Journal of Sustainability Science and Management
Volume 20 Number 5, May 2025: 896-907
eISSN: 2672-7226

THE SUSTAINABILITY OF MALAYSIAN PALM OIL AND FORECASTING OF FOREST AND PLANTATION LAND AREA USING MATHEMATICAL MODELLING APPROACH

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http://doi.org/10.46754/jssm.2025.05.001
Submitted: 10 March 2024 Revised: 1 October 2024 Accepted: 21 November 2024 Published: 15 May 2025

Abstract: The palm oil industry in Malaysia plays a vital role in the global market. In 2021, it significantly boosted Malaysia's agricultural sector. This study explores mathematical modelling to assess palm oil supply chain sustainability, especially in light of biodiversity concerns related to industrial monoculture cultivation. We apply supervised machine learning to determine sustainability weights, which are then used to assess supply chain risks and develop a mathematical model that balances sustainability considerations. This dynamic relationship is modelled using differential equations, particularly the Lotka-Volterra equations, which capture the interaction between palm oil plantation areas and their impact on the surrounding environment (forests). The analysis reveals several possible equilibrium points: (i) Extinction of both the palm oil plantations and forests, (ii) coexistence with a stable forest population and declining palm oil plantations, and (iii) coexistence of both populations. These equilibrium points represent different scenarios where the dynamics of palm oil plantations and the environment can reach a stable state. The palm oil plantations are modelled as predators while the forests are considered prey. In conclusion, this study applies mathematical modelling to advance sustainable practices in the palm oil industry, focusing on the equilibrium dynamics between the environment and palm oil cultivation.

Keywords: Palm oil, sustainability, deforestation, mathematical modelling, machine learning.

Introduction

Palm oil is the main vegetable oil globally and has remained one of the world's major sources of oils and fats (Nambiappan *et al*., 2018; Yap *et al*., 2021). Indonesia and Malaysia have been recognised as the leading and second-largest palm oil contributors, exporting over 90% of their palm oil production and accounting for around 80% of worldwide palm oil production, respectively (Tan & Lim, 2019). As of 2023, Malaysia produced approximately 18.55 million tonnes of Crude Palm Oil (CPO) and exported about 24.49 million tonnes while Indonesia produced around 47 million tonnes of palm oil (MPOB, 2022).

Malaysia's palm oil supply chain is complex, involving many entities, from smallholders to major mills to manufacturers. The process starts with smallholders who grow and cultivate oil palm trees on their land. Smallholders gather the fruits and sell them to larger mills once the trees mature. The fruits are then processed in mills to extract the oil. This procedure involves several processes, including fruit sterilisation, oil extraction, purification, clarification, and packaging (Mba *et al*., 2015). The result is CPO, a thick, reddish-brown oil. CPO can be found in many products such as biodiesel, margarine, and cooking oil. The refinement of CPO is the next stage in the supply chain. The oil is further processed to remove contaminants and increase its quality. Consequently, the refined oil can be used in various products such as cosmetics, soaps, and detergents (Barriuso *et al*., 2013). The distribution and marketing of palm oil products is the final stage in the supply chain. These items are sold to people all over the world. Palm oil has overtaken soybean oil as the most important vegetable oil in the world (Bharti *et al*., 2024).

However, the palm oil industry is controversial since it is a major contributor to deforestation (Meijaard *et al.*, 2020). Forests are destroyed to make way for palm oil plantations, destroying the habitat of many endangered species. Deforestation also contributes to climate change (McAlpine *et al.*, 2018). Malaysia continuously strives to strengthen and raise the palm oil sector to global standards by addressing various stakeholder requirements and meeting the expanding global demand for vegetable oils (Kannan *et al*., 2021). With the current sustainable practices being implemented in the palm oil industry, it is crucial to consider the potential future implications.

Therefore, we utilise mathematical models to investigate the equilibrium sustainability and forecast the future of Palm Oil Plantation. Forecasting techniques can be inculcated, thereby assisting in designing better strategies and making productive decisions. These techniques assess the situations of the past, thereby enabling better predictions. Hence, these predictions might help to prepare against possible threats and consequences. Forecasting techniques play a crucial role in yielding accurate predictions.

