Indices for Extreme Rainfall Risk Mapping in Thailand Using XGBoost

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Abstract— **This research evaluates satellite rainfall data for monitoring heavy rainfall events in Thailand with two objectives: comparing the accuracy of CHIRPS versions 2.0 and 3.0 with ground station data, and developing an approach for creating heavy rainfall risk maps at the national level using machine learning techniques. We compared CHIRPS data with records from 92 meteorological stations of the Thai Meteorological Department between 1991-2020 and applied the XGBoost algorithm together with six ETCCDI extreme rainfall indices. Results show that CHIRPS v3.0 clearly performs better than v2.0, with correlation coefficients increasing from 0.49 to 0.56 and mean absolute error decreasing from 5.0 to 4.7 millimeters. The XGBoost model achieved 97.6% balanced accuracy when tested with independent data from 2021-2024. Analysis using SHAP methods found that consecutive wet days (CWD) was the most important predictor, accounting for 47% of decision weight. Risk maps show high-risk areas distributed across multiple regions of Thailand, corresponding with historical rainfall patterns and monsoon system influences. These research findings are useful for disaster management planning and preparedness for heavy rainfall events in different regions.**

I. INTRODUCTION

Heavy rainfall events have increased in frequency and intensity throughout Southeast Asia, resulting in more complex disaster management. Alexander et al. [1] recommended using ETCCDI indices for tracking such events, particularly in tropical zones. In Thailand, Limsakul et al. [2] found high rainfall variability along the Gulf of Thailand coast during winter, reflecting complex weather patterns. Frequent flooding problems in many areas have major economic impacts. Monitoring and surveillance still have limitations because weather station installations are not comprehensively distributed, especially in rural areas, areas far from urban zones, and mountainous areas.

Funk et al. [3, 4] developed CHIRPS to monitor droughts and extreme events globally by combining infrared satellite imagery with ground station data, providing daily rainfall data at 0.05-degree resolution since 1981. However, performance varies by region. Wu et al. [5] found limitations in Yunnan mountain areas, López-Bermeo et al. [6] identified challenges in tropical mountain regions, while Harrison et al. [7] reported good performance in Africa. Studies in Jordan [8] suggested correcting bias before analyzing extreme events.

Machine learning techniques have been developed and increasingly used in meteorological work. Poola and Sekhar [9] succeeded in rainfall forecasting with XGBoost, achieving high accuracy, which aligns with this study's approach of also choosing XGBoost. Zhao et al. [10] developed methods combining XGBoost with SHAP to assess flood risk in urban areas. This approach helps understand factors influencing risk. Meanwhile, Leggesse et al. [11] tested multiple algorithms for risk mapping in Ethiopia. Additionally, integrated risk assessment has gained more attention, with Pal et al. [12] presenting an analytical framework covering both historical rainfall data and future trends, while Garcia-Rosabel et al. [13] highlighted the importance of considering social factors alongside physical factors.

From these advances, however, CHIRPS v3.0 has never been tested for performance in Thailand. Additionally, no previous studies have combined ETCCDI indices with machine learning techniques to assess risk at the national level. Therefore, this study has two objectives: (1) comparing the accuracy of CHIRPS versions 2.0 and 3.0 with ground station data, and (2) developing extreme heavy rainfall risk maps using XGBoost algorithms.

II. METHODOLOGY

The research methodology consisted of four main steps. First, we collected and prepared two datasets: CHIRPS satellite rainfall data (versions 2.0 and 3.0) covering 1991-2024 at 0.05-

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degree resolution, and ground station data from 92 Thai Meteorological Department stations between 1991-2020.

Second, we evaluated CHIRPS performance by comparing both versions against TMD station data using statistical metrics including Pearson correlation coefficient, mean absolute error, bias, and false alarm ratio, with analysis covering all five regions of Thailand.

Third, we developed a risk assessment model by calculating six ETCCDI extreme rainfall indices from CHIRPS v3.0 data, then trained an XGBoost classifier using data from 1991-2020, analyzing feature importance through SHAP methods to understand which indices contributed most to risk classification.

Finally, we validated the model using independent data from 2021-2024 and generated national-scale risk maps, identifying areas with composite risk scores exceeding the 75th percentile as high-risk zones.

