Severe Weather Threat Index (SWEAT), and Total-totals Index (TTI)—to predict thunderstorm events at Minangkabau International Airport (MIA). Radiosonde and daily synoptic reports from 2018–2022 were analyzed using Rawinsonde Observation Programs (RAOB) and Statistical Package for the Social Sciences (SPSS) with a dummy regression approach. The model was validated using a confusion matrix, measuring accuracy, precision, and recall. Results show that the use of locally calibrated thresholds leads to higher and more consistent accuracy, precision, and recall values compared to global benchmarks, due to better adaptation to local weather parameters such as vertical humidity, mid-layer temperature, and wind structure. KI, SI, and TTI showed high sensitivity (recall >88%), while LI and CAPE performed moderately. Monthly variation in index performance was observed, with KI, SI, and TTI dominant in the wet and transition seasons, and SWEAT effective in the dry season when shear-driven convection increases. Thus, locally calibrated indices are recommended for thunderstorm early warning systems in aviation.

1. INTRODUCTION

Thunderstorms are a type of extreme weather event characterized by lightning, thunder, intense precipitation, and strong winds. Their formation is primarily driven by atmospheric instability, which promotes the development of large cumulonimbus clouds (Umakanth et al., 2020a). The dynamic processes that lead to thunderstorms are influenced by a combination of meteorological factors, including high relative humidity, substantial wind shear, and sufficient surface heating (Vujović & Protić, 2017; Yavuz, 2023). In tropical regions such as Indonesia, the frequent occurrence of thunderstorms presents a considerable hazard to air transportation, often causing operational disruptions and safety concerns (Škultéty et al., 2022). Consequently, accurate forecasting of these events is essential for mitigating risks to aviation, infrastructure, and public safety.

Early detection of atmospheric conditions favorable for thunderstorms often relies on quantitative assessments using atmospheric stability indices. These indices—such as the Lifted Index (LI), K-Index (KI), Total Totals Index (TTI), Showalter Index (SI), and Convective Available Potential Energy (CAPE)—are derived from radiosonde data to evaluate the potential for convective activity

(Umakanth et al., 2020b; Dutta & Pal, 2022). While widely adopted, standardized global threshold values for these indices are often less effective due to significant geographical and climatological variations influencing atmospheric dynamics. This limitation underscores the need for location-specific thresholds to achieve more reliable forecasts. Integrating advanced warning systems that combine weather radar, satellite, and lightning sensor data can further enhance detection capabilities, providing vital support for air traffic control and airline operational decision-making (Mohammed, 2024; Firdaus et al., 2024).

An increasing number of studies in Indonesia have highlighted the necessity of defining thresholds tailored to specific locations. For example, in Merauke, the optimal LI and SI values were found to be −3 and −0.1, respectively, with CAPE at 1500 J/kg during the December–February period (Putri & Pratama, 2016). Similarly, research at Iskandar Airport identified different optimal values, namely LI ≤ −2.4 and SWEAT > 215.9, for more accurate thunderstorm detection (Zahrina et al., 2017). A study on the dominant thunderstorm season in Makassar determined distinct ranges for the Showalter Index (−0.1 to 3.0) and K-Index (31.1 to 39.0) (Bangsawan & Tjasyono HK, 2015). These findings reaffirm the importance of recalibrating stability indices to improve extreme weather detection accuracy. More recent work at Sultan Hasanuddin Meteorological Station successfully classified optimal thresholds for six stability indices while also differentiating between cumulonimbus cloud and thunderstorm events (Rusdin et al., 2023), further reinforcing the need for precise, localized adjustments.

Despite these advances, there remains a notable research gap in classifying stability index thresholds specifically for the MIA region. The availability of radiosonde data in this area provides an opportunity to develop objective and measurable atmospheric parameters for short-term forecasting. Therefore, this study seeks to address this gap by identifying and classifying the optimal threshold values of atmospheric stability indices associated with thunderstorm events at MIA. The findings are expected to enhance the accuracy of extreme weather forecasts and strengthen early warning systems for Indonesia's aviation sector.

2. METHOD

This research combines quantitative and descriptive approaches. The quantitative approach is used to examine the relationship between the atmospheric stability index and thunderstorm events through statistical analysis, while the descriptive approach is used to explain the characteristics of the stability index and atmospheric conditions during thunderstorms in the Padang Pariaman region.

The meteorological data used includes temperature, pressure, humidity, wind speed, and direction parameters. The data was obtained through field observations using a radiosonde, which produces a vertical profile of the atmosphere from the surface to a certain height (Firdaus et al., 2024).