In this article, a dynamic model of interaction between forestry and palm oil plantation areas is described. This interaction follows the Lotka-Volterra-type predator-prey model. This model was first proposed by American ecologist, Alfred J. Lotka and Italian mathematician, Vito Volterra in 1925 and 1926, respectively. The prey-predator models have garnered growing interest due to their ability to define the dynamics and growth rate of competing biological species. In this model, the palm oil plantations are considered “predators” while the forests act as “prey”.

This analogy stems from the nature of the interaction between the two: Palm oil plantations expand by clearing forests, much like a predator consuming its prey. As plantation areas grow, forest areas diminish, simulating how a predator’s population depends on prey availability. On the other hand, forests are affected by the growth of palm oil plantations and reduce in size as plantations “consume” forested areas. Therefore, palm oil plantations “prey” on forests to expand their land area. This predator-prey framework simplifies and effectively captures the dynamics of deforestation caused by plantation expansion.

These models can be expressed as a system of nonlinear Ordinary Differential Equations (ODEs), which can then be solved to find their solutions (Izadi *et al*., 2022). This model may also be utilised to simulate other related models such as chemical reactions, plasma physics, and control theory (Mba *et al*., 2015). This article aims to analyse the developed mathematical model of predator-prey interaction to investigate the equilibrium points and the sustainability of palm oil plantations alongside forests. The implications of this equilibrium are then predicted.

Materials and Methods

Model Development

We must assume several assumptions to develop these model equations for the model to work correctly. Firstly, we assume that the number of forests (prey) grows exponentially without palm oil plantation areas (predator). Second, we assume that the palm oil plantation area increases at a rate that is proportional to the size of the forest population. Lastly, we assume that the two populations competitively interact with each other. The resulting system of first-order ODEs is expressed as follows:

$$\frac{dF}{dt} = aF(1 - \frac{F}{K}) - bFP,$$
$$\frac{dP}{dt} = -cP + sFP, \tag{1}$$

where $\frac{dF}{dt}$ and $\frac{dP}{dt}$ represent the rate change of forest (prey) and palm oil plantation area (predator), respectively. The represents the reproductive rate of the forest; $\left(1 - \frac{F}{K}\right)$ resembles the growth rate of the forest following the logistic growth (Acevedo *et al.*, 2012).

The carrying capacity of a forest, denoted as K, demonstrates the maximum number of forests that can be sustained in each area over time; $-b$ refers to deforestation due to human activities; $-c$ examines death at the rate of palm oil plantation such as closing of the mill; and indicate growth rate of the palm oil plantation. To ensure biological relevance, all parameter values must be positive and bounded (Khairuddin *et al.*, 2021). For instance, the growth rate of the forest (a) should be greater than zero but less than the maximum sustainable value. The carrying capacity (K) must also be a positive value derived from empirical data. Additionally, death rates such as that of the palm oil plantation (c), must be non-negative. These constraints enhance the model's reliability in predicting ecological dynamics and interactions between palm oil plantations and forests.

Relationship between the Environment and Mills

The interaction between palm oil mills and the environment involves multiple environmental impacts that directly and indirectly influence sustainability. Mills contribute to deforestation, as land must be cleared to supply palm fruits for processing (Meijaard *et al.*, 2020). Additionally, constructing new mills typically necessitates the expansion of palm oil plantations, thereby further reducing forest areas (Nambiappan *et al.*, 2018).

Moreover, palm oil mills generate pollution through waste products such as Palm Oil Mill Effluent (POME), which can contaminate local water sources and affect soil quality (Mba *et al.*, 2015). This pollution can have long-term ecological consequences, leading to biodiversity loss and degraded ecosystems (McAlpine *et al.*, 2018). Furthermore, the operation of these mills typically requires significant energy use, contributing to carbon emissions and exacerbating climate change (McAlpine *et al.*, 2018). These environmental pressures necessitate stringent regulation and monitoring to mitigate negative impacts (Kannan *et al.*, 2021).

Incorporating the relationship between mills and the environment into our model allows for a more holistic view of how plantation expansion and industrial processing affect the overall ecosystem. By understanding these interactions, we can better forecast land-use dynamics and assess the long-term sustainability of the palm oil supply chain (Yap *et al.*, 2021).