A. Study Area and Data

The study covers all five regions of Thailand: North, Central, Northeast, East, and South. Data sources comprise:

- CHIRPS v2.0 and v3.0 daily rainfall data at 0.05° × 0.05° resolution (approximately 5.5 kilometers) for 1991-2024
- Daily rainfall data from 92 weather stations of the Thai Meteorological Department (TMD) for 1991-2020

B. CHIRPS Performance Assessment

We compared both CHIRPS versions against TMD station data using statistical metrics:

- Pearson Correlation Coefficient (CC): measures linear relationship
- Mean Absolute Error (MAE): measures average prediction error
- Bias: measures systematic over- or under-estimation
- False Alarm Ratio (FAR): measures incorrect rain detection

C. ETCCDI Indices Calculation and Risk Mapping

Six ETCCDI indices were calculated from CHIRPS v3.0 following Alexander et al. [1]:

1. Rx1day: maximum 1-day rainfall (mm)
2. Rx5day: maximum 5-day consecutive rainfall (mm)
3. R90mm: days with rainfall ≥90 mm (adapted from R100mm based on TMD criteria)
4. R95pTOT: proportion of rainfall from days exceeding 95th percentile (%)
5. CWD: maximum consecutive wet days (days)
6. PRCPTOT: annual total precipitation (mm)

A composite risk score was created giving equal weight to all six indices, following integrated multi-indicator risk assessment approaches. High-risk areas were defined by composite scores at the 75th percentile.

D. XGBoost Model and Evaluation

Temporal data splitting was used to avoid data leakage, dividing data into a training set from 1991-2020 and a test set from 2021-2024. XGBoost performance was compared with logistic regression as a baseline model. Performance metrics used for evaluation included Balanced Accuracy for measuring accuracy adjusted for class imbalance, ROC-AUC for measuring area under the ROC curve, Brier Score for measuring probability calibration accuracy, and PR-AUC for measuring area under the precision-recall curve. Additionally, feature importance was analyzed using SHAP (SHapley Additive exPlanations) following the approach of Zhao et al. [10].

III. RESULTS

A. CHIRPS v3.0 versus v2.0 Performance

CHIRPS v3.0 showed clear improvements over v2.0 across all regions. Table 1 presents the detailed performance comparison, with average correlation increasing from 0.49 to 0.56.

Table 1 CHIRPS Performance Comparison by Region

Region	Stations	Correlation Coefficient		Mean Absolute Error		Bias		False Alarm Ratio	
		v2	v3	v2	v3	v2	v3	v2	v3
Southern	18	0.53	0.64	6.40	5.70	-0.28	-0.11	0.30	0.42
Eastern	12	0.47	0.55	6.20	5.70	-0.27	-0.04	0.29	0.45
Northern	24	0.47	0.54	4.40	4.00	-0.04	0.01	0.26	0.48
Central	13	0.47	0.52	4.30	4.10	0.00	-0.11	0.30	0.47
Northeastern	25	0.51	0.55	4.50	4.40	-0.13	0.00	0.27	0.48
Overall	92	0.49	0.56	5.00	4.70	-0.14	-0.04	0.28	0.46

The southern region showed the largest improvement (0.53 to 0.64, or +21%). Bias improved from -0.14 to -0.04 mm, indicating better accuracy. While FAR increased, this reflects the new algorithm's sensitivity to light rainfall.

B. Model Performance and SHAP Analysis

The XGBoost model demonstrated strong performance on the independent test set from 2021-2024. Table 2 compares the performance metrics between XGBoost and logistic regression baseline model. Both models achieved high accuracy, with

XGBoost reaching 97.6% balanced accuracy and logistic regression achieving 98.7%.

Table 2 Model Evaluation on Independent Test Set (2021-2024)

Model	Accuracy (BalancedAcc)	ROC-AUC	Brier Score	PR-AUC
XGBoost	0.976	0.997	0.018	0.997
Logistics (baseline)	0.987	0.999	0.009	0.999

Risk class predictions shown in Table 3 demonstrate how the model handles different categories. F1-scores reached 0.980 for low-risk and 0.974 for high-risk groups. SHAP analysis in Figure 1 highlights an unexpected finding - CWD index dominates decision-making at 47%, yet R90mm contributes just 1%. This disparity suggests the model prioritizes rainfall duration over single-day intensity when assessing risk patterns.

Table 3 Evaluation of model performance by class (independent test set, 2021–2024)

Class	Precision	Recall	F1-score
Low-risk	0.969	0.990	0.980
High-risk	0.987	0.962	0.974
Avg	0.978	0.976	0.977

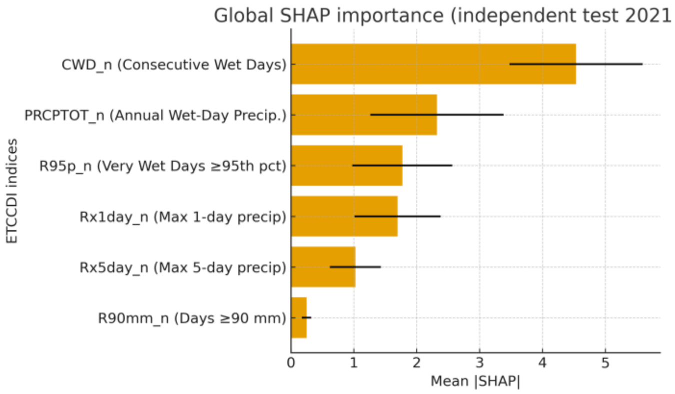

Fig. 1 Displays the SHAP importance analysis results. SHAP analysis clearly shows CWD dominance over other indices, accounting for nearly half of total decision weight.

