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Intelligent LSTM-based deforestation prediction model and dashboard for *Kalimantan* using global forest change and night-time light data

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Abstract

Forest assessment based on predictions and evidence is an appropriate step toward environmental conservation. This study developed a Long Short-Term Memory (LSTM) based prediction model to monitor and predict forest cover and light intensity in Kalimantan. Using Global Forest Change (GFC) and Night-Time Light data, the prediction results are applied to a web-based dashboard. The data were available for the period from 2001 to 2023 and has been processed and aggregated to the provincial level. The LSTM model was trained using five optimizers, namely Adam, RMSprop, Stochastic Gradient Descent (SGD), Adadelta, and Adamax. Model performance was evaluated using Root Mean Squared Error (RMSE). The results showed that the Adam and RMSprop optimizers produced lower RMSE values compared to the other optimizers on the GFC dataset, making them more effective at learning patterns and forest cover change. On the NTL dataset, Adam, RMSprop, and Adamax demonstrated relatively similar performance due to the data's more stable characteristics. Overall, Adam provided the most accurate and consistent predictions. The prediction results are presented via a web-based dashboard that allows for the visualization of historical trends as well as predictions of change in forest cover and nighttime light intensity. These findings suggest that the combination of the LSTM model and an interactive dashboard can support more effective deforestation monitoring.

Keywords

Deforestation, global forest change, long short-term memory, night-time light, time-series forecasting

Article History

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Introduction

Forests are vital ecosystems that support human life through their biodiversity, which helps regulate the environment. Forests contribute to oxygen production, absorb atmospheric mercury, and provide suitable habitats for flora and fauna (Shrestha et al., 2025; X. Wang et al., 2022). Therefore, ecological stability and environmental sustainability must be fully preserved to achieve a healthy environment in the long term (Gupta et al., 2026; Kumar et al., 2024; Thakur et al., 2025). However, massive land-use changes, such as natural resource extraction, infrastructure development, settlement expansion, plantation expansion, and population pressure, have had a significant impact on forest ecosystems (Francesconi et al., 2022). In Kalimantan, Indonesia, significant changes in forest cover have occurred over the past few decades, particularly in areas prone to deforestation, namely, border regions, densely populated areas, and regions outside conservation zones (Singh & Yan, 2021). These changes underscore the importance of more accurate, data-driven forest cover monitoring.

Data from the Global Forest Watch report on forest cover in Kalimantan showed that forest cover declined from 73,3% to 49,5% between 2000 and 2020 (Forest Monitoring, Land Use & Deforestation Trends | Global Forest Watch, n.d.). Furthermore, a 62% contribution from grasslands, tree plantations, and commercial land expansion helped offset global forest loss during the 2005 to 2013 period. On the other hand, 26% of deforestation was driven by international demand. International trade in agricultural and forestry commodities contributes approximately 29-39% to emissions resulting from deforestation in tropical regions. This indicates that stakeholders need to develop policies that can align economic demand with emissions reduction (Pendrill, Persson, Godar, & Kastner, 2019). These patterns and data presented confirm that the ecological issues are not the sole cause of deforestation; rather, good governance must also be implemented through monitoring based on valid and reliable spatio-temporal data. Forests in Kalimantan span a vast area, making remote sensing an effective tool for identifying and assessing changes in forest cover. Satellite imagery provides evidence of land cover changes and human activities contributing to deforestation, allowing relevant parties to fully evaluate this evidence as a basis for mitigation measures and forest protection policies (Fadli et al., 2019; Goetz & Dubayah, 2011; Idbraim et al., 2023).

Satellite-based monitoring is typically conducted using optical imagery and synthetic aperture radar (SAR). For example, optical imagery captures visible light reflected from Earth's surface, while SAR uses microwave signals that penetrate clouds and fog (Sommervold et al., 2023). In Indonesia, Landsat, SPOT, Terra, Himawari, VIIRS, and Aqua MODIS are the optical satellite data sources used in remote sensing and data monitoring applications in the fields of agriculture, forestry, and mining (Kushardono & Arief, 2020), (Zubaidah et al., 2019). The Visible Infrared Imaging Radiometer Suite (VIIRS) on the Suomi NPP and NOAA-20 satellites can provide high-quality data for analyzing and evaluating surface phenomena and nighttime light intensity by capturing visible and infrared radiation.

Furthermore, the phenomenon of forest loss requires further analysis to determine whether it is related to human activities, making satellite data a relevant tool for this purpose. In fact, good forest management by local communities can be one of the steps to reduce deforestation while improving the well-being of villages in Indonesia (Santika et al., 2017). However, ecological conditions can undergo negative changes due to intense human activities both within and around forest ecosystems. Ecosystem stability disrupted by artificial light at night used by humans also indicated an increase in human activity in the area (Svechkina et al., 2020).

Previous studies have examined deforestation and nighttime light dynamics using related geospatial data. The Studies analyzed spatiotemporal deforestation hotspots in Sumatra and Kalimantan from 2001 to 2018 and found that many hotspots were located outside protected areas, particularly along protected-area boundaries. In Kalimantan, hotspots were mainly concentrated along the eastern and southern coastal regions (Singh & Yan, 2021). Meanwhile, other related studies used night-time light data to detect changes in human activity intensity during the PPKM period in Jakarta, reporting a 16% reduction in night-time light intensity across sectors. However, this decrease did not closely align with mobility data, which showed a 60% reduction in activity. These findings suggest that night-time light data can represent certain dimensions of human activity, but its relationship with land-cover change requires further investigation (Sanjaya & Fianty, 2023).

In addition, optimizer comparison has been explored in several prediction and classification tasks, such as earthquake signal classification, consumer price index prediction, and ocean wave height prediction (Mustika et al., 2021; Zahara et al., 2020; Jörges et al., 2021). Long Short-Term Memory (LSTM) networks are particularly suitable for time-series forecasting because they can capture sequential dependencies and handle temporal patterns effectively. Prior studies have demonstrated the robustness of LSTM in predictive tasks, including sentiment analysis and time-series forecasting using neural networks, RMSE evaluation, and parameter tuning (Kristiyanti & Hardani, 2023; Zahara et al., 2020; Jörges et al., 2021; Nilsen, 2022).

Recent research has also shown the potential of integrating Global Forest Change (GFC) and Night-Time Light (NTL) data with machine learning for environmental monitoring. (Singh & Yan, 2021), (Ball et al., 2022), (Huacani et al., 2022). In addition, optimizer comparison has been explored in several prediction and classification tasks, such as earthquake signal classification, consumer price index prediction, and ocean wave height prediction (Mustika et al., 2021), (Zahara et al., 2020), (Jörges et al., 2021). Forecasting frameworks and time-series algorithms have been applied in various domains, including deforestation modeling, environmental prediction, and sequential data analysis (Ball et al., 2022; Huacani et al., 2022; Nilsen, 2022). Long Short-Term Memory (LSTM) networks are particularly suitable for time-series forecasting because they can capture sequential dependencies and handle temporal patterns effectively. Prior studies have demonstrated the robustness of LSTM in predictive tasks, including sentiment analysis and time-series forecasting using neural networks, RMSE evaluation, and parameter tuning (Kristiyanti & Hardani, 2023; Zahara et al., 2020; Jörges et al., 2021; Nilsen, 2022).

Despite these developments, previous studies have not sufficiently integrated GFC and NTL data within an LSTM-based predictive framework for analyzing forest-cover transformation in Kalimantan. The study did not focus on data integration but rather on the identification of historical hotspots, satellite-based mapping, or light intensity analysis separately. In fact, these data can be integrated to predict future forest change patterns, and the results can be used to interpret the relationship between these changes and human activities. Therefore, this study aims to develop a predictive model for forest cover transformation in Kalimantan using the Cross Industry Standard Process for Data Mining

(CRISP-DM) framework and by analyzing the relationship between Global Forest Change (GFC) and Night-Time Light (NTL) data. This study uses Hansen Global Forest Change v1.11 data from 2001 to 2023 and VIIRS Night-time Day/Night Band Composites Version 1 data from 2013 to 2023 for the cities and regencies in the province of Kalimantan. Long Short-Term Memory (LSTM) was used to develop a predictive model, and Root Mean Square Error (RMSE) was the primary evaluation metric. The prediction results are presented through visualization maps and a web-based dashboard that can be further analyzed to identify patterns of forest loss and light distribution. Through this approach, the study seeks to provide a data-driven understanding of how human activity and land conversion relate to forest-cover change in Kalimantan (Cen & Wang, 2019; Fadli et al., 2019).