Parameter Estimation

Parameter estimation involves a multi-step process to derive realistic and context-specific values for the model's parameters. Firstly, the growth and death rates of the forest and palm oil plantations are calculated using historical data spanning from 2011 to 2020. Mathematical formulas are employed to systematically extract growth and death rate values, ensuring a data-driven foundation for the model.

To provide further context, Table 1 presents the historical data for the total forest area and palm oil plantation area in Malaysia, spanning from 2011 to 2022. This dataset forms the backbone of our parameter estimation process.

Table 1: Total forest area and palm oil plantation area in Malaysia (2011-2022). Data for total forest area in 2021 and 2022 are not available

Year	**Total Forest Area (Million Hectares)**	**Total Plantation Area (Million Hectares)**
2011	17.931424	5.000109
2012	18.013251	5.076929
2013	18.056155	5.229739
2014	18.277602	5.392235
2015	18.389686	5.642943
2016	18.241716	5.737985
2017	18.332583	5.811145
2018	18.273487	5.84933
2019	18.135292	5.900157
2020	18.0456	5.865297
2021	-	5.737731
2022	-	5.674742

Using this data, the growth and death rates for both the forest area (prey) and the palm oil plantation area (predator) are calculated as follows:

Growth Rate Formula (%): $$\frac{\sum \frac{|Year_{i+1} - Year_i|}{Year_i} \times 100}{n_{Year}}, \quad (2)$$

Death Rate Formula (%): $$\frac{\sum \frac{|Year_{i+1} - Year_i|}{Year_i} \times 100}{n_{Year}}. \quad (3)$$

These formulas are applied to the data to compute the annual growth and death rates for the forest and palm oil plantation areas between 2011 and 2020. The calculated values allow for the precise estimation of model parameters related to forest growth, deforestation, palm oil plantation expansion, and plantation death rates.

Next, following the data-driven estimation, a normalisation step is introduced to enhance the robustness of the model. This involves transforming the parameter values to a common scale, ensuring they fall within the range of 0 to 1. The normalisation process is particularly crucial for parameters with varying magnitudes, preventing disproportionate influence on the model's dynamics. This step standardises the parameters and minimises bias, promoting a more balanced representation of their impact on the system (Sinha *et al*., 2023).

The normalisation of the parameters is performed as follows:

(1) Rank of X_i: Each parameter value X_i, representing the original parameter value is ranked according to its magnitude, and its position in this ranking is denoted as R_i.

(2) Find the range: The range of the parameter, denoted by X_R, is calculated as the difference between the maximum and minimum values of the parameter:

$$X_R = Xmax - Xmin$$

where *Xmax* is the maximum value and *Xmin* is the minimum value of the parameter.

(3) Normalise each parameter value X_i is then normalised using the formula:

Normalised $X_i = \frac{X_i - Xmin}{X_R}$.

This formula ensures that the normalised parameter values fall within the range of 0 to 1, with the smallest value mapped to 0 and the largest value mapped to 1.

In this context,

- X_i represents the original value of a parameter.
- R_i refers to the rank of X_i based on its value compared to other parameters.
- *Xmax* and *Xmin* are the minimum and maximum values of the parameter, respectively.
- X_R is the range of the parameter values, i.e., the difference between the largest and smallest values.

By normalising the parameters, this process standardises their scales, allowing for a more balanced and unbiased representation of the model.

Stability Analysis

However, not every equilibrium point is stable under the condition of environmental shift. We implemented the Jacobian matrix to determine the eigenvalue of each group and decided which equilibrium point of each group was stable. The stability of an equilibrium point is determined by assessing the sign of the real parts of the eigenvalues. Negative real parts indicate stability, while positive real parts suggest instability. This analysis provides insights into the long-term behaviour and sustainability of the system. If the equilibrium point is stable, it suggests that the corresponding equilibrium will occur in the future. Conversely, if the equilibrium point is unstable, such equilibrium will not materialise (Khairuddin *et al*., 2021).

