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Predictive modeling of unrest situation in a Southern province of Thailand using machine learning models

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Abstract: The southern provinces of Thailand continue to experience persistent unrest and insurgency, creating an urgent need for reliable forecasting methods to support decision-making. This study aims to improve the forecasting of unrest and insurgency cases by evaluating alternative model selection approaches using unrest databases. We analyzed records of deaths, incidents, and injuries from 2004 to 2019 across all 12 districts of Pattani province, employing Artificial Neural Networks (ANN), Support Vector Regression (SVR), and Autoregressive Integrated Moving Average (ARIMA) models. Forecasting accuracy was assessed using the mean square error criterion. The findings indicate substantial variation in the monthly time series of deaths, incidents, and injuries, with the ARIMA model consistently producing the most accurate forecasts for injuries across districts. These results underscore the importance of model choice when applying forecasting techniques to conflict-related datasets. In conclusion, ARIMA offers a robust and practical approach for anticipating short-term unrest trends. The study has practical implications for policymakers, security agencies, and researchers seeking evidence-based strategies to anticipate and mitigate the effects of insurgency in southern Thailand.

Keywords: *Insurgency, Machine learning model, Southern border provinces, Thailand, Unrest situation.*

1. Introduction

Over the past decade, insurgent issues have escalated across various countries and regions worldwide. Recent areas experiencing ongoing unrest and insurgency crises include Africa (Algeria, Burkina Faso, Burundi, Cameroon, the Democratic Republic of Congo, Libya, Mali, Mozambique, Niger, Nigeria, Uganda, Chad, Tanzania, and Tunisia), Asia (Afghanistan, Bangladesh, Indonesia, Iraq, Nepal, Turkey, Thailand, and the Philippines), South America (Colombia), and Europe (Chechnya). In Thailand, the southernmost region has been grappling with one of Asia's longest-running conflicts. In the 1960s, a separatist movement emerged to establish the region, whose inhabitants are predominantly Muslim, as an independent state. Since the conflict began, levels of violence have increased, with multiple insurgency waves occurring from the early 2000s to the present. This persistent unrest in Southern Thailand has prompted various organizations and agencies to investigate the origins of insurgency, the societal factors driving it, and practical strategies to counter it. Preventing the emergence of unrest or insurgency in a region or country is a highly complex process requiring a deep understanding of its underlying causes [1]. In the past two decades, several studies have employed hybrid methodologies to gain a deeper understanding of the emergence and escalation of unrest and insurgency. For example, Waeto, et al. [2] combined support vector regression (SVR) and autoregressive integrated moving average (ARIMA) models to forecast insurgency trends in Southern Thailand, while Domrongphol and Yared [3] applied the Variable Relation Model (VRM) to analyze violence levels in the Pattani, Yala, and Narathiwat provinces from 2010 to 2018.

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In computational studies, Chaturvedi, et al. [4] employed agent-based modeling (ABM) to examine the interactions among government agencies, firms, and adversaries in scenarios of unrest and insurgency. Giabbanelli [5] developed a computational framework to address the numerous relevant interactions and approaches for modeling the spatial and social dynamics of insurgency. Davis, et al. [6] demonstrated that incorporating computational models into unrest and insurgency analysis enables flexible scenario and behavioral analysis across various contexts. Although data on insurgency and predictive modeling techniques have rapidly expanded, their application has not yet yielded fully effective early warning systems.

This study addresses this gap by analyzing and forecasting unrest data, including deaths, incidents, and injuries, from 12 districts in Pattani Province, Southern Thailand. Forecasting is conducted using SVR, ANA, and ARIMA models. For each dataset, the mean squared error is used as a criterion for forecasting accuracy, incorporating different characteristics levels, slopes, and epsilon derived from a structural time series model.

2. Literature Review

Mathematical modeling plays a crucial role in understanding the dynamics of insurgency, with researchers developing models for various applications [7, 8]. Traditional warfare models used for insurgency, such as the Guerrilla Warfare model and the McCormick and Giordano model, are based on the Lanchester equations Misra [9] and Bettencourt, et al. [10]. Atangana and Gómez-Aguilar [11] employed a nonlinear mathematical model to study the effect of police force on crime, deriving an explicit expression for the critical baseline police force needed to combat crime. Misra and Singh [12] developed a simple yet realistic mathematical model for unemployment based on real data from Portugal, reaching significant conclusions. These practical applications of mathematical modeling enhance both understanding and real-world implications.