The main contribution of this study is threefold. First, this research integrates two complementary geospatial time-series datasets, namely Global Forest Change and Night-Time Light, to capture both environmental change and indicators of human activity in Kalimantan. Second, this study evaluates the performance of several LSTM optimizers, including Adam, RMSprop, SGD, Adamax, and Adadelta, to identify the most stable and accurate configuration for predicting forest loss and night-time light intensity. Third, the predictive results are operationalized through a web-based dashboard that provides maps, temporal charts, filtering functions, and one-year-ahead predictions. This integration of predictive modeling and interactive visualization distinguishes the proposed system from prior studies that mainly focused on retrospective deforestation mapping without deploying the prediction results into a decision-support platform.

Literature Review

Forest cover and deforestation

Land cover is a critical component of ecosystems and human life, encompassing forests, agricultural land, settlements, water bodies, and open areas. Forest cover can reveal how human impacts on forests and the environment also affect the distribution and characteristics of forests (Löf et al., 2019). Forests that lose their identity will experience disrupted forest functions.

Threats to forest integrity and function include deforestation, such as large-scale logging, land use changes that are inconsistent with the forest's intended function, and human activities that destabilize the forest. Sustainability can also be threatened by inappropriate land conversion for agriculture and plantations, especially when driven by rapid population growth. These activities are highly detrimental to forests and result in numerous violations, including boundary encroachments, illegal logging, wildfires, and the illegal trade in flora and fauna (Putra et al., 2019). As beings capable of conscious decision-making regarding conservation, humans must protect forests to ensure their integrity is preserved.

Long short–term memory (LSTM)

The vanishing and vanishing gradient problems in traditional RNNs have paved the way for a specialized Recurrent Neural Network (RNN), namely the Long Short-Term Memory (LSTM), to address these limitations (Kang et al., 2024; Ravikumar & Sriraman, 2023; Sahu et al., 2023). The predictive model developed in this study relies on long-term data, and LSTM networks are considered effective at understanding sequential data across various machine learning tasks, including time series forecasting, natural language processing, and speech recognition (Mealey & Taha, 2018; J. Wang & Ozbayoglu, 2022). Predictions of stock prices, energy consumption, and weather patterns are other applications of LSTM (Wijaya & Overbeek, 2025). The superior performance of LSTM was the basis for choosing it for the predictive model in this study over traditional methods, such as ARIMA (Andhika Viadinugroho & Rosadi, 2021; Song & Brown, 2019; Yadav et al., 2020).

Predictive model

The predictive models in this study use patterns and historical data to forecast future monitoring results. These models are categorized into supervised, unsupervised, and reinforcement learning (Alkan et al., 2022). The complex data structures in time series and image data can also be effectively captured by advanced models, such as LSTMs, CNNs, and RNNs (Bhavya & Pillai, 2021; Patharkar et al., 2024).

Web-based information system dashboard

Decision-making across various fields requires valid data as a supporting foundation. Visualizations in web-based information system dashboards are an effective way to analyze and present data in various formats. Dashboards are also used in business intelligence to help organizations operate competitively and efficiently, with key features including financial data summaries, operational metrics, and forecasts. Proper dashboard presentation through planning, monitoring, communication, and analytics can support strategic, tactical, and operational decision-making (KOWAL et al., 2018; Rahman et al., 2017). This provides the basis for concluding that the predictive model in this study is suitable for presentation via a dashboard.

Spatiotemporal hotspot patterns, satellite-based forest monitoring, and the use of nighttime light (NTL) data as an indicator of human activity in previous studies on deforestation in Indonesia have provided important insights and data for the development of predictive models in this study. However, those studies have three limitations. First, most deforestation studies have not focused on forecasting future changes in forest cover but rather on using GFC data for historical mapping and hotspot detection. Second, the dynamics of the relationship between light intensity and forest loss predictions have not been explicitly explained in previous studies because analyses of urbanization, mobility, or activity intensity using NTL data were conducted separately. Third, attention to model optimization comparisons and to translating model results into interactive dashboards for practical use remains limited, even though the application of LSTM models in environmental monitoring should prioritize the accuracy of time-series predictions. Therefore, the methodological and practical gaps identified served as the impetus for this study to integrate GFC, NTL, the LSTM optimizer, and dashboard visualization to monitor deforestation within a single predictive model comprehensively.

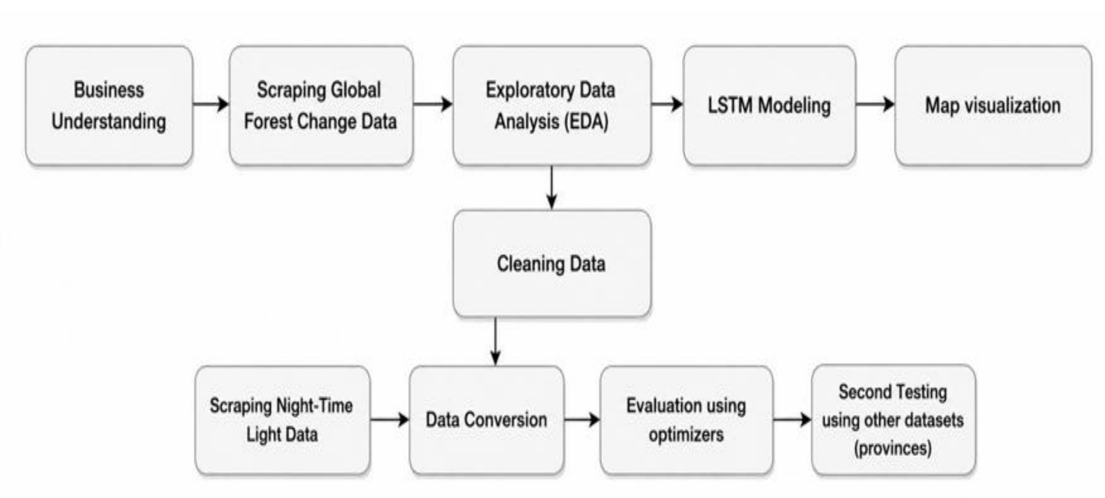
Methodology

This pilot study was conducted between July and October 2022 as part of the Teachers' Training for Teaching Democracy program administered by the Paramadina Institute for Education Reform (PIER). A quantitative research design using a Likert scale questionnaire

(Groves et al., 2009) was administered to answer the research questions. Based on the 2020 report on the index of democracy in the civil liberties aspect by BPS, two provinces with low democracy index scores, West Sumatra and South Kalimantan, and two provinces with high democracy index scores, DI Yogyakarta and DKI Jakarta, were selected as the sites for data collection. Conveniently chosen, the respondents were students from twelve high schools in Indonesia; 6 schools were located in low democracy index areas, and six were in high democracy index areas. In particular, 180 participants (15 students from each school) responded to the questionnaire. Participation is voluntary, and anonymity is assured.

The primary criterion for selecting a method for developing a predictive model is a robust data-handling structure for data-driven projects. CRISP-DM is considered suitable for combining time-series analysis and data mining techniques within its framework (Liang & Zhang, 2021). The combined data were obtained from Hansen Global Forest Change v1.11 for Global Forest Change (GFC) for the period 2001 to 2023, and from VIIRS Night-Time Day/Night Band Composites Version 1 for Nighttime Light (NTL) for the period 2013 to 2023. This study collected data at the city/regency and provincial levels, which then produced four core datasets: two at the city/regency level and two at the provincial level (Abraham et al., 2020). The raw data was converted into a numerical format to be compatible with the developed model. Data preprocessing involved data cleaning to maintain data quality and integrity, including detecting missing and outlier values. The identification of patterns and anomalies in the time-series data was performed through attribute selection and exploratory data analysis (EDA) as a foundation for effective modeling (Putri, 2021). Furthermore, this study selected the LSTM network because it can capture long-term dependencies and map the complex interactions between changes in forest cover and nighttime light emissions. The effectiveness of the LSTM model was validated by training the model on various geographic scales, city/regency level, and provincial level, separately. The model generated two datasets, a training dataset and a test dataset, which were used for model tuning and evaluation of prediction accuracy (Yuliantono et al., n.d.).

