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Forecasting Land Use Trends Using Long Short-Term Memory Networks for Rubber Plantations in Johor

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ABSTRACT

In this paper, we use LSTM to predict the future land-use trend based on trends from within rubber plantations in Johor state of Malaysia. These predictions are particularly important for improved agricultural planning and policy, which rely on accurate estimates of how land use may change over long time periods. The purpose of this study is to build a powerful prediction model, i.e., an LSTM network. The paper details the training procedure, introduces model architecture and several data pre-processing methods. In other terms, time series analysis is used to see the patterns or trends in historical data. The model is evaluated based on its performance measures (e.g., accuracy and consistency). The findings showed that the LSTM networks are able to perform reliable prediction by land usage in Johor, granting much-required knowledge essential for agriculture planning and polices making. The main findings of this paper are that LSTM networks can be used to forecast land use changes and help in long-term strategic planning for rubber plantations in Johor.

1. Introduction

1.1 Background

Land usage changes significantly impact the ecology, agriculture, and economics, particularly in Johor, Malaysia as reported by Tan *et al.,* [1]. Rubber plantations in this region occupy a sizable percentage of agricultural land and are vital to both the local and national economies. The growth and decline of these plantations are influenced by numerous variables, including past land use patterns, agricultural regulations, and market demand as discussed by Singh *et al.,* [2].

1.2 Historical Approaches to Land Use Forecasting

Historically, in land use forecasting statistical methods and spatial econometric models such as ARIMA (autoregressive integrated moving averages), linear regression and Markov chains have been used for a long time as highlighted by Koehler and Kuenzer [3]. While effective, these methods are

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challenged by the complex temporal dependencies and non-linear patterns inherent to land use data, as emphasized by Ali *et al.,* [4]. Although ARIMA models have, to some extent, been able to predict urban expansion, this has been proven by several authors [5,6], that they fail in the presence of non-stationary data and long-term dependencies.

1.3 Advances in Machine Learning for Land Use Forecasting

Machine learning algorithms, particularly Long Short-Term Memory (LSTM) networks, have proven to be highly effective in predicting time-series data by Hua *et al.,* and Sahoo *et al.,* [7,8]. As a type of recurrent neural network (RNN), LSTM networks excel at understanding and retaining long-term relationships. This ability makes them particularly suitable for analyzing and forecasting land use patterns influenced by various interconnected factors over time, as demonstrated by Papastefanopoulos *et al.* and, Azad and Wang [9,10]. Unlike traditional methods, LSTM networks can efficiently handle large datasets and complex patterns, leading to superior performance in various fields of time series forecasting, as evidenced by Siami-Namini *et al.* and Ahmed *et al.*, [11,12].

Numerous studies have recognized the effectiveness of Long Short-Term Memory (LSTM) networks. These models have been successfully applied in predicting industrial equipment failures, as reported by Wahid *et al.*, [13], while their reliability in forecasting financial time series has been extensively documented by Wu *et al.*, [14]. Their capability to capture non-linear interactions and long-term dependencies makes them especially suitable for land use forecasting, as observed by Azad and Wang, and Bharadiya [10,15].

1.4 Recent Advancements in Land Use Forecasting

Recent advancements in machine learning have significantly enhanced land use forecasting. For example, random forests have been employed to predict land use changes by evaluating feature significance and interactions, leading to improved prediction accuracy, as shown by Gounaridis *et al.* and Rodriguez-Galiano *et al.*, [16,17]. Furthermore, innovative approaches like object-based CNN (OCNN) have demonstrated high classification accuracy and computational efficiency in urban land use classification, as evidenced by Zhang *et al.*, [18]. The use of time series remote sensing data combined with the extreme gradient boosting (XGBoost) method has also proven effective in generating land use maps, revealing substantial spatial variations over time, as demonstrated by Matyukira and Mhangara [19].

1.5 Importance of Land Use Forecasting for Environmental Changes

Land use forecasting plays a vital role in understanding environmental changes. For instance, deforestation and urbanization patterns have been effectively tracked using remote sensing and machine learning techniques, as demonstrated by Nguyen *et al.* and Brovelli *et al.*, [20,21]. These methods offer valuable insights for policy-making and sustainable development, as highlighted by Lin *et al.* and Ly *et al.*, [22,23].