More recently, Galindro and Torres [13] employed a compartmental modeling approach to examine the radicalization of terrorism, demonstrating how multiple ideologies interact to influence the recruitment and persistence of extremist groups. Similarly, Wang and Bu [14] employed time-series forecasting and control chart methods to analyze the Boko Haram insurgency in Nigeria, demonstrating the value of ARIMA and SARIMA models in anticipating trends in violent conflict. Braimah, et al. [15] and Johnson, et al. [16] statistically analyzed incidents within insurgent conflicts, revealing power law scaling indicative of scale invariance. This suggests insurgent conflicts may share common characteristics. Clauset, et al. [17] presented an analytical particle model for the dynamic evolution of insurgent populations, emphasizing group dynamics of fragmentation and coalescence. Their model suggests counterinsurgency (COIN) efforts should prioritize breaking insurgent movements into smaller groups. Conversely, Bohorquez, et al. [18] proposed that larger, more experienced insurgent organizations conduct more frequent and deadlier attacks. Their mathematical model describes feedback mechanisms between attacks, recruitment, and experience, indicating that limiting the growth of insurgent groups is most effective early in conflicts. While these analytical models provide valuable insights, their operational validity is limited by challenges in assessing the actual impact of COIN efforts on insurgent group behavior.

Clauset and Gleditsch [19] explored the spatial-temporal analysis of insurgent conflicts, addressing the tactical decisions made by insurgent groups. They suggest attacks with improvised explosive devices cluster in time and space due to dynamics such as competition for popular support, rather than solely COIN provocations. However, these approaches are limited in their ability to analyze adaptive reactions, focusing mainly on attack tactic patterns. Network analysis in conflict studies examines the structural properties and internal dynamics of insurgent groups. Dynamic network models aim to unravel internal dynamics and identify COIN tactics to disrupt these groups. Braithwaite and Johnson [20] provided dynamic network analysis models for insurgent networks adapting to COIN efforts. Despite their potential, operational validation remains limited due to a lack of calibration and testing with actual data. Ilachinski [21] proposed one of the initial system dynamics models (SDM) to help researchers understand emergent patterns in insurgent conflicts. Their model examines the emergence of insurgent movements, the development of regime resilience, and the dynamic interaction between insurgent pressures (load) and regime capabilities (resilience).

A review of the literature reveals various methods proposed to solve insurgency problems. However, because insurgency features vary by region, none of these methods has proven effective universally. According to Choucri, et al. [22] different algorithms applied to solve a problem can yield different outcomes, with one method performing better than another depending on context. Wolpert [23] applied this concept to tourism data, which shares behavioral characteristics with data on violence. Multiple factors affect the performance of different methods; therefore, identifying such factors is crucial for selecting accurate methods applicable to various problems.

3. Materials and Methods

3.1. Data Description

In this study, we utilized monthly incident, injury, and death data from Pattani Province, covering the period from 2004 to 2019. These datasets were utilized for data validation, with detailed information collected daily, including the nature of the event and specific information about the individuals affected by the incident.

3.2. Statistical Analysis

The data used in this study include monthly incident, injury, and death data for each of the 12 districts in Pattani Province, providing valuable insights into the dynamics of civil unrest during the study period. The districts were the same three datasets. For this study, we will analyze the data for all 12 districts simultaneously across the three datasets of monthly incidents, injuries, and deaths—research steps designed to compare different forecasting methods.

1. Data management includes the Monthly number of incidents, deaths, and injuries, classified by district, including 12 districts in Pattani province

2. Preliminary statistical analysis of data and checking of model construction conditions for data in step 1

3. Creating a model from compacting the data in step 1 to find model parameters, analyzing and comparing forecast results with the Structural model, the ARIMA model, the ANN models, and the SVM.

4. Analysis and comparison of the prediction results from the model created in the third step by dividing the training data and the prediction data in the proportion of 70:30

5. Creating modeling rules based on epsilon, level, and slope, selected as 3 features used to create rules and tolerances for forecasting.