Figure 1. *Research workflow following the CRISP-DM framewok*



Moreover, the research workflow diagram illustrates the complete CRISP-DM process, ranging from business understanding and data understanding to data preparation, LSTM-based modeling, and optimizer evaluation, and from implementation in a web-based dashboard to GFC and NTL data acquisition, preprocessing, time series transformation, model training, RMSE-based evaluation, and dashboard visualization. This workflow illustrates how raw geospatial data is transformed into predictive and visual outputs that support decision-making.

RMSE measures model performance; a low RMSE value indicates high accuracy and minimal prediction error. However, if the RMSE value exceeds an acceptable threshold, the model parameters are adjusted by re-evaluating data quality and exploring different LSTM configurations or other time-series models (Hesananda, 2021). This study uses Tableau dashboard visualizations to accurately depict dynamic changes in forest cover and nighttime light intensity. This study employs the CRISP-DM framework and quantitative methods to collect and manage data, from initial understanding through model implementation. The study follows six stages to develop the prediction model: business understanding, data understanding, data preparation, data modeling, model evaluation, and model implementation (Martinez-Plumed et al., 2021).

Data collection

This study uses GFC data from Global Forest Watch and NTL data from VIIRS. GFC data contain information on forest ecosystems over time, and NTL data capture light emitted from the Earth's surface at night (D. Zhang et al., 2020). These datasets provide valuable insights into ecological consequences and critical urban expansion, and serve as essential data for assessing human activities and their spatial distribution (Wilson & Xiong, 2022). The combination of GFC and NTL data yields a powerful dataset that offers a more comprehensive picture of forest landscape patterns shaped by human activities and urban development.

Data collection was performed using Python functions on Google Colab and Google Earth Engine to process the data, extracting it separately into four types. The data were then converted into numerical form. The types of data are as follows: (a) GFC data for cities and regencies at 56 locations as primary data, (b) City and regency NTL data at 56 locations as primary data, (c) Provincial GFC data from 5 provinces as secondary test data, (d) Provincial NTL data from 5 provinces as secondary test data.

The provinces involved are Central Kalimantan, East Kalimantan, North Kalimantan, South Kalimantan, and West Kalimantan. The data collection periods cover the years 2001 through 2023 and 2013 through 2023, making the potential for integrating GFC and NTL data very high. However, GFC time-series data is available in annual format, while NTL data is available in monthly format; therefore, the NTL data must be adjusted to an annual format to align with the GFC data.

Data modeling and evaluation

This study uses an LSTM network to improve sequence modeling, which is limited in conventional RNNs (ref). LSTMs can retain information for longer periods through a system that uses memory cells and gates that selectively store and forget details (Y. Zhang et al., 2020). LSTMs have three gates, input, forget, and output, that regulate the flow of information entering and exiting the cells. The sigmoid function determines what is retained from the previous state at the forget gate (Aldi et al., 2018). The sigmoid function is as follows (Choi, 2018):

$$f_t = \sigma\left(W_{hf} \cdot h_{t-1} + W_{xf} \cdot x_t + b_f\right) \quad (1)$$

The input gate and the candidate state determine which values in the cell state need updating. The candidate state updates the cell state with new information, as represented by:

$$\tilde{c}_t = \tanh(W_{hc} \cdot h_{t-1} + W_{xc} \cdot x_t + b_c) \quad (2)$$

The cell state integrates the outputs from the input gate, candidate state, and forget gate, following the equation:

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{c}_t \quad (3)$$

The output gate controls the amount of information passed on to the next state, which can influence the final state's output. This is crucial for identifying long-range dependencies in data sequences, as illustrated by:

$$h_t = o_t \odot \tanh(C_t) \quad (4)$$

Moreover, RMSE is used to evaluate model performance and assess the difference between the model's predicted values and the actual observed values in a dataset. A lower value indicates better performance. Here is the formula for calculating RMSE:

$$\mathrm{RMSE} = \sqrt{\frac{\sum(y_t - \hat{y}_t)^2}{n}} \quad (5)$$

The total number of samples representing the actual values is denoted by n, while the predicted values are denoted by y^t (Bode, 2017). A model's predictions that align with the actual data are indicated by a low RMSE value close to 0; conversely, if the RMSE value is higher, the predictive model's performance is considered poor and unable to accurately represent the actual conditions.

Results

Business understanding

From a business perspective, this study develops a model to monitor and predict changes in forest cover in Kalimantan, linking these changes to human activities indicated by nighttime light intensity in specific regions of Kalimantan. This study provides insights into whether areas with increased light emissions also experience more significant changes in forest cover. The results of this study are visualized on a Tableau dashboard using the Adam, RMSprop, Stochastic Gradient Descent (SGD), Adamax, and Adadelta optimization options to help understand deforestation trends. The dashboard visualizations can then be used as a basis for evaluation and decision-making regarding forest conservation.

Data understanding

This study uses forest loss area and light intensity, integrated with additional geographic data, for precise spatial analysis and accurate visualization in the Kalimantan region. The study utilizes GFC data, which reports forest loss in hectares at 56 locations, as well as NTL data, which provides monthly light intensity measurements at the same locations. This data was then analyzed to assess deforestation patterns and link them to human activities. This analysis enables more detailed insights into long-term patterns and predictions because data collection was conducted at the provincial level and was not limited to cities or regencies. The data extraction methods for the GFC and NTL data produced four core datasets. These datasets consist of two datasets for each city and regency (one GFC and one NTL) and two for each province (one GFC and one NTL). The resulting datasets are as follows:

Table 1. *GFC dataset for cities and districts*

Variables	Description	Data Types
Nama	Name of a city or district	Text
Wilayah	Type of area	Text
Provinsi	Name of province	Text
Longitude	Longitude coordinates	Float
Latitude	Latitude coordinates	Float
Year	Year timestamp	Date
Area	Forest loss area (Ha)	Float

Table 2. *NTL dataset for cities and districts*

Variables	Description	Data Types
Nama	Name of a city or district	Text
Wilayah	Type of area	Text
Provinsi	Name of province	Text
Longitude	Longitude coordinates	Float
Latitude	Latitude coordinates	Float
Date	Date timestamp	Date
Mean	Average light intensity	Float

Table 3. *GFC dataset for provinces*

Variables	Description	Data Types
Provinsi	Name of province	Text
Longitude	Longitude coordinates	Float
Latitude	Latitude coordinates	Float

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Variables	Description	Data Types
Year	Year timestamp	Date
Loss_year	Forest loss area (Ha)	Float

Table 4. *NTL dataset for provinces*

Variables	Description	Data Types
Provinsi	Name of province	Text
Longitude	Longitude coordinates	Float
Latitude	Latitude coordinates	Float
Date	Date timestamp	Date
Mean_radiance	Average light intensity	Float

Data preparation

Data collection was performed using Python with libraries such as geemap and ee to ensure accurate access to satellite imagery. Data were collected at the city, district, and provincial levels to ensure alignment with administrative boundaries. Data processing required numerical values representing forest loss in hectares as well as light intensity; therefore, the dataset was first converted into numerical form and stored in Excel. Preliminary data analysis was performed by importing the data into Python to analyze the distribution of the dataset, including the mean, standard deviation, and range.

Furthermore, EDA analyzed data that included visualizations of the spatial distribution of forest loss and light intensity across the entire province of Kalimantan. Median values were used to obtain central tendencies, thereby making the visual analysis more stable. These visual results can aid in understanding forest cover and human activities, as indicated by partially varying light emissions. Moreover, the visualization is presented as a line graph of time-series data from 2001 to 2023 for the GFC data and from 2013 to 2023 for the NTL data, along with predictions for both datasets for 2024 based on future trend projections using the forecaster function.