First, the equilibrium values are determined by setting the model's equations (1) to zero and solving them simultaneously. Next, substitute the obtained equilibrium points into the Jacobian Matrix. It is essential to understand that every equilibrium value corresponds to a unique Jacobian matrix. Proceed by calculating the eigenvalues of each Jacobian matrix using the equation $det|\lambda - IJ| = 0$, where λ denotes the eigenvalues, I is the identity matrix, and J is the Jacobian matrix. Finally, the stability of the equilibrium points will be assessed by examining the signs of the eigenvalues. This methodology is based on Mohd Roslan *et al*. (2019).

Error Analysis

The performance of the models was evaluated based on the predicted outcome values using common statistical measures. In this study, the evaluation metrics of Chi-Square, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) are computed for the forecasting models within the Excel environment (Table 1) (Karaman, 2023). These metrics provide a quantitative assessment of the model's accuracy and reliability in predicting the future dynamics of the forest and palm oil plantation areas in Malaysia.

Table 2 summarises key evaluation metrics, their corresponding formulas in Excel, and the associated goodness-of-fit criteria. The table provides a comprehensive guide for understanding and applying these metrics to enhance the robustness of Lotka-Volterra model assessments.

Results and Discussion

Table 2 presents the variables and parameters for both forest and palm oil plantations in Malaysia. The historical data was obtained from the Malaysian Palm Oil Board and the Forestry Department (MPOB, 2022; FDPM, 2023). These values were then used in a Lotka-Volterra model to predict their future sustainability and potential ecological interactions. Table 3 shows parameter of the Lotka-Volterra model. Particularly, the palm oil plantation area has a higher growth rate than the forest area, mirroring Malaysia's real-life trend of rapid mill development (Mohd Hanafiah *et al*., 2022), as evidenced (Table 1). This rapid expansion while contributing to economic growth, raises concerns about potential ecological consequences such as deforestation and biodiversity loss. The

Table 2: Evaluation metrics and goodness of fit criteria. Total; Σ, actual value; O_i, predicted value; E_i, absolute value; ||, square root; $\sqrt{\ }$

Error Metric	Formula	Goodness of Fit
Chi-Square (χ^2)	$X^2 = \sum \frac{(O_i - E_i)^2}{E_i}$	Lower values indicate a better fit
Mean Absolute Error (MAE)	$MAE = \frac{1}{n} \sum \lvert O_i - E_i \rvert$	Smaller values are preferred
Mean Squared Error (MSE)	$MAE = \frac{1}{n} \sum (O_i - E_i)^2$	Smaller values are better useful for comparisons
Root Mean Squared Error (RMSE)	$RMSE = \sqrt{MSE}$	Smaller values are better more interpretable than MSE

Table 3: Parameter of the Lotka-Volterra model

Variable	Value		Description
F	1		Based on normalised actual data of forest area ($Xyear_1/Xyear_1$).
P	0.3		Based on normalised actual data of plantation area ($Yyear_1/Yyear_1$).
Parameters	**Actual Rate Value (%)**	**Normalisation Rate Value**	**References**
a	0.6144	0.0501	(FDPM, 2023)
b	0.6131	0.0499	
c	1.9553	0.3332	(MPOB, 2022)
s	1.9138	0.3245	
K	-	100	Assume

model can enhance understanding of complex interactions and inform sustainable development strategies for Malaysia's future.

Based on the error analysis, Model (1) appears to be a good fit and highly accurate for predicting sustainability in Malaysia (Table 4). This is because the chi-square value is close to 1. A chi-square value close to 1 indicates that the observed and predicted values are similar, meaning the model accurately captures the real-world scenario (Mcdonald, 2009). Consequently, the MSE, MAE, and RMSE values are also close to zero, suggesting a near-perfect fit. Having all three metrics close to zero suggests that Model (1) consistently makes predictions very close to the actual sustainability levels in Malaysia.

Table 4: Error analysis of a model distinguishing between forest and palm oil areas in Malaysia

Error Analysis	Chi-Square	Mean Square Error (MSE)	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)
Forest	1	0.00905	0.08358	0.09515
Palm oil	1	0.00194	0.03722	0.04408

This means the Lotka-Volterra model fits the data well and can make accurate predictions. This model is commonly used in ecology to represent predator-prey dynamics. Hence, it can also be applied to other systems with competition or exploitation such as the relationship between forests and palm oil plantations.