Training machine learning models, including Support Vector Machines. It offers various preprocessing functions and evaluation metrics that aid model selection and optimization. The SVM command in the caret library was used to divide the train-to-test dataset at a ratio of 75:25 and to fit a Support Vector Machine model to the data. These programs and packages were selected based on their effectiveness in managing the data analysis required for the study. The choices were based on the study's requirements and the compatibility of the packages with R. Overall, these programs and packages were utilized to ensure accurate data analysis and effective presentation of the findings.

3.3. Autoregressive Integrated Moving Average (ARIMA)

In 1970, George Box and Gwilym Jenkins introduced a methodology to analyze the probabilistic, or stochastic, properties of time-series data under the philosophy "let the data speak for themselves," which later became popularly known as the Box–Jenkins (BJ) methodology based on autoregressive (AR) and moving average (MA) models [24]. The ARIMA model is widely used for time series forecasting due to its ability to handle non-stationary data by differencing and combining autoregressive and moving average components [25].

An AR(p) model assumes that the output variable depends linearly on its p-lagged values. In contrast, an MA(q) model expresses the output variable as a linear combination of q-lagged disturbance or error terms. It is also possible that a time series is best described by a combination of both AR(p) and MA(q) components, leading to the ARMA(p, q) model. The flexibility of this methodology allows explicit identification of whether a time series follows an AR, MA, or ARMA process.
For a time series (Y_t), the functional form of an ARMA(p, q) model is:

$$y_t = \emptyset_1 y_{t-1+} \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + w_t = \sum_{i=1}^{p} \emptyset_i y_{t-i} + w_t$$

Where y_t is stationary, $\emptyset_1, \dots, \theta_p$ are constants ($p \neq 0$), and w_t is Gaussian white noise series with mean zero. The auto-regressive moving average (ARMA) model, abbreviated as ARMA (p, q), combines the autoregressive and moving average models and is in the form:

$$y_t = \theta_1 w_{t-1+} \theta_2 w_{t-2+} + \cdots + \theta_q w_{t-q+} + w_t = \sum_{j=1}^{q} \theta_j w_{t-j} + w_t$$

Where y_t is stationary $\theta_1, \dots, \theta_j$ θ_p are constants ($q \neq 0$), and w_t is Gaussian white noise series with mean zero. The auto-regressive moving average (ARMA) model, abbreviated as ARMA (p, q) , combines the autoregressive and moving average models and is in the form:

$$y_t = \delta + \sum_{i=1}^{p} \emptyset_i y_{t-i} + \sum_{j=1}^{q} \theta_j w_{t-j} + w_t$$

3.4. Artificial Neural Network Models

Artificial Neural networks (ANNs), inspired by neurobiology, have become prominent tools in machine learning and artificial intelligence [26]. NNs require carefully structured input; missing values in the test data must be handled, commonly by imputation with default or average values, as the network cannot function properly otherwise.

In this study, 12 lagged inputs, selected based on the SARIMA model results, were used as input features for the neural network. The architecture of the NN is defined by the number of hidden nodes, which can be mathematically determined by:

$$H_{max} = M_{data}/2(J + 2)$$

Where J is the number of lags, and M_{data} denotes the number of elements in the training set.

Beyond traditional NNs, deep learning techniques have gained prominence due to their ability to learn complex, hierarchical features and achieve superior performance across many domains [27]. Unlike conventional NNs, deep neural networks (DNNs) consist of multiple hidden layers, enabling the learning of multifaceted representations from simpler concepts [28, 29]

3.5. Support Vector Regression

Support vector regression (SVR) is a supervised machine learning method that addresses regression issues. SVR is beneficial for examining the connections between a dependent variable and one or more independent variables by framing an optimization problem. It is advantageous as it balances model complexity and prediction error, demonstrating strong performance, particularly with high-dimensional data.

For linear regression, the function f is approximated as:

$\tilde{f}(x) = w^T x + b \quad w \in R^d, b \in R$

Where w is the weight vector, and *b* is constant. SVR can also handle nonlinear regression problems by applying a transformation function Φ from the input space to higher- dimensional feature space J: $\tilde{f}(x, w) = < w, \ \Phi(\mathrm{x}) > +\mathrm{b}$

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4. Results and Discussion

This section evaluates the forecasting accuracy of SVR, ARIMA, and NN models. The analysis focuses on the incidents, deaths, and injuries in the Pattani dataset. Detailed information for each dataset is presented in tabular form to provide a comprehensive overview.