Figure 2. *Global Forest Change (GFC) Forecaster*

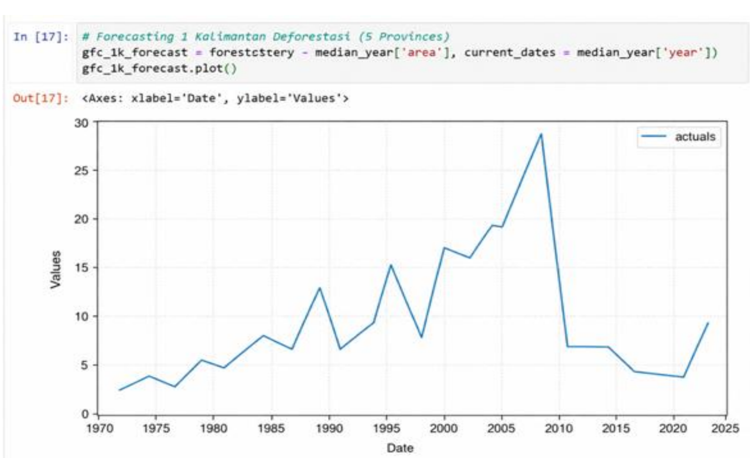
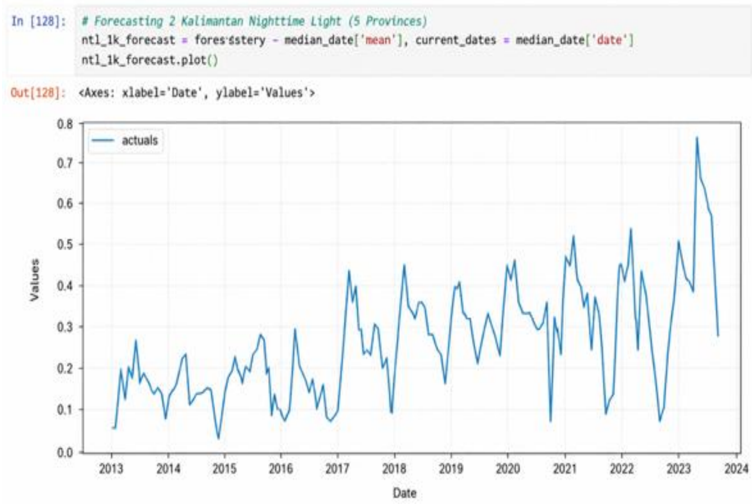


Figure 3. *Night time life (NTL) forecaster*



Data modelling

The research described involves detailed modeling for forecasting future trends in GFC and NTL data across Kalimantan using the LSTM method. After data preparation and Exploratory Data Analysis (EDA), models were built using the last 12 observations to predict the forthcoming year. Given the annual time-series nature of the data, the model uses the last two GFC observations to predict the next two years. Two separate LSTM models were developed:

Table 5. *LSTM Hyperparameters*

Parameters	Values
set_test_length	2
generate_future_dates	2
set_estimator	lstm
call_me	Base_Hutan_Kalimantan
lags	4
batch_size	10
epochs	100
validation_split	0.25
shuffle	TRUE
activation	tanh
optimizer	Adam
learning_rate	0.001
lstm_layer_sizes	(72, 72, 72, 72)
dropout	(0, 0, 0, 0)
plot_loss	FALSE

Table 6. *NTL LSTM Hyperparameters*

Parameters	Values
set_test_length	12
generate_future_dates	12
set_estimator	lstm
call_me	Base Kalimantan
lags	4-12
batch_size	20
epochs	100
validation_split	0.25
shuffle	TRUE
activation	tanh
optimizer	Adam
learning_rate	0.001
lstm_layer_sizes	(72, 72, 72, 72)
dropout	(0, 0, 0, 0)
plot_loss	FALSE

This evaluation aims to determine how accurately the model predicts actual data, using RMSE as the key metric. RMSE quantifies the model's prediction errors, with lower values indicating higher accuracy. The evaluation process involves checking whether the LSTM algorithm's results across various optimizers align with the data, ensuring high predictive accuracy. The effectiveness of each model is assessed by examining RMSE values, which provide insights into its performance.

Evaluation

Table 7. Comparison table of RMSE evaluation results with optimizers of GFC

RMSE	Adam	RMSprop	SGD	Adamax	Adadelta
Kalimantan Barat	0.989486	0.596151	3.44835	1.232895	6.912944
Kalimantan Utara	2.545307	3.095865	1.581704	2.545931	2.298615
Kalimantan Timur	2.876306	2.740781	2.305006	3.515821	4.64493
Kota	2.361938	2.686694	2.052986	1.615685	3.846367
Kabupaten	3.249937	3.210676	2.541245	4.140925	3.234159

Table 8. *Comparison table of RMSE Evaluation Results with optimizers of GFC (2nd testing)*

RMSE	**Adam**	**RMSprop**	**SGD**	**Adamax**	**Adadelta**
Kalimantan Utara	13.9611	15.939192	5.197355	16.741475	8.129547
Kalimantan Selatan	31.07752	23.981983	29.246119	27.668068	36.126962
Kalimantan Barat	39.8789	40.048026	86.910263	42.101404	135.87228

Using the GFC dataset, Adam and RMSprop showed the best stabilization across all models, with the lowest RMSE scores in Tables 7 and 8. For example, Adam scored 0.989486 and 13.9611 in two tests for West Kalimantan, while RMSprop scored 0.596151 and 15.939192. The SGD optimizer also performed well, achieving a best RMSE of 5.197355 in the second test for North Kalimantan, making Adam and RMSprop suitable for GFC data analysis. Further study is needed to confirm the best optimizer, with SGD as a viable alternative.

Table 9. *Comparison table of RMSE evaluation results with optimizers of NTL*

RMSE	**Adam**	**RMSprop**	**SGD**	**Adamax**	**Adadelta**
Kalimantan Tengah	0.182753	0.193039	0.390835	0.178792	0.419421
Kalimantan Barat	0.196439	0.206883	0.322814	0.201574	0.34671
Kalimantan Utara	0.221021	0.222626	0.503445	0.211025	0.534944
Kota	0.390592	0.376906	0.713796	0.395315	0.759153
Kabupaten	0.204139	0.201786	0.385884	0.213429	0.412449

Table 10. *Comparison table of RMSE evaluation results with optimizers of NTL (2nd testing)*

RMSE	**Adam**	**RMSprop**	**SGD**	**Adamax**	**Adadelta**
Kalimantan Utara	0.191947	0.191962	0.434778	0.191847	0.469589
Kalimantan Barat	0.202141	0.216777	0.320139	0.203547	0.344173
Kalimantan Tengah	0.208535	0.176219	0.375989	0.201556	0.411517

Comparing optimizers across datasets using NTL data yielded varied results. Table 3 compares optimizers for the initial NTL dataset (city and district level), and Table 4 compares optimizers for the secondary NTL dataset (provincial level). Adam consistently produced the lowest RMSE values in the first dataset, while RMSprop excelled in the second test, though both optimizers performed comparably across datasets. Specifically, in the first test, Adam led with the lowest RMSE scores in two models: Central Kalimantan at 0.182753 and West Kalimantan at 0.196439, though the absolute lowest was with Adamax at 1.78792. In the second test, the RMSE for the North Kalimantan model was 0.191962. For the Central Kalimantan model at 0.176219, and RMSprop matched Adam's performance, indicating that both Adam and RMSprop are suitable optimizers for NTL data. However, Adam is slightly preferred as the primary optimizer in this analysis.

The LSTM model's performance depends on the RMSE value. This study shows that adaptive optimizers, such as Adam and RMSprop, have lower RMSE values than SGD, Adamax, and Adadelta, indicating that they are better suited to time-varying data, such as forest loss time series in the GFC dataset. Both Adam and RMSprop perform well on LSTM models. Adam's momentum and adaptive learning enhance weight updates amid the instability of GFC data, while the latest gradient updates allow RMSprop to adjust its learning rate better. Both of these optimizers perform strongly when learning from unstable temporal data compared to other optimizers. Meanwhile, SGD shows fairly good results but lacks consistency due to its sensitivity to the learning rate and the limited dataset size. At the same time, Adadelta and Adamax exhibit higher prediction errors on the GFC dataset.