The Model (1) output compares actual and predicted data for forest and palm oil cover in Malaysia (Figures 1 and 2). The forest model output indicates that the forest area in Malaysia has been declining since the first year. However, it has started to increase again in recent years. The palm oil plantation area

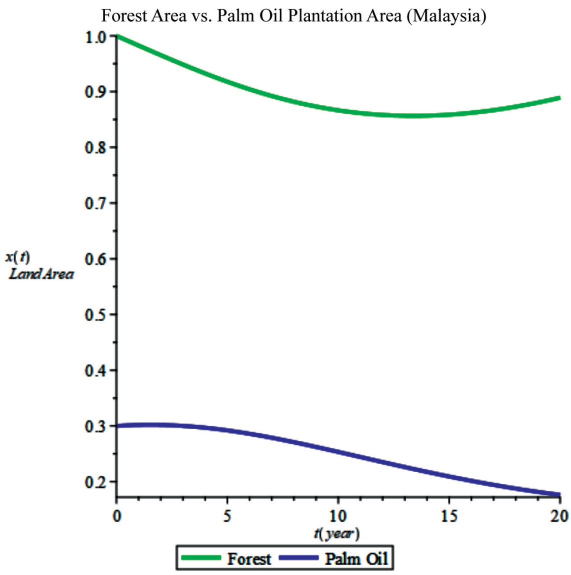

Figure 1: A comparative analysis of forested and palm oil plantation areas in Malaysia

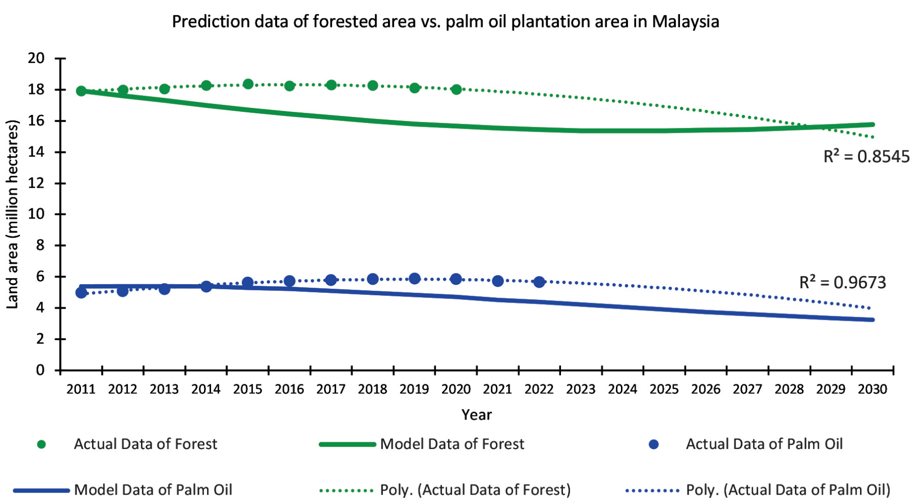

Figure 2: Predicted data for forested and palm oil plantation areas in Malaysia (2011-2030). R^2 indicates a polynomial trendline with an order of two. The green line shows the model's prediction for forest cover and the green dots show the actual data for forest cover. The blue line shows the model's prediction for palm oil cover and the blue dots show the actual data for palm oil cover. The actual data (dots) and the model's predictions (lines) are very close together for both forest and palm oil cover in all three regions

has remained relatively stable for the first five years but has declined recently (Figure 1). One possibility is that the decline in forest area is due to deforestation, which is clearing forests for other uses such as agriculture or development. Another possibility is that the decline in forest area is due to logging. Moreover, the increase in forest area in recent years could be due to reforestation efforts. The decline in palm oil plantation areas could be due to several factors such as a decrease in demand for palm oil or an increase in the cost of production. It is also possible that the decline in palm oil plantation areas is due to concerns about the environmental impact of palm oil production.

Nonetheless, Figure 1 illustrates that the estimated total forest area in 2030 is 15.8 million hectares while the projected area for palm oil plantations in the same year is 3.3 million hectares. This indicates that the expected forest area will exceed palm oil plantations. Consequently, it can be argued that the development of mills or palm oil plantations does not lead to deforestation, highlighting the sustainability and positive aspects of the Malaysian palm oil industry.