Research has indicated that integrating socio-economic data with remote sensing enhances the accuracy of land use predictions, as noted by Seto and Kaufmann, and Chrysoulakis *et al.*, [24,25]. Additionally, machine learning models, which can process diverse datasets, have been recognized for their effectiveness in complex environmental and socio-economic analyses, as evidenced by Feldmeyer *et al.* and Casali *et al.*, [26,27].

1.6 Objective of the Study

This study aims to contribute to the advancement of land use forecasting methodologies through the use of LSTM networks. By focusing on rubber plantations in Johor, Malaysia, this research seeks to develop a robust predictive model that offers valuable insights for agricultural planning and policy-making. The forecasts generated by this study are expected to guide sustainable land management practices and inform strategic decisions regarding land allocation, agricultural subsidies, and conservation efforts.

2. Methodology

This study employs a comprehensive methodology to forecast future land-use patterns for rubber plantations in Johor, Malaysia, using Long Short-Term Memory (LSTM) networks implemented in R software. The data utilized in this research is secondary data, specifically historical records of land use for rubber plantations in Johor. These records include detailed information on the size and location of rubber plantations over various periods. The data collection process involves extracting relevant fields such as the year and size of rubber plantations and formatting this data into a structured time series format suitable for analysis.

2.1 Long Short-Term Memory (LSTM) Networks

LSTM (Long Short-Term Memory) models are a powerful form of artificial intelligence widely applied in forecasting analysis, particularly in data science and pattern recognition. These models excel at analyzing long and complex time series data due to their ability to retain information over both short-term and long-term periods, as highlighted by Tang *et al.*, Yunpeng *et al.*, and Haider *et al.*, [28,30].

LSTM models function by utilizing previous time series data to forecast future trends. This is achieved through a memory unit known as the "cell state," which retains essential information from past sequences, thereby improving prediction accuracy, as demonstrated by Gajamannage *et al.* and Ballarin *et al.*, [31,32].

Additionally, LSTM models incorporate three key gates: the forget gate, the input gate, and the output gate. These gates control the flow of information within the cell state, selectively retaining or discarding data to ensure relevant information is preserved for accurate forecasting. This mechanism enables LSTM models to efficiently process time series data while addressing the vanishing gradient problem commonly encountered in traditional neural networks, as highlighted by Yunpeng *et al.* and Pyo *et al.*, [29,33].

LSTM models have been successfully utilized across various fields, including financial market trend forecasting, water demand prediction, and macroeconomic forecasting. Their capacity to effectively process time-dependent data has led to superior performance in financial market predictions compared to traditional approaches, as noted by Gajamannage *et al.*, [31].

In macroeconomic forecasting, LSTM models excel in handling mixed-frequency data, aligning high-frequency and low-frequency data points to enhance predictive accuracy, as highlighted by Ballarin *et al.*, [32]. Moreover, their application in water demand forecasting has proven effective in predicting short-term consumption patterns, showcasing their adaptability and precision across different domains, as demonstrated by Pyo *et al.*, [33].

2.2 Data Pre-processing

The data analysis process begins with data pre-processing, which involves collecting and cleaning the data to ensure its quality before analysis. Data pre-processing includes several key steps: removing missing values and correcting discrepancies in the dataset to ensure accuracy and consistency, normalizing the data to ensure consistency and facilitate the learning process of the LSTM model, and synchronizing data points to a common time frame, such as monthly or yearly intervals, to create a coherent time series. Feature engineering techniques are employed to enhance the predictive power of the model, including creating lag variables to capture temporal dependencies and calculating moving averages to smooth out short-term fluctuations and highlight long-term trends.