However, on the NTL dataset, Adam, RMSprop, and Adamax performed nearly identically because the patterns of change in the NTL data are more stable and gradual, making them easier for the model to learn. Thus, on the GFC dataset, Adam and RMSprop are superior and more effective at capturing deforestation patterns compared to non-adaptive methods. In contrast, on the NTL dataset, Adam, RMSprop, and Adamax are superior at capturing patterns of light intensity changes. Furthermore, Adam and RMSprop are overall stable optimizers and appropriate choices.

The advantages of the proposed model extend beyond achieving low prediction errors; they also lie in the accurate interpretation of the transformed predictions. Prediction accuracy alone is insufficient to encourage decision-makers to access and interpret results from environmental monitoring. The implementation of LSTM results in a web-based dashboard that bridges the gap between machine learning evaluation and more practical monitoring needs. These features support dynamic deforestation monitoring in Kalimantan by presenting evidence. The dashboard allows users to filter data by province and year, then examine the history of forest loss, compare prediction values, and observe patterns through maps and graphs.

Deployment

Following a comparative evaluation of LSTM optimizers, the web-based dashboard implements the best-performing predictive models: Adam, RMSprop, and Adamax. Figure 10-14 shows the optimizer implementation in the prediction model. This dashboard serves as the main page displayed to users after they log in. There are two main menus: GFC and NTL. The top navigation bar includes a drop-down menu that provides users with access to the profile page and a logout option.

Figure 4. *Map of GFC in Kalimantan for 2001*

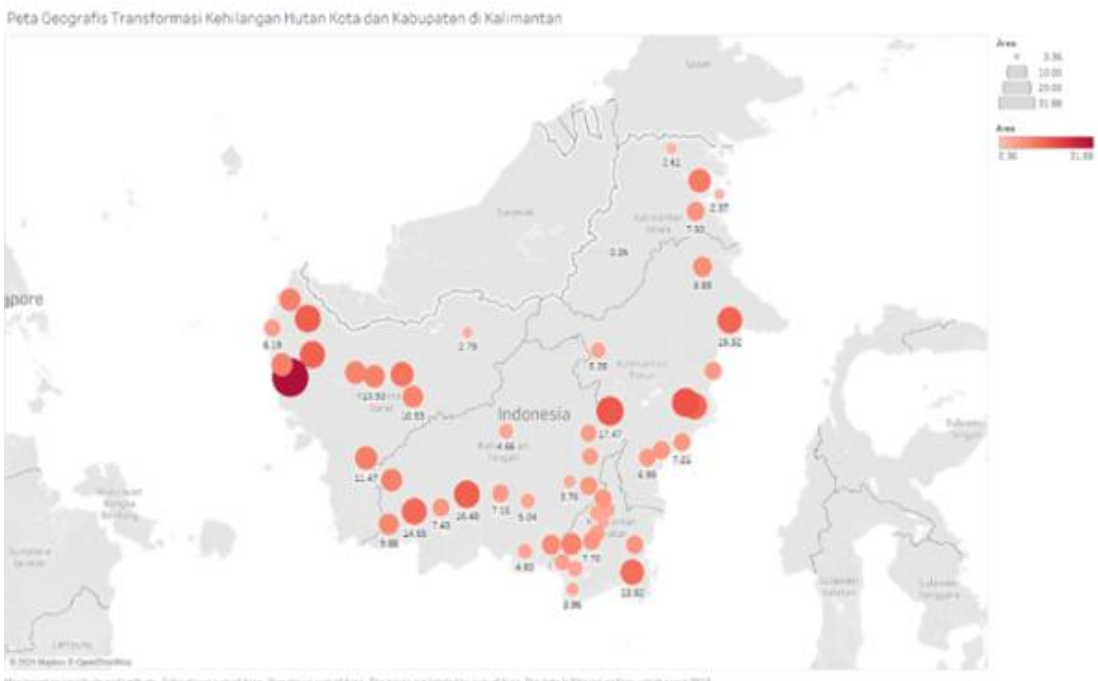


Figure 5. *Map of GFC in Kalimantan for 2023*

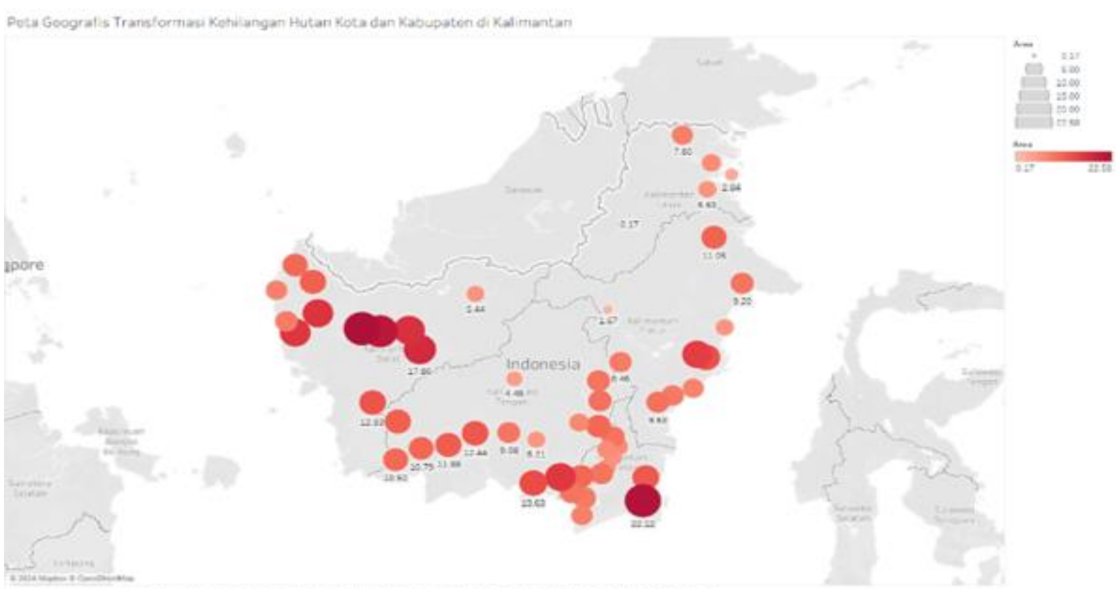
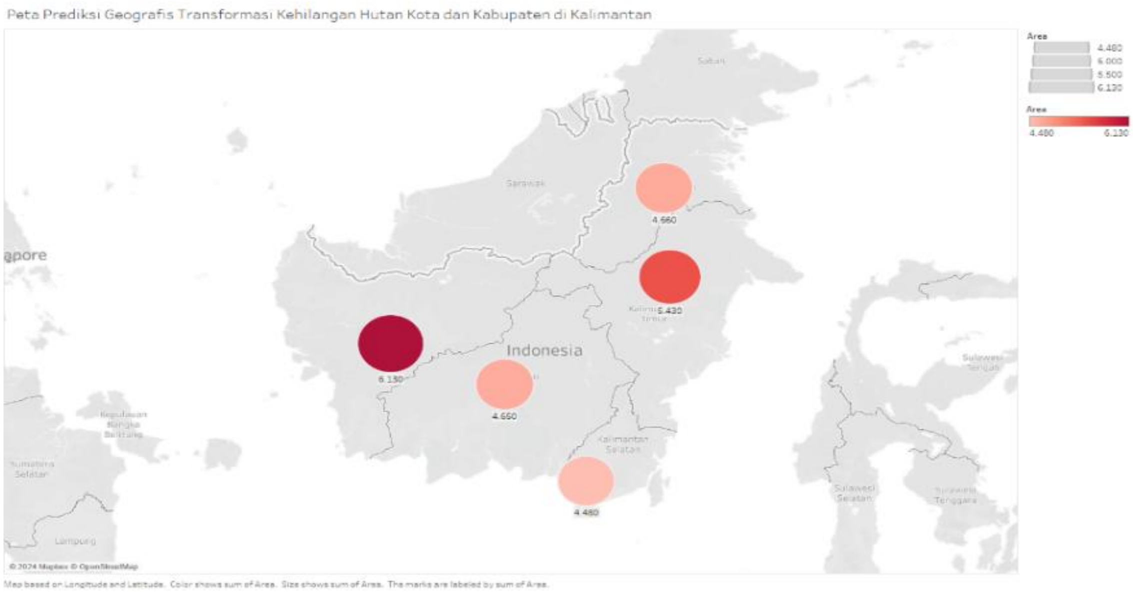


Figure 6. *Visualization map of global forest change data in Kalimantan for 2024 prediction*



Figures 4, 5, and 6 show an analysis of forest loss maps indicating a gradual decline in the number and area of affected regions in Kalimantan from 2001 to 2024. Furthermore, the maps show that deforestation still occurred in 2001 and 2023, with widely scattered hotspots and varying intensities. By 2023, areas with high rates of forest loss had decreased significantly. The 2024 prediction map also displays a combined average estimate based on data from all of Kalimantan.