Further confirmation comes from the polynomial trendlines for actual data, closely mirroring the model's forecast (Figure 2). Polynomial trendlines are statistical curves fitted to the actual data, and they act as a "reference line" for the overall data trend. The trendline model was fitted using a second-degree polynomial. Other degrees of polynomials and other trend functions were fitted, too. However, it had the least and seemed to explain the curve growth as poorer than the other functions. In this case, the close mirroring of the model's predictions to these trendlines indicates that the model captures the underlying patterns in the data accurately.

Since the model followed a logistic growth, a polynomial trendline is the best choice because it can capture this S-shaped pattern well (Wang *et al.*, 2022). Unlike a linear trendline, it could not capture the acceleration and saturation phases of logistic growth, leading to a poor fit and low R-squared value. Similarly, an exponential trendline also leads to a poor fit because it would not level off and would predict continuous, unsustainable growth, making it unrealistic for forecast data.

The polynomial regression order of (R^2) values for forest area is 0.8545 and for palm oil plantation is 0.9673. These values are near to 1 and further strengthen the model's reliability. This successful prediction and data types position the Lotka-Volterra model as a valuable tool for informing land-use and sustainability decisions in Malaysia.

Derived from the presented graph, it can be inferred that in the context of Malaysia, the coexistence of palm oil plantations with forested areas indicates sustainability, dispelling concerns about deforestation despite the stable development of the palm oil industry. New palm oil plantations are likely being established on previously cleared land rather than encroaching on existing forests (Nursyamin *et al.*, 2023). However, it is important to note that the Malaysian government has taken steps to ensure that the palm oil industry is sustainable and environmentally friendly. The Malaysian Sustainable Palm Oil (MSPO) certification scheme was launched in 2015 to promote the production and use of sustainable palm oil in Malaysia (Yap *et al.*, 2021). Note that the MSPO certification covers all aspects of palm oil production, including environmental, social, and economic sustainability. The certification is mandatory for all palm oil producers in Malaysia and it ensures that the palm oil produced in Malaysia is sustainable and meets international standards.

The stability analysis shows the dynamic relationship between forest and palm oil plantations in Malaysia, as modelled by the derivative of Lotka-Volterra Equations (1). By analysing the equilibrium points and their stability, we can gain valuable insights into the long-term sustainability of these two land uses.

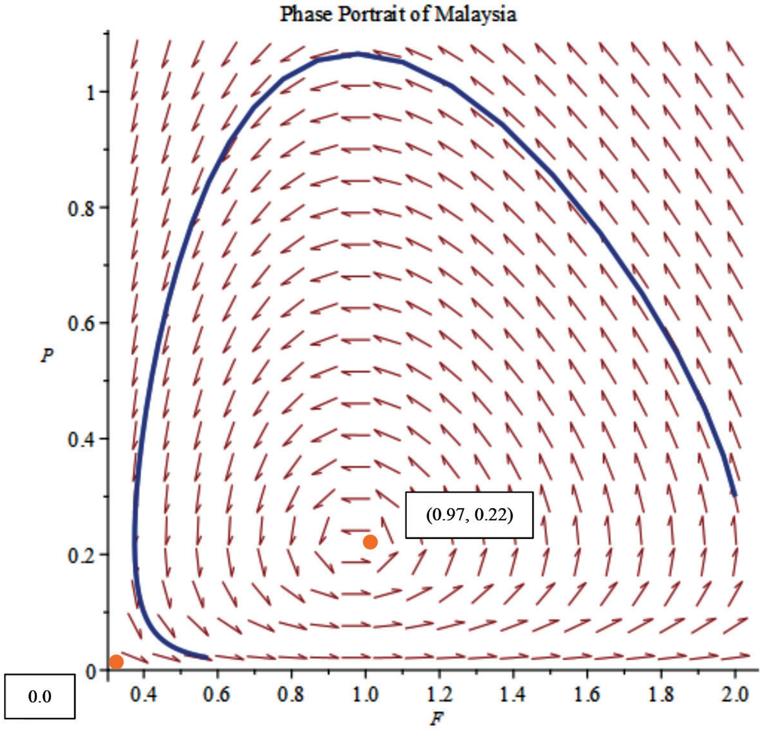

Figure 3: Phase portrait plot with stable equilibrium point for Model (1) in Malaysia

The phase portrait reveals three equilibrium points (Figure 3):

(1) (0.0): This point represents no forest area or palm oil plantations. This is not a realistic or attainable state in Malaysia. As such, it is classified as an unstable equilibrium. Trajectories starting near this point will inevitably disappear, indicating its unsustainable nature.