2.3 Model Development

The LSTM model is then developed. Hyperparameters such as the number of LSTM units, the number of layers, dropout rates, and the sequence length of input/output data are determined. The equations governing the LSTM network include the forget gate, input gate, cell state, and output gate. The forget gate equation is,

$$f_t - \sigma_g\left(W_f \cdot \left[h_{t-1}, x_t\right] + b_f\right) \tag{1}$$

the input gate equation is,

$$i_t - \sigma_g\left(W_i \cdot \left[h_{t-1}, x_t\right] + b_i\right) \tag{2}$$

and

$$C_t - \tanh\left(W_c \cdot \left[h_{t-1}, x_t\right] + b_c\right) \tag{3}$$

the cell state equation is,

$$C_t - f_t * C_{t-1} + i_t * C_t \tag{4}$$

the output gate equation is,

$$\sigma_t - \sigma_g\left(W_0 \cdot \left[h_{t-1}, x_t\right] + b_0\right) \tag{5}$$

and,

$$h_t - \sigma_t * \tanh\left(C_t\right) \tag{6}$$

2.4 Model Training and Evaluation

The model is trained using a supervised learning approach, implemented in R software. The training process involves dividing the dataset into training and testing sets to evaluate the model's performance, typically using an 80-20 split. Mean Squared Error (MSE) is employed as the loss function to quantify the difference between predicted and actual values, while the Adam optimizer is used for its efficiency in handling large datasets and its ability to adapt the learning rate. The model is trained over several epochs with a defined batch size to ensure thorough learning. During training, the model's performance is monitored using Mean Absolute Error (MAE), calculated as

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left[y_i - y_i \right] \tag{7}$$

where y_i is the actual value and y_i is the predicted value.

2.5 Model Validation and Forecasting

After training, the model's performance is evaluated using a testing dataset. The predictions made by the model are compared to the actual values, and metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Error (ME) and R-squared (R^2) are calculated to measure accuracy and reliability. With the validated LSTM model, a trend line is created to illustrate both historical and predicted land use patterns for rubber plantations in Johor. Additionally, the model forecasts land use trends for the next five years, offering valuable insights for future planning and policy-making. This approach highlights the effectiveness of LSTM networks in predicting land use trends and provides crucial information for sustainable land management practices in Johor's rubber plantations.

Tepe and Safikhani [34] introduced a machine learning-based spatio-temporal land-use change (LUC) modeling framework that leverages advanced algorithms and GPU parallel processing to handle large-scale urban development. By utilizing artificial neural networks and random forests, they analyzed Florida’s land-use data, comprising nearly 9 million parcels, to predict changes based on historical patterns and neighborhood characteristics.Significant computational improvements were achieved by accelerating the construction of spatial weight matrices and optimizing model training, leading to a prediction accuracy of approximately 92%. This framework offers a valuable tool for policymakers to refine budget allocations and strategize sustainable urban development effectively.

Karimi *et al*., [35] examined the potential of the support vector machine (SVM) technique to create a model for urban expansion. The research looked into three different sampling methods to establish a suitable training dataset and identified a comprehensive set of the most important predictor variables. Various configurations of the SVM were tested by adjusting the penalty parameter, kernel function, and parameters of the kernel. The study also introduced new goodness-of-fit metrics to specifically assess the SVM model's performance in modeling land use and land cover (LULC) changes. When applied to Guilford County, NC, from 2001 to 2011, the developed model showed highly accurate and dependable results, with the top-performing model achieving a training accuracy of 98% and a testing accuracy of 85%. This model has the potential to significantly enhance prediction accuracy and support the development of effective plans and policies to address the negative effects of urban expansion.

3. Results and Discussion

3.1 Model Performance and Evaluation

The LSTM model was assessed using key performance metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Error (ME), and the R-squared (R^2) value. The dataset was partitioned into training and testing sets following an 80-20 split.The results indicated an MAE of 922.636 hectares, RMSE of 1393.967 hectares, MAPE of 79.37%, ME of 57.73, and an R-squared value of 0.81. These findings confirm that the model achieved a reliable accuracy level in predicting historical land use trends for rubber plantations in Johor, demonstrating a strong alignment between projected and actual values, as documented by Chlingaryan *et al.*, [36].