This study uses six atmospheric stability indexes, namely CAPE, KI, LI, SI, SWEAT, and TTI. These indices are used to predict the likelihood of thunderstorm occurrence (Sabri et al., 2019; Umakanth, 2020; Yavuz, 2024). Each stability index has a specific calculation method and interpretation. For example, the LI is calculated based on the temperature difference between the uplifted air parcel and the ambient temperature at the 500 hPa layer, where a negative LI value indicates atmospheric instability (Umakanth et al., 2020a; Arora et al., 2023).

$$LI = T_{lp} - T_{gp} \tag{1}$$

SI is similar, but lifts the air parcel from 850 hPa (Yavuz, 2024; Kolay et al., 2025).

$$SI = T_{500} - T_x \tag{2}$$

KI considers humidity and vertical temperature gradients in the 850-500 hPa layer to project thunderstorm potential (Umakanth et al., 2020b; Sulik, 2021).

$$KI = (T_{850} - T_{500}) + (Td_{850} - \Delta_{700}) \tag{3}$$

TTI combines temperature and humidity to predict thunderstorm risk (Umakanth et al., 2020b; Mondal et al., 2024; Rafiuddin et al., 2025).

$$VT = T_{850} - T_{500}$$
$$CT = Td_{850} - T_{500} \tag{4}$$
$$TT = VT + CT$$

The SWEAT Index assesses the risk of extreme severe weather by considering thermodynamic parameters and wind shear (Rabbani et al., 2020; Yavuz, 2024).

$$SWEAT = 12(Td_{850}) + 20(TT - 49) + 2(f850\ ) + f500 + 125(sin\varphi + 0.2) \tag{5}$$

Whereas CAPE is used to measure the amount of energy available for vertical convection in the atmosphere, which is an important indicator in detecting potential thunderstorms (Umakanth et al., 2020b; Cheng et al., 2021; Wahiduzzaman et al., 2022).

$$CAPE = \int_{z_f}^{z_n} g(\frac{T_{parcel} - T_{env}}{T_{env}})\, dz \tag{6}$$

The research was conducted in the working area of Minangkabau Meteorological Station, Padang Pariaman, which is located at coordinates 00°47'18" LS - 100°16'51" BT. The data analyzed included all radiosonde observations for the period 2018-2022, which were conducted twice a day at 00 UTC and 12 UTC.

This study uses two main types of data: Upper air data from radiosonde observations (coded TEMP), processed using RAOB software to generate six atmospheric stability indices: CAPE, KI, LI, SI, SWEAT, and TTI; Thunderstorm occurrence data were obtained from daily synoptic weather observation reports. The software used included RAOB for sounding analysis and SPSS for advanced statistical analysis.

Data processing steps include grouping data based on observation time (00 UTC and 12 UTC), processing radiosonde data using RAOB to obtain stability index values, and combining the index data with thunderstorm events at the corresponding time.

As part of the data analysis, this study used a dummy regression analysis approach to examine the effect of categorical variables such as specific weather conditions (e.g., the presence of thunderstorms) on the dependent variable (e.g., flight delays), as described by Zhou et al. (2021) and Zhao et al. (2024). Model validation was conducted using a confusion matrix to evaluate the model's prediction performance against actual thunderstorm events, with evaluation metrics such as accuracy, precision, and recall (Bishop, 2006).

Dummy regression is used in this study because the dependent variable (TS occurrence) is categorical (TS = 1; No-TS = 0), while the independent variable is a numerical value of the atmospheric stability index. This dummy regression model can be formulated as follows:

$$TSi = \beta 0 + \beta 1 Xi \tag{7}$$

Where TSi is a dummy variable of thunderstorm occurrence (1 = TS occurred, 0 = not), Xi is a stability index value, and $\beta 0, \beta 1$ is a constant and the regression coefficients.

Regression was performed separately for each index: LI, SI, TTI, KI, CAPE, and SWEAT. The evaluation of stability index threshold classification accuracy was conducted using a confusion matrix, with accuracy, precision, and recall metrics measured. As a validation stage, the obtained stability index threshold values were then tested using thunderstorm event data in 2023 to measure the performance of the predictive model.

3. RESULTS AND DISCUSSION

The distribution of thunderstorm events (TS) in the Minangkabau International Airport area during the 2018-2022 period shows significant monthly variations. Based on data obtained from synoptic observations, the highest number of TS events occurred in January and April, with 52 events each, followed by February (49 events), May (48 events), and March (44 events). This indicates that the first half of the year has a relatively high frequency of TS.

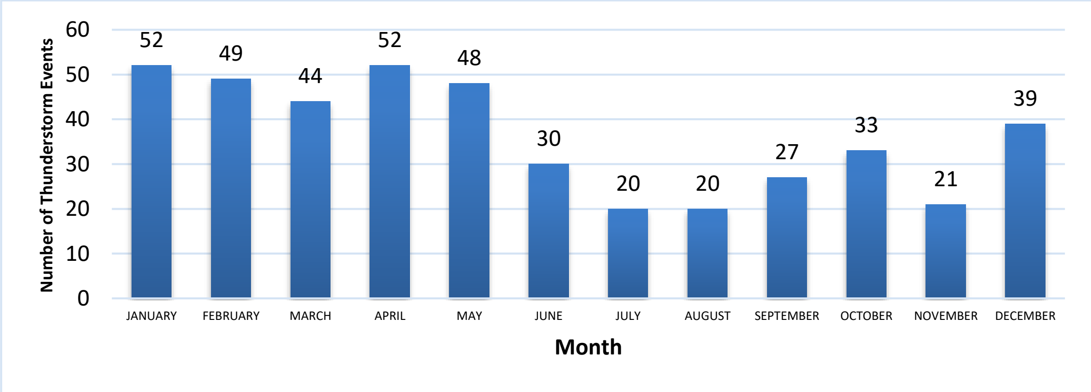

Figure 1. Monthly Distribution of Thunderstorm Events at MIA from 2018 to 2022.