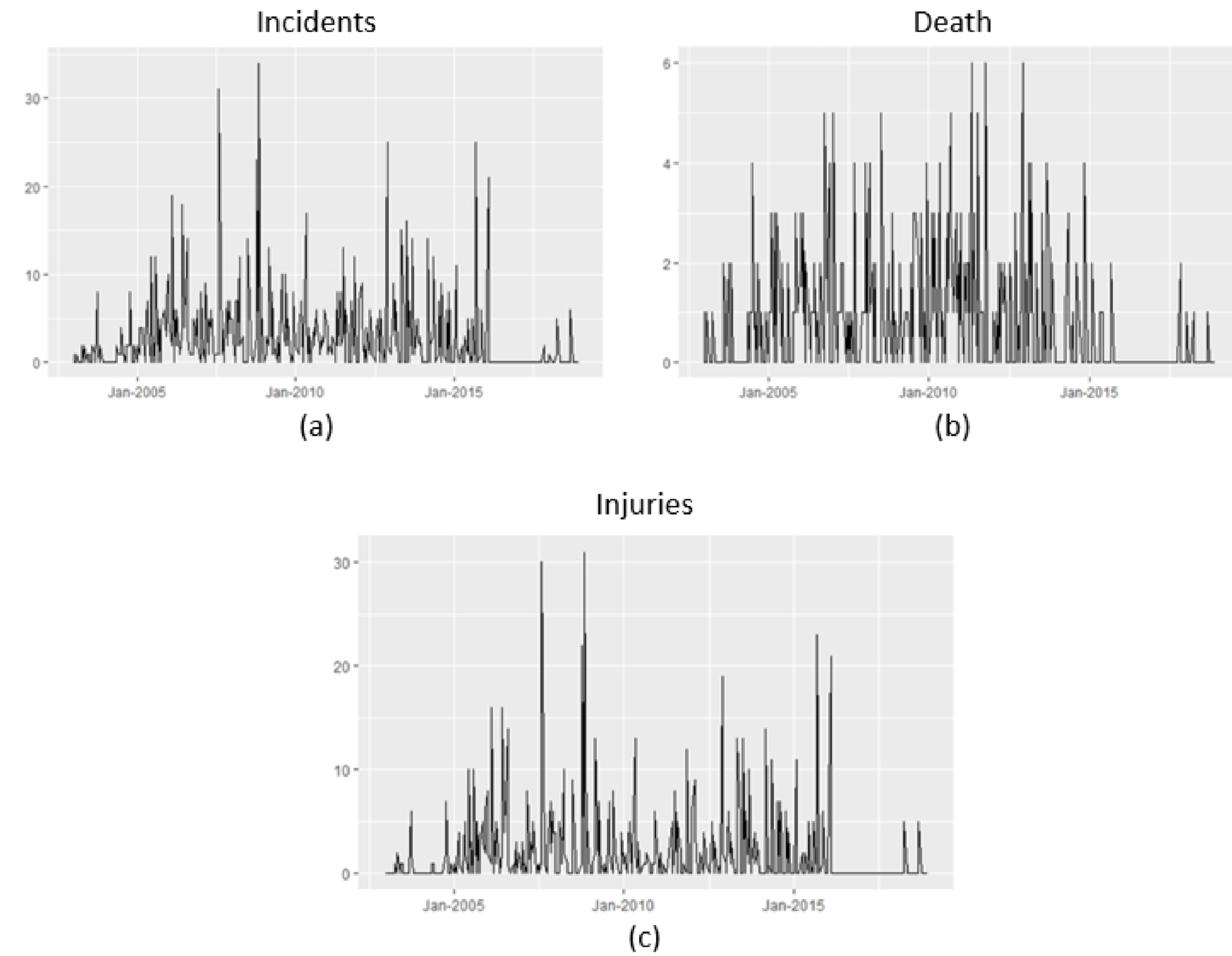

Figure 1.
Time series of unrest in Khok Pho district, Pattani: (a) Monthly incidents, (b) Monthly deaths, and (c) Monthly injuries.