Figure 7. *Night-time light data in Kalimantan for 2013*

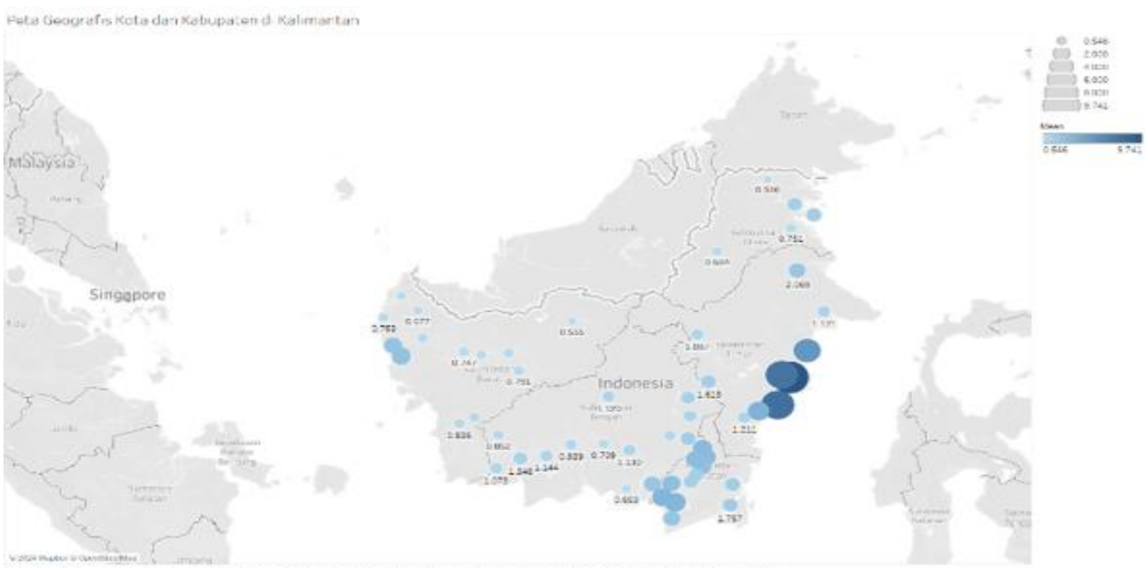


Figure 1. *Night-time light data in Kalimantan for 2023*

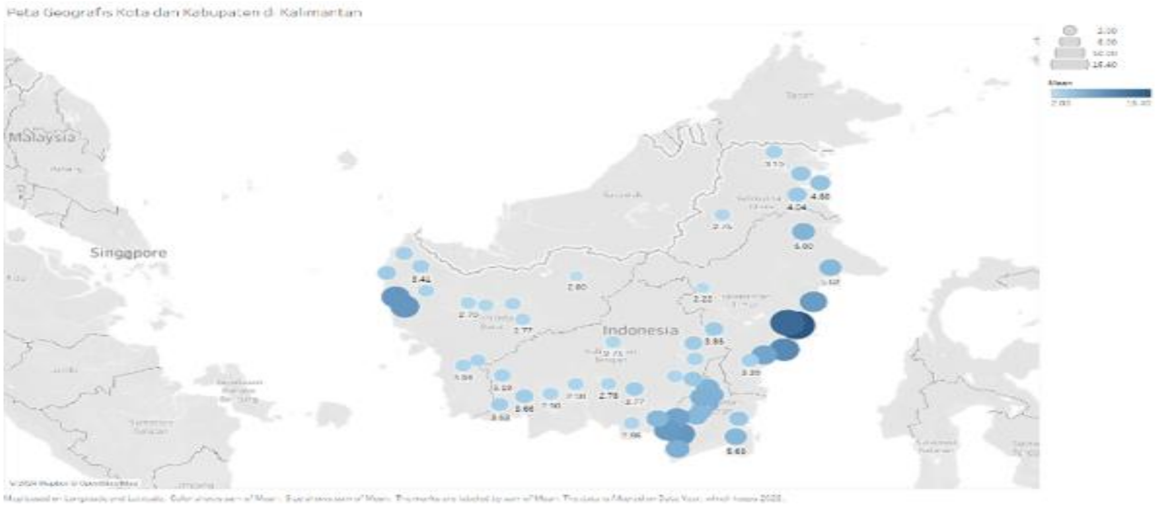
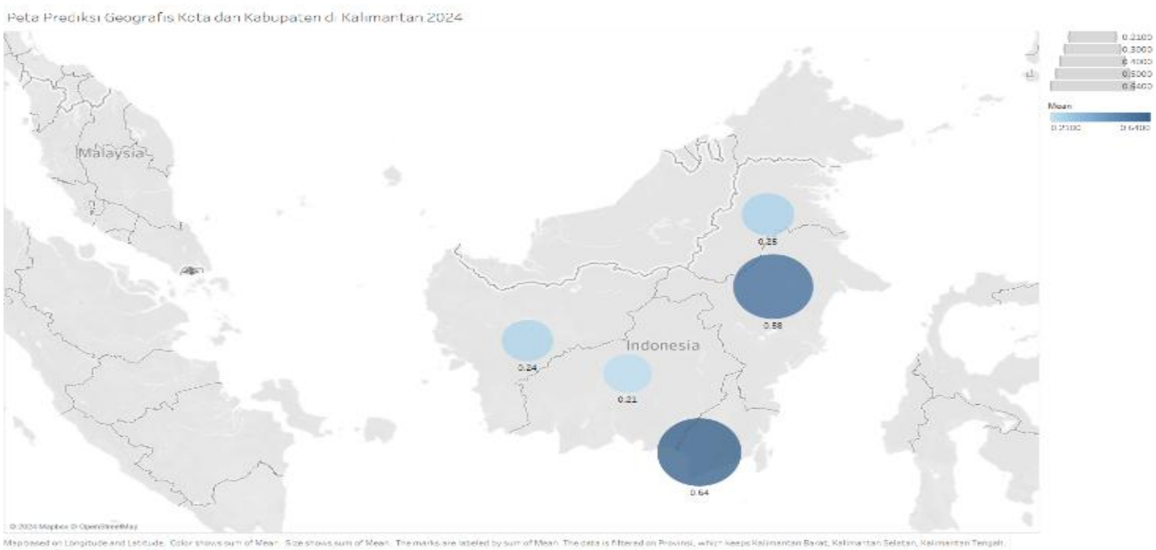


Figure 9. *Map visualizing night-time light data in Kalimantan for 2024 forecasting*



Furthermore, Figures 7, 8, and 9 display maps of light intensity distribution in Kalimantan from 2013 to 2024. The 2013 and 2023 maps show numerous varied hotspots across regencies and cities, indicating human activity and its impact on nighttime light. The 2024 prediction map also displays the combined average light intensity for all cities, regencies, and provinces in Kalimantan. It demonstrates that the dashboard can display the distribution of locations at both general and specific scales in Kalimantan.

Furthermore, this study assumes that higher nighttime light intensity indicates increased human activity and correlates with forest cover. However, the study's findings show that high light intensity does not contribute to an increase in forest cover. This suggests that light is not a primary indicator of forest loss. According to NTL data, nighttime light intensity does not directly reduce forest area. Thus, the assumption that increased nighttime light indicates forest degradation is irrelevant.