C. *Spatial Distribution of Risk*

Fig. 2 presents the spatial distribution of extreme rainfall risk across Thailand. Risk maps from composite scores of all six ETCCDI indices show high-risk areas (composite score ≥P75) distributed across multiple regions. High-risk zones are found in the eastern region, southern coastal areas, as well as some parts of central and northeastern regions, while the northern region shows limited high-risk coverage. This spatial pattern corresponds with historical rainfall patterns and monsoon influences.

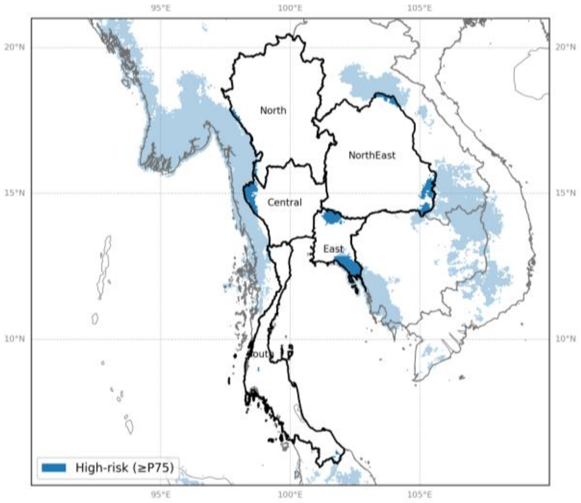

Fig. 2 Spatial risk map of extreme rainfall in Thailand. Areas with composite scores ≥75th percentile are shown in blue, indicating high-risk zones.

IV. DISCUSSION

The results demonstrate that CHIRPS v3.0 shows clear performance improvement compared to v2.0, particularly in southern Thailand where correlation increased by 21%. This improvement aligns with reports by Funk et al. [4] stating that increased reference station numbers and algorithm development enhance CHIRPS accuracy. However, limitations persist in mountainous areas, consistent with findings by Wu et al. [5] in Yunnan and López-Bermeo et al. [6] in tropical mountain regions of South America.

The developed XGBoost model achieved 97.6% balanced accuracy when tested on 2021-2024 data. This high performance may result from data characteristics and risk area definition methods using the same ETCCDI indices. However, SHAP analysis shows the model assigns different importance weights among indices, with CWD accounting for 47% while R90mm only 1%. This difference suggests the model may capture certain patterns of heavy rainfall occurrence. Temporal data splitting without overlap helps reduce data leakage problems, though additional testing with data from other sources would help confirm performance.

The dominance of CWD aligns with work by Limsakul et al. [2] who found Thailand's monsoon systems typically cause rainfall continuing for several days rather than single-day heavy rain. This finding has significant implications for warning systems, which should focus on monitoring continuous rainfall rather than only watching for very heavy rain days. Using the R90mm criterion from the Thai Meteorological Department, which defines rainfall from 90.1 millimeters upward as very heavy rain, is appropriate for Thailand's tropical monsoon climate.

The developed risk map reveals high-risk areas distributed across multiple regions of Thailand, reflecting the complex interplay of monsoon systems and geographical factors. These findings can be applied for disaster management planning, where areas with elevated risk should be considered for appropriate infrastructure development and warning system implementation. Using SHAP methods following Zhao et al. [10] allows users to understand which factors influence risk area classification, increasing model credibility and transparency.

V. Conclusions and Recommendations

CHIRPS v3.0 shows significant performance improvement over v2.0 for rainfall estimation in Thailand, especially in the southern region with the highest improvement. Integration of ETCCDI indices with XGBoost and SHAP can accurately identify risk areas, with CWD being the most important factor at 47% of decision weight.

Risk maps show high-risk areas distributed across multiple regions of Thailand, reflecting the influence of different monsoon systems and geographical factors in each area. This information is important for spatial disaster management planning and infrastructure development appropriate to each region's risk level.

VI. STUDY LIMITATIONS AND FUTURE WORK

This study has not yet considered other climate variables and topographic data that may affect rainfall intensity. Additionally, the model cannot yet provide seasonal forecasts. Models should be developed to include additional variables such as topographic and other climate data, develop seasonal forecasting capabilities, and study impacts of climate change on rainfall patterns and frequency, including air pollution influences that may affect rain formation and intensity.

VII. ACKNOWLEDGMENT

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