The LSTM model effectively captures historical patterns and trends in the land use of rubber plantations. The close alignment between the model's predictions and actual data demonstrates its capability to retain essential information from long-term time series and utilize it for precise forecasting.The projected values for 2023 to 2028 indicate a continuation of the existing trend, with a steady expansion in the land area dedicated to rubber plantations. Reliable forecasting facilitates improved resource allocation and strategic planning, optimizing the management of agricultural inputs such as seeds, fertilizers, and labor, as evidenced by Farooqui *et al.*, [37].

3.2 Forecasting Land Use Trends

Figure 1 illustrates the actual versus predicted and forecasted land use trends for rubber plantations in Johor. The actual land use data (blue line) represents the historical trend, while the predicted values (red line) show the model's performance during the training and testing phases. The forecasted values (green dots) extend from 2023 to 2028, indicating the future trend as predicted by the LSTM model. The plot includes dashed trend lines fitted to both the actual and predicted data, highlighting the overall trends in land use over time. These trend lines were generated using linear regression to provide a clearer view of the long-term patterns.

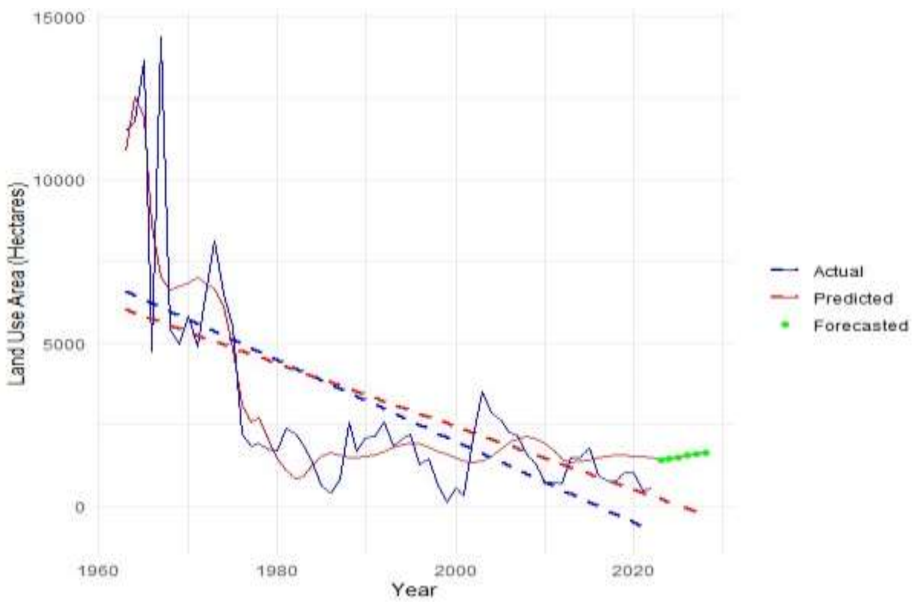

Fig. 1. Actual, predicted, and forecasted land use area (hectares) for rubber plantation from 1960 to 2020

Table 1 presents the forecasted land use values for rubber plantations in Johor from 2023 to 2028.

Table 1
Forecasted values for rubber plantation (2023-2028)

Year	Forecasted land use area (Hectares)
2023	1540.393
2024	1518.181
2025	1557.457
2026	1617.981
2027	1662.692
2028	1698.754

3.2 Discussion

The findings of this study highlight the effectiveness of the Long Short-Term Memory (LSTM) model in capturing historical patterns and trends in the land use of rubber plantations in Johor. Through the analysis of long-term time series data, the model has shown a strong ability to generate predictions that closely align with actual observations, demonstrating its capacity to retain crucial information over extended periods and facilitate accurate forecasting.The high degree of consistency between the model's predictions and real-world data not only confirms the reliability of the LSTM model but also showcases its ability to handle the complexities of temporal dependencies and non-linear relationships inherent in land use data, as demonstrated by Li *et al.*, [38].