Figure 10. *Web-based global forest change (GCF) dashboard*

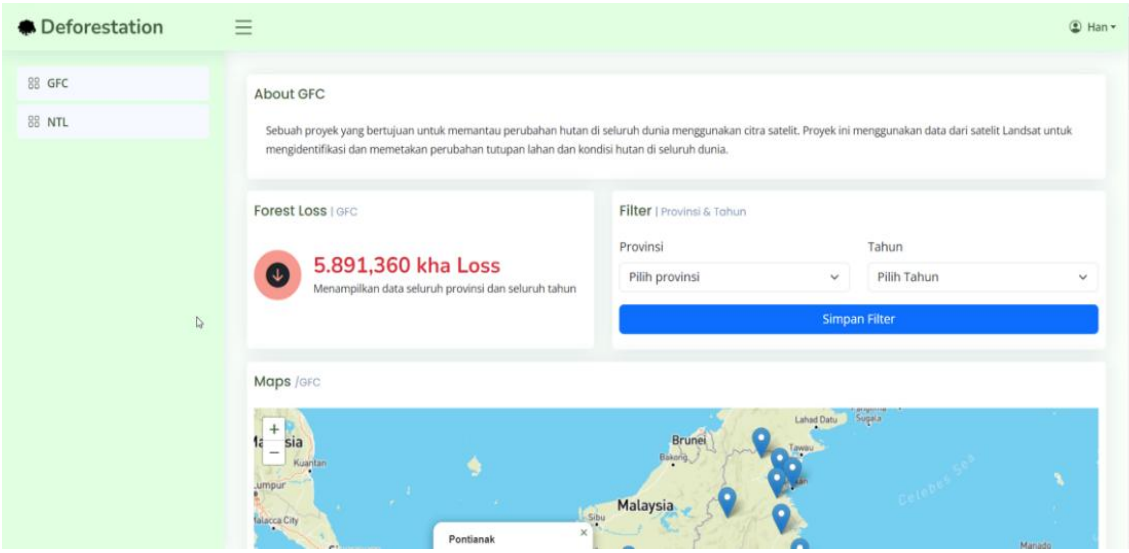


Figure 10 shows several GFC menus containing the GFC card, the forest loss card, the filter card, and the map card. The GFC information card contains descriptive information about the GFC dataset and its role in monitoring deforestation in Kalimantan. The forest loss card displays the extent of forest loss in Kalimantan, expressed as a percentage and in hectares. The filter card lets the user select the desired province and year, with interactive results that update the other cards on the page. The visualizations are presented in various formats, including both graphs and maps. The map cards show each city and regency in Kalimantan, each represented by a point on the map. These points on the map represent the average forest loss in the selected area, specifically, land that has been converted to non-forest use.

Figure 11. *GFC dashboard (2)*

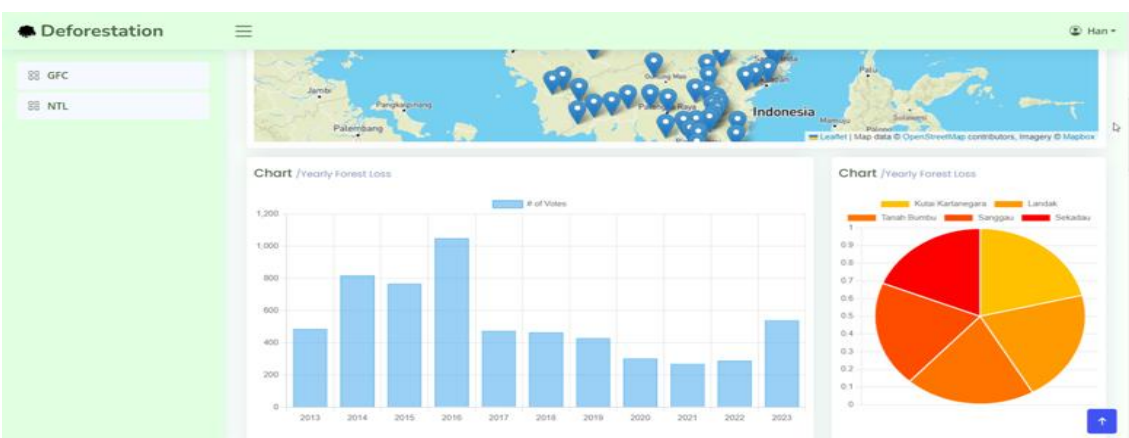


Figure 12. *GFC Dashboard (3)*

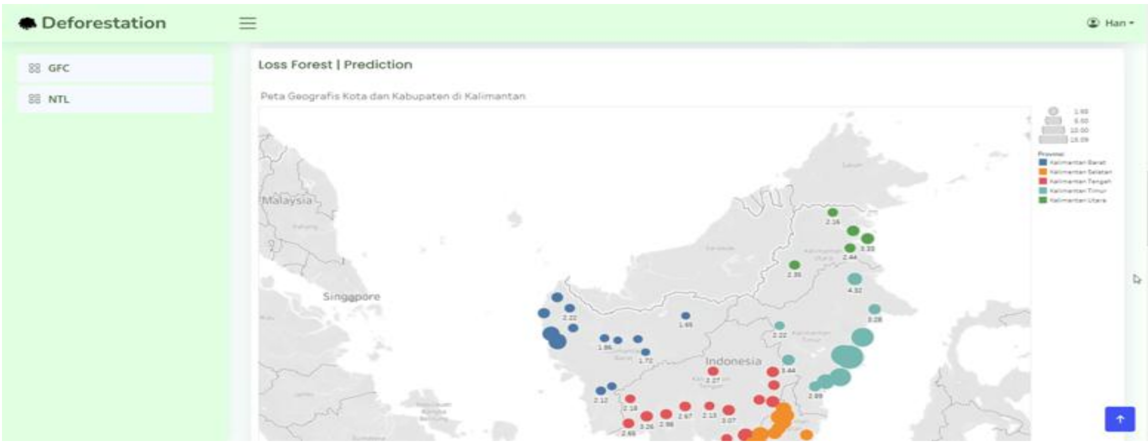
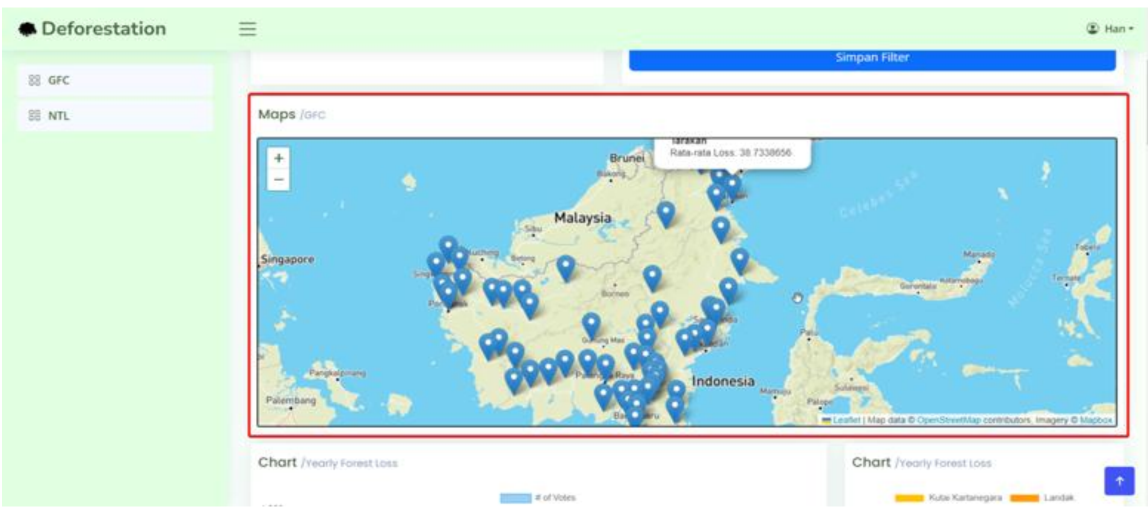


Figure 13. *GFC Card Maps*



Furthermore, Figures 11-13 show additional components on the GFC dashboard. The forest loss prediction card generated by the LSTM model displays historical forest loss data from 2013 to 2023, along with predictions for 2024. The slider option allows users to navigate between years, providing an overview of forest loss trends and projections. Additionally, a card labeled "News" presents an interactive graph showing forest areas affected by deforestation. Users can hover over graph elements to view numerical values and explore temporal and regional patterns in greater detail. Figure 13 displays a map card showing the average decline in forest cover across the dimensional distribution in each city or district. Furthermore, adjusting the province and year on the filter card will automatically update the view to be more specific to the selected province and year.