(2) (100.0): This point represents complete deforestation with maximum palm oil cover. Similar to the first point, this is not a desirable or sustainable scenario for Malaysia. Therefore, it is also classified as an unstable equilibrium. Trajectories initially close to this point will drift away, emphasising the unsustainability of complete deforestation.

(3) (0.97, 0.22): This point represents a coexistence of forest and palm oil cover, with approximately 90% forest area and 20% palm oil plantation area exhibiting asymptotic stability. This equilibrium point is particularly interesting as it appears to be stable. This implies that if the system deviates slightly from this balance, it will naturally tend to return to it over time.

The trajectories in the phase portrait show that the system will evolve over time, starting from different initial conditions (Figure 3). The arrows indicate the change in direction and the curves represent the paths the system will take. Any trajectory that starts near the unstable equilibrium points (0.0) or (100.0) will eventually move away from them while trajectories that start near the stable equilibrium point (0.97, 0.22) will eventually approach it. The eigenvalues of (0.0) and (100.0) being positive reveal their instability, representing an unrealistic scenario (Table 5). Meanwhile, the negative real parts of both eigenvalues for (0.97, 0.22) solidify its stable nature.

Table 5: Summary of stability for Malaysia

Country/State	Equilibrium Point	Eigenvalue	Type of Stability
Malaysia	$x = 0$ $y = 0$	$\begin{pmatrix} 0.05019285100 \\ -0.3245221390 \end{pmatrix}$	Unstable
	$x = 100$ $y = 0$	$\begin{pmatrix} -0.05019285100 \\ 33.00436306 \end{pmatrix}$	Unstable
	$x = 0.9736963509$ $y = 0.2224636061$	$\begin{pmatrix} -0.0002443629850 + 0.1270040522i \\ -0.0002443629850 - 0.1270040522i \end{pmatrix}$	Stable

Conclusions

This study developed a modified Lotka-Volterra predator-prey model to meticulously evaluate the long-term sustainability and forecast future landscape dynamics between forest areas (prey) and palm oil plantations (predator) in Malaysia until 2030. The model's parameters were rigorously estimated from historical government reports and normalised to a 0 to 1 scale, yielding highly accurate results as evidenced by comprehensive error analyses. The analysis identified three equilibrium points. However, only the equilibrium points with approximately 90% forest and 20% palm oil plantation area exhibited long-term stability. This stable equilibrium suggests that coexistence between forest and palm oil plantation areas is achievable under specific conditions.

The sustainability of palm oil plantations depends heavily on maintaining sufficient forest cover, which provides crucial ecological services such as carbon sequestration and biodiversity support. Reforestation efforts, as well as the protection of existing forests are essential for achieving long-term sustainability. Moreover, expanding plantations must be carefully regulated to prevent excessive deforestation and environmental degradation.

From a policy perspective, this research underscores the importance of sustainable land management practices. The integration of certifications such as the MSPO certification can further ensure that palm oil production aligns with global sustainability standards. If managed properly, palm oil plantations can coexist with forest ecosystems without leading to significant deforestation, promoting a sustainable balance between economic development and environmental conservation.

In conclusion, this study offers valuable insights into the dynamic relationship between palm oil plantations and forests, providing a basis for informed decision-making regarding land-use strategies. The results emphasise the importance of sustainable practices in the palm oil industry to ensure the coexistence of plantations and forested areas, promoting environmental sustainability while supporting economic growth.

Acknowledgements

This project was funded via Dana Penyelidikan Universiti Malaysia Terengganu (DP-UMT), Talent and Publication Enhancement Research Grant (TAPE-RG), DP-UMT/TAPE-RG/vot. 55297. The authors would like to express their gratitude to the anonymous reviewers for their valuable suggestions, which greatly contributed in improving the manuscript.

Conflict of Interest Statement

The authors agree that this research was conducted without any self-benefits or commercial or financial conflicts and declare the absence of conflicting interests with the funders.

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