3.1 Threshold Classification of Atmospheric Stability Indices for Thunderstorm Events

The threshold of each atmospheric stability index is determined by categorizing atmospheric conditions into three levels: stable, transitional, and unstable, based on the range of values associated with the occurrence or non-occurrence of thunderstorms each month. Table 1 shows the threshold classification of each index for January-June, and Table 2 shows the threshold classification of each index for July-December.

Table 1. Threshold Classification of Atmospheric Stability Index for Thunderstorm Occurrence January-June

		Jan	Feb	Mar	Apr	May	Jun
CAPE	Stable	<1141.02	<974.55	<607.41	<889.94	<888.88	<526.13
	Unstable	>1306.04	>1198.39	>1254.76	>1187.85	>1173.90	>937.53
KI	Stable	<32.80	<33.31	<32.96	<32.63	<30.93	<32.28
	Unstable	>34.77	>35.56	>34.30	>36.24	>35.59	>35.32
LI	Stable	>-2.56	>-2.10	>-1.87	>-1.95	>-1.52	>-1.22
	Unstable	<-3.21	<-3.07	<-3.16	<-3.14	<-3.04	<-3.04
SI	Stable	>0.68	>0.81	>0.44	>0.88	>0.84	>1.49
	Unstable	<-0.47	<-0.56	<-0.41	<-0.94	<-0.90	<-0.08
SWEAT	Stable	<204.85	<198.16	<204.53	<202.15	<202.28	<186.98
	Unstable	>212.33	>211.79	>212.70	>220.83	>217.45	>266.59
TT	Stable	<43.05	<42.95	<43.49	<42.58	<42.43	<42.32
	Unstable	>44.52	>44.57	>44.38	>44.53	>44.64	>43.98

The CAPE threshold for unstable conditions tends to increase during the wet season and reaches the highest value in December (>1486.46 J/kg). Stable values tend to be lower in the dry season, such as June (<526.13 J/kg) and October (<418.09 J/kg). The intermediate range reflects the threshold values between stability and convection potential, e.g. January (1141.02-1306.04 J/kg) and April (889.94-1187.85 J/kg). The unstable threshold for KI shows consistency above 34 throughout the year, with the highest value appearing in December (>36.08). Stable values are generally <30-33, as in May (<30.93) and July (<29.44). KI transition zones, such as 32.80-34.77 (January), are particularly important for identifying periods of potential convection development.

The LI value indicates that the atmosphere is classified as unstable if the LI is smaller than -3, such as in July (<- 3.38) and December (<-3.48). The stable threshold is in the >-2 range, such as January (>-2.56) and November (>- 1.22). The intermediate range, which describes an atmosphere that is starting to become unstable, is, for example, -2.56 to -3.21 in January. SI has unstable thresholds lower than 0, such as -0.41 in March and -0.94 in April. Stable conditions are generally characterized by SI values >0.8, such as June (>1.49) and August (>1.63). Transitional conditions range from low positive values to small negative values.

Table 2. Threshold Classification of Atmospheric Stability Index for Thunderstorm Occurrence July-December

		Jul	Aug	Sep	Oct	Nov	Dec
CAPE	Stable	<664.79	<634.55	<546.59	<418.09	<437.86	<943.31
	Unstable	>1166.79	>1182.90	>861.80	>629.48	>523.82	>1486.46
KI	Stable	<29.44	<29.94	<29.98	<32.56	<32.67	<34.66
	Unstable	>34.66	>34.87	>33.94	>34.64	>34.41	>36.08
LI	Stable	>-1.67	>-2.36	>-1.19	>-1.27	>-1.22	>-2.44
	Unstable	<-3.38	<-3.36	<-2.51	<-1.95	<-1.82	<-3.48
SI	Stable	>1.37	>1.63	>1.61	>0.96	>1.58	>0.56
	Unstable	<-0.59	<-0.58	<-0.04	<0.16	<0.20	<-0.63
SWEAT	Stable	<183.01	<184.53	<190.94	<197.39	<196.54	<210.38
	Unstable	>208.23	>213.71	>205.38	>208.89	>213.36	>215.76
TT	Stable	<42.84	<42.77	<42.29	<42.86	<41.73	<42.83
	Unstable	>45.01	>45.02	>44.47	>43.61	>43.27	>44.33

The SWEAT unstable threshold varies but is always >210, with the highest value in December (>215.76). Stable values are seen below 200 (e.g., <183.01 in July). Intermediate ranges often reflect sensitivity to convection disturbances, such as 204.85-212.33 (January) or 190.94-205.38 (September). TTI shows unstable conditions at values >44, with fairly consistent annual variations. Transitional ranges are, for example, 43.05-44.52 (January) and 42.86-43.61 (October). Stable conditions occur when TTI <43, as recorded in June (<42.32) and November (<41.73).

The evaluation was conducted by applying the atmospheric stability index thresholds obtained through dummy regression to actual thunderstorm events in 2023. The evaluation method uses a confusion matrix with the main metrics: accuracy, precision, and recall to measure the effectiveness of each index in detecting TS (thunderstorm) events, as shown in Figure 2.