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Table 1.
Descriptive statistical analysis of three key variables related to civil unrest, incidents, injuries, and deaths across 12 districts in Pattani Province.

Variable	District	Mean	S.D.	Median	IQR	Minimum	Maximum
Incidents	Kapho	1.472	2.218	1.000	2.000	0.000	16.000
	Khok Pho	4.135	5.086	3.000	4.000	0.000	46.000
	Mae Lan	0.590	1.381	0.000	1.000	0.000	12.000
	Mai Kaen	0.962	1.974	0.000	1.000	0.000	15.000
	Mayo	2.385	2.534	2.000	3.000	0.000	19.000
	Muang Pattani	4.705	4.680	3.000	5.000	0.000	22.000
	Nong Chik	4.731	4.592	3.000	4.000	0.000	36.000
	Panare	2.276	2.169	2.000	2.000	0.000	9.000
	Sai Buri	5.122	5.108	4.000	4.000	0.000	28.000
	Thung Yang Daeng	1.596	1.973	1.000	3.000	0.000	11.000
	Yarang	6.487	6.493	4.500	7.000	0.000	39.000
	Yaring	2.782	3.438	2.000	3.000	0.000	22.000
Injury	Kapho	1.322	3.072	0.000	1.000	0.000	21.000
	Khok Pho	3.038	4.905	1.000	4.000	0.000	30.000
	Mae Lan	0.519	1.892	0.000	0.000	0.000	13.000
	Mai Kaen	0.4359	1.2453	0.0000	0.0000	0.0000	7.0000
	Mayo	1.404	3.077	0.000	2.000	0.000	27.000
	Muang Pattani	5.513	10.878	2.000	6.000	0.000	80.000
	Nong Chik	2.686	3.870	1.000	3.000	0.000	27.000
	Panare	0.962	1.977	0.000	1.000	0.000	14.000
	Sai Buri	3.801	6.731	2.000	5.750	0.000	67.000
	Thung Yang Daeng	0.686	1.548	0.000	1.000	0.000	8.000
	Yarang	3.269	3.732	2.000	3.000	0.000	18.000
	Yaring	2.032	3.609	0.000	2.000	0.000	20.000
Death	Kapho	0.5722	1.1037	0.0000	1.0000	0.0000	6.0000
	Khok Pho	1.365	1.545	1.000	2.000	0.000	9.000
	Mae Lan	0.288	1.285	0.000	0.000	0.000	14.000
	Mai Kaen	0.1667	0.4930	0.0000	0.0000	0.0000	4.0000
	Mayo	1.0000	1.2287	1.0000	2.0000	0.0000	6.0000
	Muang Pattani	1.962	3.455	1.000	2.750	0.000	39.000
	Nong Chik	1.712	1.839	1.000	2.750	0.000	10.000
	Panare	1.038	1.494	0.000	2.000	0.000	8.000
	Sai Buri	1.872	2.069	1.000	3.000	0.000	10.000
	Thung Yang Daeng	0.7436	1.1798	0.0000	1.0000	0.0000	7.0000
	Yarang	2.128	2.199	2.000	3.000	0.000	13.000
	Yaring	0.9615	1.1799	1.0000	1.7500	0.0000	5.0000

Results of data compaction based on the feature level, slope, and epsilon in the structured model, along with the best predictions for forecasting between NN, SVM, and ARIMA models under appropriate conditions, are shown in Figure 1 and Table 1.