Figure 14. *Night time life web-based dashboard*

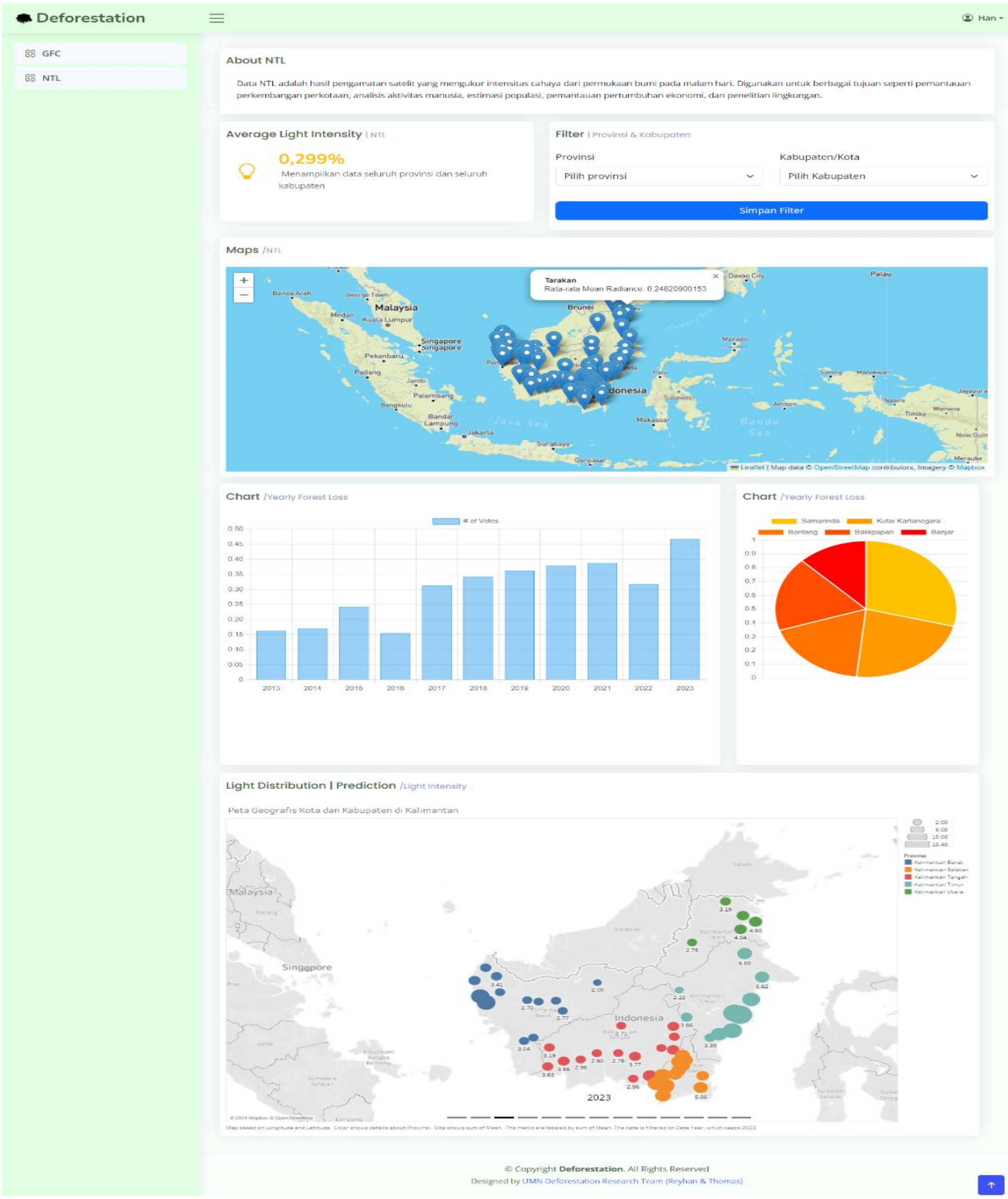


Figure 14 shows the NTL dashboard. This menu includes tabs for NTL, filters, and maps. The menu illustrates the geographic distribution of artificial light at each coordinate point across Kalimantan. The light distribution cards, generated from LSTM modeling results, display visualizations of average nighttime light intensity from 2013 to 2023, as well as predictions for the coming year. Users can apply filters to all cards on the NTL dashboard.

Each filter operates independently. This approach supports a web-based environment that integrates forest loss data and nighttime light predictions, enabling an accurate understanding and evaluation of the relationships among deforestation patterns, human activities, and infrastructure development in Kalimantan.

The findings of this study offer another insight from previous research. A study by Singh and Yan (2021), for example, found that the eastern and southern coastal regions of Kalimantan were deforestation hotspots. The categories of deforestation hotspots, sequential, sporadic, and oscillating, are distributed along the eastern, southern, and western coasts of Kalimantan. Additionally, other studies indicate that West, Central, and East Kalimantan are the provinces experiencing the most significant loss of forest area. However, deforestation patterns in Kalimantan are considered more stable compared to those in Sumatra, where deforestation hotspot categories are more diverse (Singh & Yan, 2021). Most of the affected forests are production or plantation forests, such as in East Kalimantan, which is currently undergoing the Nusantara Capital City (IKN) development project.

Furthermore, a study analyzed satellite data from 2000 to 2016 regarding changes in forest cover in Indonesia (Fadli et al., 2019). The analysis predicted that Indonesia's forest cover was approximately 338,000 km² in 2000, peaked in 2011 due to human activities, and underwent significant changes in 2015. This study focuses on Kalimantan and shows that forest cover loss occurred from 2001 to 2023, peaking in 2011 and 2016. After 2016, a downward trend in forest cover loss was observed, although annual variations continued to occur.

Discussion

This study found that the relationship between nighttime light intensity and forest loss is not always linear. NTL data serve only as proxies for human activity, infrastructure development, settlement expansion, and economic activity. However, increased light intensity in Kalimantan does not automatically indicate direct forest conversion. Several mechanisms may explain the mismatch between increased nighttime lighting and forest loss.

First, nighttime light in urban centers, highways, ports, industrial zones, or administrative facilities is located outside dense forest areas. This causes light intensity to be concentrated on development activities rather than on recent deforestation. Second, forest loss may occur in plantation, mining, or logging areas in remote regions, where artificial lighting is still limited. Third, GFC and NTL data aggregated at the city/regency or provincial level allow for the inclusion of non-forest urban areas in deforestation averages, thereby weakening the direct relationship between the two variables.

Furthermore, NTL data should be interpreted contextually, rather than as a direct cause of forest loss. Artificial light may indicate ordinary human activity, unrelated to plantation or forestry activities. Therefore, NTL data is most useful when analyzed in conjunction with GFC data. This study integrates both datasets, enabling a more comprehensive interpretation by identifying locations of forest cover loss while accounting for the intensity and spatial distribution of human activities around forested areas. This research demonstrates that geospatial datasets from diverse sources are necessary to explain the dynamic, complex patterns of deforestation.

Conclusion

This study has developed a model to predict changes in forest cover using GFC data and nighttime light intensity from NTL data in Kalimantan, employing an LSTM. The most consistent and effective optimizers for time-series data modeling are Adam and RMSprop. The prediction model is then presented in a web-based dashboard that can display historical data and prediction results comprehensively and interactively. Visualization of GFC and NTL data can further aid in deforestation monitoring and decision-making to preserve forest functions. Furthermore, this study demonstrates that light intensity resulting from human activities is not a primary indicator of deforestation. Future research could incorporate additional variables related to deforestation causes or expand the study area.

Disclosure Statement

No potential conflict of interest was reported by the authors.

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