The KI, SI, and SWEAT indices recorded very high recall values (>88%) throughout the year, making them the most sensitive to TS events. However, all indices were imprecise, especially SI and SWEAT, which tended to overpredict (high false positives). CAPE and LI demonstrated moderate performance with inconsistent accuracy and precision and a limited ability to distinguish between TS and non-TS conditions. SI achieved perfect recall (100%) for seven consecutive months (June-December); however, this was accompanied by a fairly high rate of non-TS classification errors. TTI demonstrated the most balanced performance in May, achieving the highest accuracy (70.8%) with no false negatives. From May to August, LI showed fairly good performance, balancing sensitivity and precision.

CAPE and KI showed optimal performance in June, with high recall and accuracy (>83%). In July and August, the KI, SI, and SWEAT indices dominated, each recording 100% recall. However, they still showed moderate precision due to high false alarm rates. LI remained stable throughout the year and is a suitable filtering index for a combined TS prediction system. In September, all the main indices (KI, SI, SWEAT, and TTI) recorded a perfect performance (100% accuracy, precision, and recall), indicating ideal atmospheric conditions for stability index–based predictive models. In October, the KI again demonstrated superior performance (78.6% accuracy and 100% recall), while the SI and SWEAT remained sensitive but weak in identifying non-TS conditions. TTI was the most stable index in November and December, with 100% recall and a precision above 60%. Meanwhile, CAPE and LI showed moderate performance, with fluctuating accuracy and precision values over the past two months.

The performance of the stability indices at MIA is widely consistent with previous studies across other Indonesian regions. For instance, the high sensitivity (recall >88%) of KI and SI at MIA aligns with findings from (Bangsawan & Tjasyono HK, 2015) In Makassar, they identified specific operational ranges for KI (31.1 to 39.0) and SI (-0.1 to 3.0) during periods with frequent thunderstorm activity.

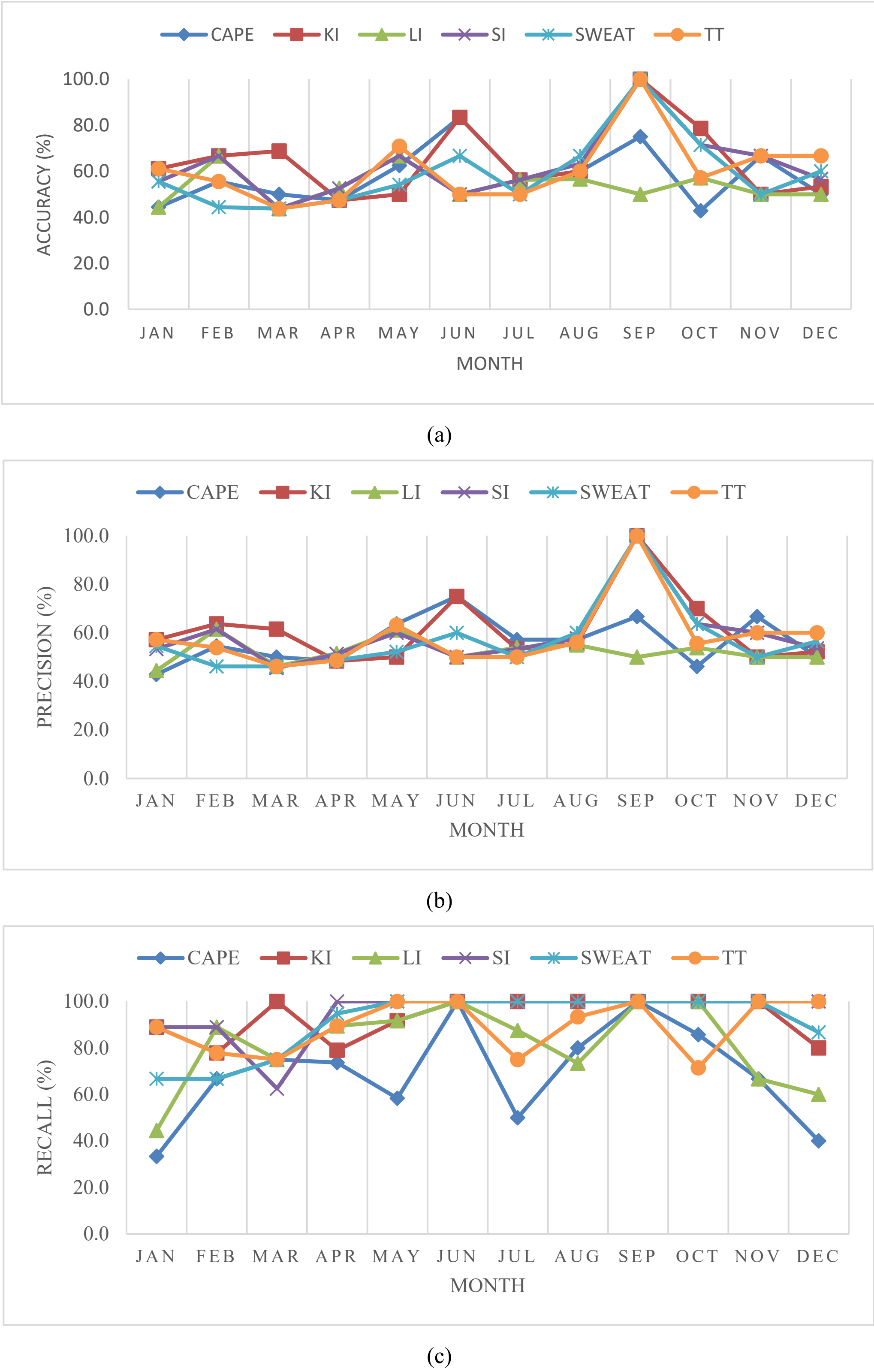

Figure 2. Performance results of each index: (a) accuracy, (b) precision, and (c) recall.