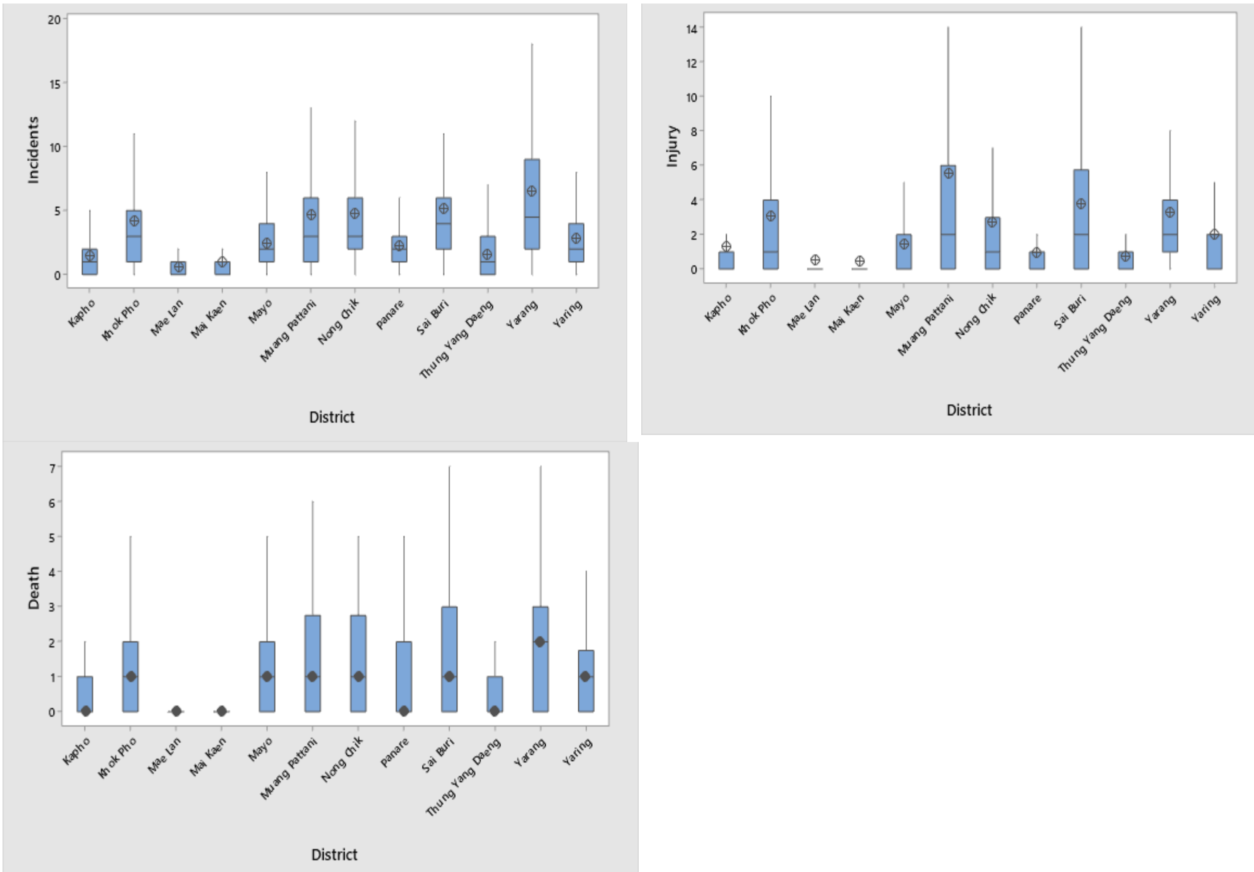

Figure 2.
Boxplot of the number of three key variables related to civil unrest, incidents, injuries, and deaths across 12 districts in Pattani Province.

Table 2.
Presents the forecasting results using the incident, injury, and death datasets.

District	Incident			Death			Injury		
	ARIMA	NN	SVR	ARIMA	NN	SVR	ARIMA	NN	SVR
Nong Chik	44.0	75.2	268.8	0.3	14.9	8.1	33.8	332.6	251.9
Sai Buri	0.8	709.1	72.6	0.0	8.2	94.1	1.1	3926.5	1686.9
Mueang Pattani	50.1	257.6	40.2	1.2	151.6	12.9	32.3	519.7	258.1
Khok Pho	0.9	154.1	1316.1	0.1	12.2	117.9	1.9	119.4	22.7
Yaring	1.3	221.3	65.7	0.4	10.9	10.9	2.9	47.9	138.3
Yarang	2.8	293.2	2218.4	1.3	38.8	17.0	0.4	36.4	16.7
Panare	4.0	55.6	41.9	0.1	36.2	21.7	3.9	96.8	31.5
Mayo	0.8	30.1	270.0	0.1	28.4	17.6	2.0	20.6	5.5
Thung Yang Daeng	0.9	68.7	10.7	0.1	24.0	3.1	0.5	1.6	5.5
Kapho	0.9	43.8	35.3	0.1	9.4	39.0	0.3	140.7	16.7
Mae Lan	0.5	16.0	36.7	2.6	NaN	0.3	0.2	15.2	19.8
Mai Kaen	0.1	59.4	6.1	0.0	1.1	5.4	0.2	NaN	29.0

For each district and variable, measures of central tendency (mean and median), variability (standard deviation and interquartile range), and range (minimum and maximum values) are reported.