The projected values for rubber plantation areas in Johor from 2023 to 2028 offer valuable insights into future trends, building on historical data. The model indicates that the area allocated for rubber plantations will see some fluctuations in the upcoming years, starting with 1540.393 hectares in 2023, followed by a slight decrease to 1518.181 hectares in 2024. However, a recovery is expected in 2025, with the area increasing to 1557.457 hectares. This upward trajectory is anticipated to continue, with plantation areas growing to 1617.981 hectares in 2026, 1662.692 hectares in 2027, and reaching 1698.754 hectares by 2028. Although a minor decline is expected in 2024, the overall forecast indicates a positive trend in the growth of rubber plantation areas over the next five years. This information is particularly useful for stakeholders involved in land use planning and agricultural policy-making, as it underscores the expected changes in rubber plantation areas and facilitates strategic adjustments as outlined by Szulecka *et al.*, [39].

The accuracy of the LSTM model's predictions and its ability to generate reliable forecasts hold significant value for sustainable land management practices. The insights provided by these forecasts can serve as a foundation for strategic decision-making processes related to rubber plantations in Johor. Stakeholders, including policymakers, agricultural planners, and environmental conservationists, can leverage these insights to anticipate changes in land use patterns and implement appropriate measures to mitigate potential risks or capitalize on projected trends. This proactive approach is crucial for ensuring the sustainability of rubber plantations, particularly in the face of changing environmental conditions and market dynamics. Furthermore, the use of such advanced forecasting techniques supports the development of informed policies that balance economic growth with environmental stewardship, conducted by Chuku *et al.,* [40].

LSTM networks offer several distinct advantages when it comes to land use forecasting, making them particularly well-suited for this application. One of the primary strengths of LSTM networks lies in their capacity to capture long-term dependencies in time series data. This capability is crucial for accurate forecasting, especially in scenarios where past events significantly influence future outcomes, as is often the case with land use changes as explained by Wunsch *et al.,* [41]. Additionally, LSTM networks are adept at managing non-linear relationships within the data, which is particularly important for land use forecasting where the relationships between different variables, such as environmental factors and human activities, are often complex and non-linear.

Another critical advantage of LSTM networks is their ability to address the vanishing gradient problem, a common issue that affects traditional neural networks. In conventional neural networks, the gradients used during training can diminish to near-zero values as they are propagated backward through the network layers, leading to poor model performance. LSTM networks mitigate this problem through their unique architecture, which includes memory cells and gating mechanisms that allow the network to retain important information over time. This results in enhanced model performance, particularly in tasks that involve learning from long sequences of data, such as land use forecasting.

4. Conclusions

4.1 Conclusion

This study highlights the effectiveness of Long Short-Term Memory (LSTM) networks in forecasting land use trends for rubber plantations in Johor, Malaysia. By utilizing a robust LSTM model alongside historical data, the research achieved high accuracy in predicting future land use patterns, as evidenced by favourable assessment metrics such as R-squared (R^2), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). The results indicate a continuation of existing trends, providing valuable insights into the potential future configuration of rubber plantations. The LSTM model is particularly adept at handling long-term dependencies and non-linear interactions within time series data, making it well-suited for complex forecasting tasks in land use planning and agricultural management, as shown by the accurate predictions.

4.2 Recommendations

Some recommendations are made in light of the findings. Policymakers should use the insights gained by the LSTM model to influence strategic choices on land allocation, agricultural subsidies, and conservation activities, ultimately supporting sustainable land management practices. The expected continuance of existing trends underscores the necessity for proactive actions to minimize environmental deterioration caused by the growth of rubber plantations. Continuous monitoring of land use changes, as well as frequent updates to the historical information, are required to ensure that projections are accurate and relevant. The LSTM model should be rebuilt on updated data regularly to guarantee that the predictions are current and reliable.

To increase the precision of land use pattern modelling, it would be beneficial to investigate the possibility of combining remote sensing data with LSTM networks in future studies. Furthermore, examining the use of alternative machine learning algorithms, such random forests or convolutional neural networks, in conjunction with GIS for comparable tasks, may offer important insights into the best methods for spatial analysis. Furthermore, broadening the study's focus to encompass other temporal or geographic contexts may yield a more thorough comprehension of the suitability of the suggested methodology.

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