Our results, which indicate unstable conditions for KI values >34 and SI values <0, affirm the reliability of these indices for thunderstorm prediction in the Indonesian maritime continent. The Lifted Index (LI) exhibited moderate predictive capability in the study area, establishing an instability threshold of approximately -3.0. This result aligns closely with findings from previous research, which identified LI thresholds of -3 in Merauke (Putri & Pratama, 2016) and ≤ -2.4 at Iskandar Airport (Zahrina et al., 2017). In a similar vein, the unstable threshold for the Severe Weather Threat (SWEAT) index, set at >210 for the study area, is comparable to the >215.9 threshold identified at Iskandar Airport (Zahrina et al., 2017).

3.2 Atmospheric Stability Index Recommendations for Thunderstorm Event Prediction

In January to April, the most recommended indices for detecting TS in West Sumatra are KI and SI due to their sensitivity to temperature and humidity instability in the lower to middle layers of the atmosphere, as shown in Table 3. KI and SI show the best statistical performance with high recall and moderate precision. The TTI index can also be used as a support, as it provides an early signal of moderate to severe storm potential. In contrast, LI, CAPE, and SWEAT are less recommended because they are too sensitive to surface moisture, which tends to over-predict or produce false positives. In February, LI became more accurate as surface moisture became more variable, which was supported by the Madden-Julian Oscillation (MJO) contribution. March to May showed variations in performance: KI remained dominant in March, while April relied on a combination of KI and LI, and May put TTI and SI as the main predictors due to their 100% recall and sensitivity to tropical atmospheric instability that began to be influenced by easterly winds.

Table 3. Index Recommendation

Month	Main Index	Supporting Index
January	KI, SI	TTI
February	KI, SI, LI	TTI
March	KI	-
April	LI, KI	SI
May	TTI, SI	LI
June	KI	CAPE
July	SWEAT, TTI	KI, LI
August	SWEAT, TTI	KI, LI
September	SWEAT, TTI	KI, SI
October	SWEAT, KI	TTI, SI
November	TTI, SWEAT	KI, SI
December	TTI	SI, KI

Entering June-December, the performance of the index shifted with the dynamics of the atmosphere. June is dominated by KI with high accuracy and low false positives, and CAPE is effective due to the support of local convergence. However, indices such as LI, SI, and TTI show many false signals. July to September is characterized by shear-driven convection, making SWEAT and TTI the main indices, while in October, SWEAT remains relevant and TTI starts to weaken. November saw a return to the strength of TTI as the main index, as active surface heating and residual shear still favored TS formation. In December, TTI maintains its performance supported by SWEAT, SI, and KI, while CAPE and LI are generally not recommended throughout the year due to over-sensitivity to convective energy without considering important local drivers such as shear and mechanical lifting.

The finding that KI and SI serve as effective primary predictors during the wet and transition seasons (January-April) is consistent with research by (Bangsawan & Tjasyono HK, 2015) In Makassar. That study also highlighted the transition season as a dominant period for thunderstorms and identified specific operational ranges for both indices. This consistent high performance of thermodynamically-driven indices during periods of significant convective activity is a characteristic feature of the Indonesian maritime continent.

3.3 Comparison of Atmospheric Stability Indices Performance Between Global Thresholds and Local Thresholds

Based on the comparison graph of recall values between global and local atmospheric stability indices from January to December, it can be seen that the local indices consistently show higher performance in detecting TS in the study area. The KI and LI indices show local recall achievements of 100% in some months, reflecting high sensitivity to local atmospheric dynamics.