The data reveal substantial variation in unrest-related incidents and their consequences, with some districts consistently experiencing higher means and maxima, indicating areas of heightened conflict intensity.

Table 3.
The results for all models using the incident dataset.

Data Set	Level	Slope	Epsilon	Best Model
Nong Chik	0.000	0.000	19.460	ARIMA
Sai Buri	0.418	0.000	48.380	ARIMA
Mueang Pattani	0.433	0.000	211.732	SVR model
Khok Pho	0.036	0.000	11.904	ARIMA
Yaring	0.355	0.000	13.350	ARIMA
Yarang	0.350	0.000	16.235	ARIMA
Panare	0.095	0.000	6.159	ARIMA
Mayo	0.115	0.000	9.882	ARIMA
Thung Yang Daeng	0.028	0.000	3.946	ARIMA
Kapho	0.123	0.000	19.086	ARIMA
Mae Lan	0.009	0.000	4.402	ARIMA
Mai Kaen	0.000	0.000	2.182	ARIMA

Tables 2 and 3 summarize the forecasting outcomes and model performance metrics for predicting incidents, injuries, and deaths across the 12 districts in Pattani Province using ARIMA, Neural Network (NN), and Support Vector Regression (SVR) models. The evaluation criteria were based on structural time series features such as level, slope, and epsilon, alongside the accuracy of the forecasts. Table 2 reveals distinct variations in forecasting performance across districts and variables. Notably, ARIMA models consistently performed best in the majority of districts when forecasting incidents, as evidenced by the lowest epsilon values and selection as the "Best Model" in Table 2. This indicates that ARIMA's capability to capture the temporal dependencies and seasonality of unrest-related incidents makes it a robust approach for such time series data in these contexts. However, exceptions were observed where SVR demonstrated superior forecasting accuracy, such as in Mueang Pattani for incidents, suggesting that machine learning methods may better capture complex nonlinear patterns or abrupt changes in some districts. The Neural Network models, while powerful in theory, frequently produced higher error values, sometimes by a large margin, especially in injury forecasting, as seen in Table 3. This may reflect issues of overfitting or sensitivity to limited or noisy data in the context of civil unrest. A closer inspection of the magnitude of errors in Table 1 reveals stark contrasts between models; for example, SVR produced extremely high error values in districts such as Khok Pho and Yarang, indicating possible instability or model misfit for specific locations or data characteristics. Conversely, ARIMA consistently maintained relatively low error rates, underscoring its reliability for structured time series with stable temporal patterns. Overall, these results highlight the importance of district-specific model selection over a one-size-fits-all approach. While ARIMA offers a dependable baseline, machine learning methods like SVR can provide valuable improvements in areas exhibiting complex or non-linear dynamics. Future forecasting efforts may benefit from hybrid or ensemble approaches that dynamically adapt to the unique data characteristics of each district, thereby optimizing prediction accuracy.

5. Conclusions

This study aims to determine the rules for forecasting the time series of incidents, deaths, and injuries of unrest in the 12 Pattani districts of Thailand. In each district, we employed the monthly time series classified from three datasets compacted using NN, SVR, and ARIMA models, respectively, with epsilon, level, and slope selected as the features. These three features were derived using the structural model. The results of the data analysis revealed a different forecast result for the monthly time series datasets. Moreover, we obtained the monthly time series of unrest incidents using the forecasting rules, level, and epsilon. However, this was not possible in the monthly time series of deaths. Amongst the three models, the ARIMA model provided the best forecast result for the injuries dataset in all Pattani districts. Although the generated forecast rules revealed the specifics of the data and guided the research through an in-depth investigation, this approach should be applied to a different dataset to further understand the methods' accuracy.

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Transparency:
The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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