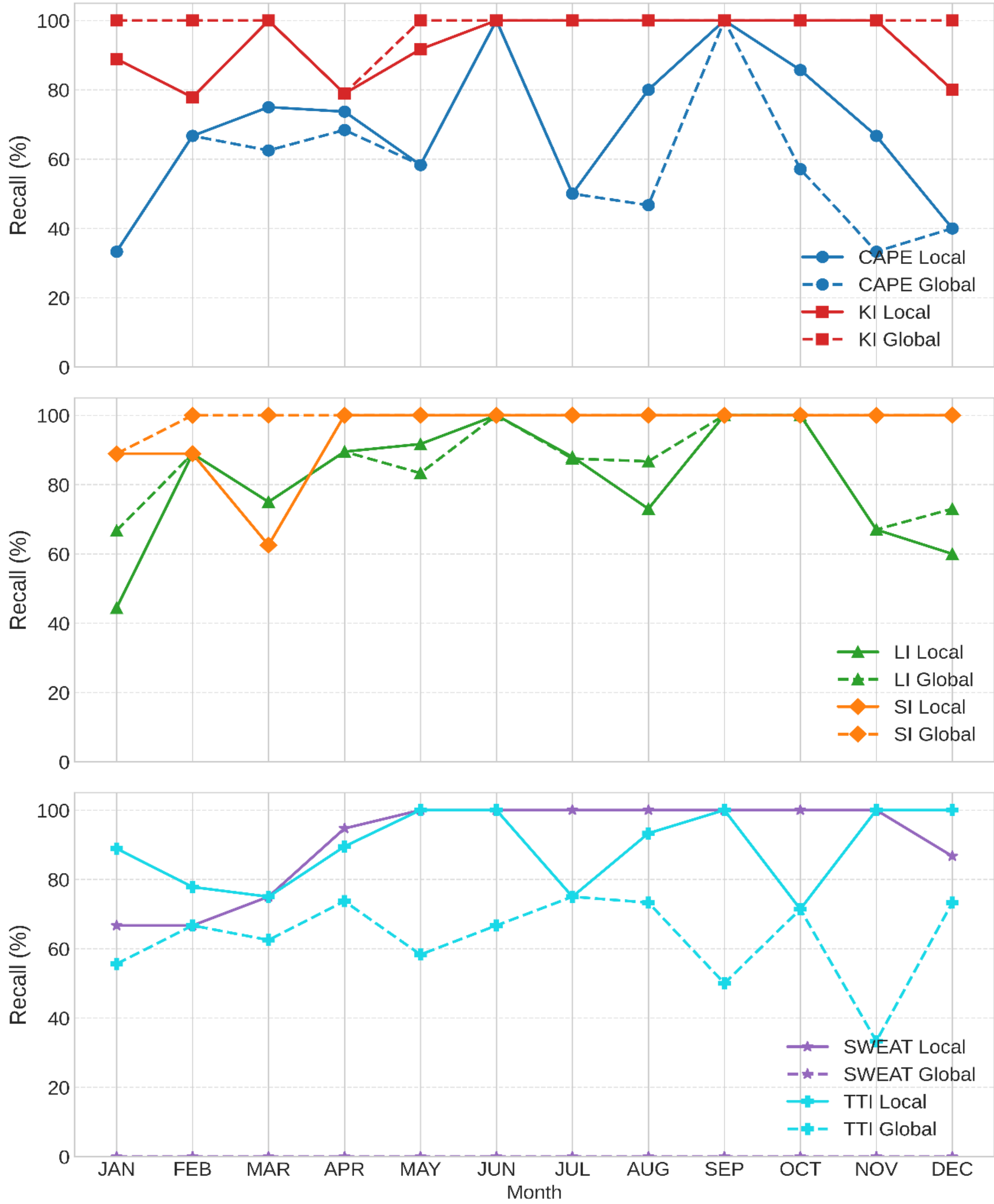

Figure 3. Comparison of recall between globally and locally calibrated atmospheric stability indices at MIA.

The SI and TTI indices also show relatively stable performance, with TTI tending to excel during the dry season (July-November), where shear-driven convection is more dominant. In contrast, the SWEAT and CAPE indices show significant fluctuations. Global recall values for these two indices tend to be low, even approaching zero in some months, while local recall values show a significant increase, indicating that the local approach is more effective in identifying potential TS than the global approach.

Overall, these results confirm that the use of locally calibrated indices is more adaptive to the maritime tropical atmospheric characteristics in the West Sumatra region, which is characterized by high humidity and local-scale convection patterns. KI was recorded as the index with the most consistent performance throughout the year and is recommended as the main indicator in the TS early detection system.

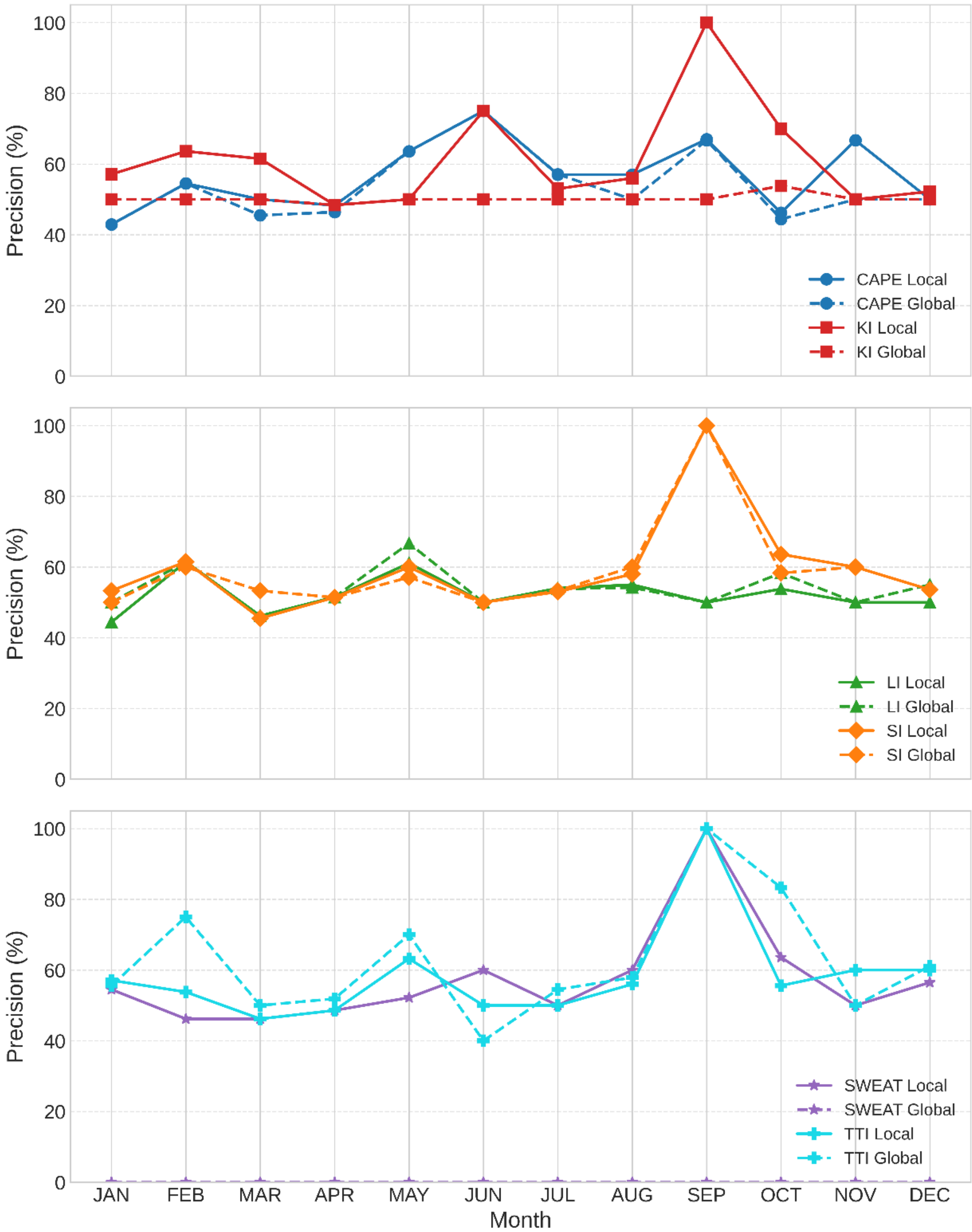

Figure 4. Comparison of precision between globally and locally calibrated atmospheric stability indices at MIA.

The unstable performance of SWEAT and CAPE, especially in the context of global indices, indicates the need for adjustment to local atmospheric parameters, such as vertical humidity, surface convergence, and mid-layer winds. Therefore, the use of locally based atmospheric stability indices is considered more representative in supporting extreme weather forecasts in the wet tropics. Based on the comparison graph of the precision values of various global and local atmospheric stability indices during the period January to December, as shown in Figure 4, it can be seen that the precision of local indices tends to be higher and more stable than that of global indices.

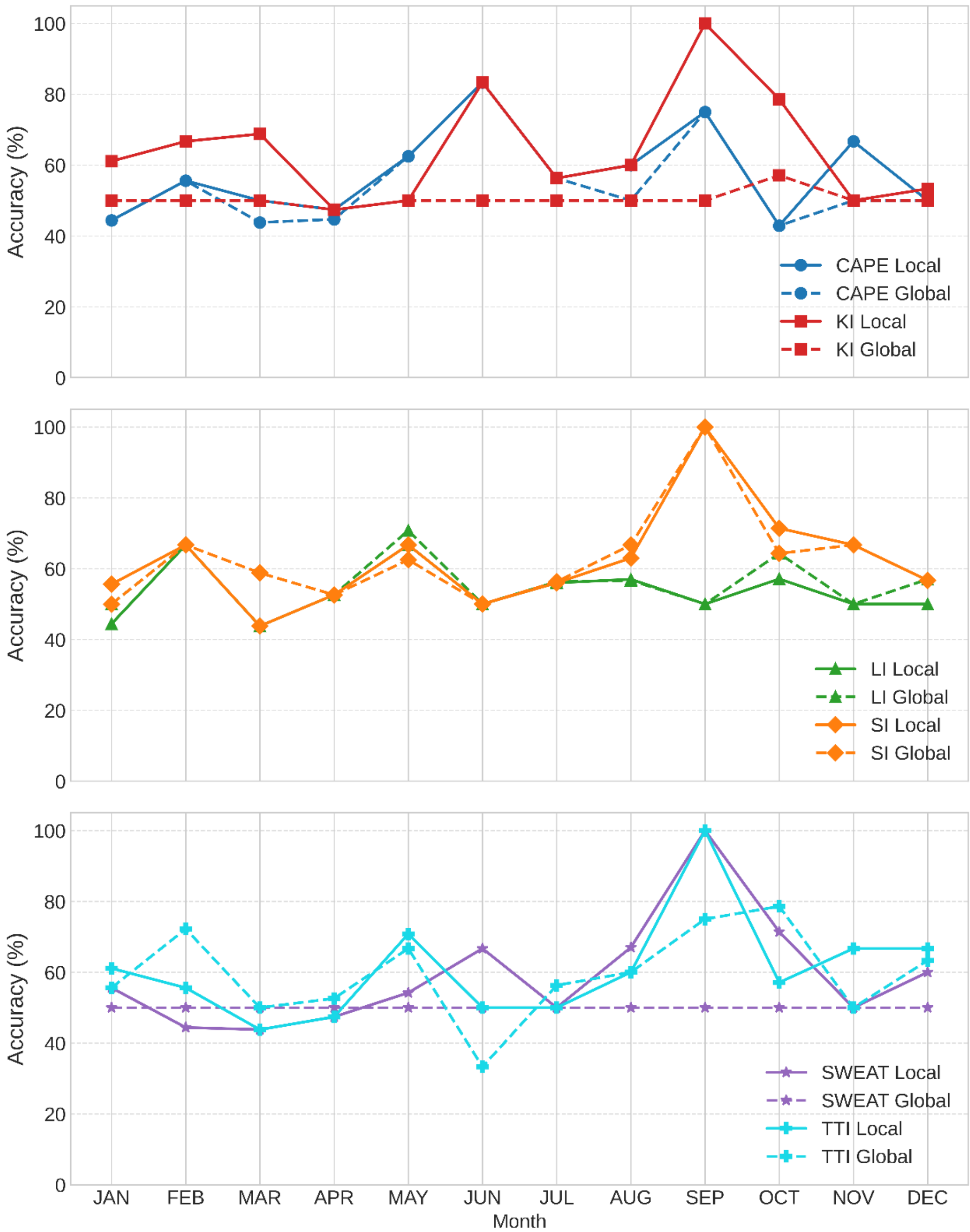

Figure 5. Comparison of accuracy between global and locally calibrated atmospheric stability indices at MIA.

The KI and LI indices show consistent precision performance with values ranging from 50-75% in the local approach, especially in March, June, and November. Meanwhile, the global indices show larger fluctuations and generally lower precision values. The SWEAT and CAPE indices, especially in the global scheme, often recorded low or even zero precision, showing a tendency to generate high false positive signals. This indicates that the global indices have limitations in adjusting to the complex variability of the tropical atmosphere.

On the other hand, the local approach produces precision that is more representative of actual atmospheric conditions in maritime tropical regions such as West Sumatra. The TTI and SI indices in the local format show a significant increase in precision in the transition months and dry season, indicating good sensitivity to seasonal convection patterns and shear changes. The superior performance of the local indices reflects the importance of adjusting the index parameters to local factors such as vertical humidity, mid-layer temperature, and wind dynamics. Thus, the use of locally calibrated atmospheric stability indices better guarantees the accuracy in detecting potential extreme weather events, and is more effective for application in early forecast systems in the tropics.

Based on the comparison graph of global and local atmospheric stability index accuracy values from January to December, as shown in Figure 5, it can be seen that locally calibrated indices tend to provide higher and consistent accuracy results throughout the year. The KI index shows the best accuracy performance in the local approach, especially in March, June, July, and September, with achievements close to or reaching 100%. The LI and SI indices also recorded relatively stable local accuracy values, ranging from 60-75% in most months.

In contrast, the global approach shows larger fluctuations in accuracy, with lower values, especially for the SWEAT and CAPE indices, which in some months only reach 40-50% accuracy. This indicates that the global model is less adaptive to local atmospheric variability in tropical regions such as West Sumatra. In general, indices developed or calibrated based on local atmospheric conditions are superior in representing regional weather realities in both wet and dry seasons. In the transition months, such as April and October, the local indices maintain stable accuracy, while the global indices show higher uncertainties. The performance of the TTI indices in the local approach also shows a significant improvement in accuracy in the dry period (July-September), which is in line with the dominance of shear-driven convection in that period. These findings strengthen the argument that the adaptation of prediction models to local parameters, such as vertical humidity, mid-layer temperature, and wind structure, is crucial to improve the reliability of extreme weather forecasts based on atmospheric stability indices in the tropics.

The clear advantage of locally calibrated thresholds demonstrated in this study is consistent with previous research conducted across various regions of Indonesia. The underlying proposition—that standardized global thresholds often underperform due to substantial geographical and climatological variability—has motivated numerous region-specific investigations. Studies by Putri & Pratama (2016) in Merauke, Zahrina et al. (2017) at Iskandar Airport, Bangsawan & Tjasyono HK (2015) in Makassar, and Rusdin et al. (2023) at Sultan Hasanuddin has confirmed this principle by successfully identifying distinct and effective thresholds tailored to their respective locations.

While these earlier works underscored the necessity of localized calibration, the present study provides direct quantitative confirmation of its superiority. Systematic evaluation of local and global thresholds across accuracy, precision, and recall metrics over a complete annual cycle reveals a substantial performance gap—for example, the local K-Index achieved accuracy rates of up to 100%, whereas its global equivalent underperformed.

4. CONCLUSION

Based on the analysis of six atmospheric stability indices—CAPE, KI, LI, SI, SWEAT, and TTI—it can be concluded that the application of locally adjusted thresholds offers significant improvements in detecting TS compared to global thresholds. These local thresholds, derived through empirical calibration and statistical evaluation (involving accuracy, precision, and recall), were adapted to the unique atmospheric dynamics and weather patterns of maritime tropical regions. The local threshold demonstrated markedly superior performance; the local KI index, for instance, achieved accuracy levels approaching 100% in March, June, July, and September, while the LI index sustained precision between 50–75%. In sharp contrast, the global SWEAT and CAPE indices were less effective, with accuracies often limited to a 40–50% range and precision values that diminished to near-zero during some months. Moreover, the local threshold adjustment addressed specific limitations of certain indices; for instance, SWEAT initially failed to detect TS under global criteria but displayed full sensitivity following local threshold calibration. These results underscore the critical importance of determining local thresholds to enhance the reliability and effectiveness of early warning systems for extreme weather events in Padang Pariaman.

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