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Research

Forecasting Green Sea Turtle (*Chelonia mydas*) Landing in Sarawak Using Grey Model

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ABSTRACT

Green sea turtles, known scientifically as *Chelonia myd*as, prefer to nest on specific sandy beaches in Sarawak, particularly within the Sarawak Turtle Islands (STI). The number of turtles landing, among other variables (number of eggs collected, eggs incubated, and eggs hatched) is an important element in assessing the population size in Sarawak. However, modeling and predicting the number of turtles landing presents challenges due to limited data availability, resulting in less accurate forecasts for medium and long-term periods. To overcome this problem, this study presents a Grey Model (GM) approach, leveraging its capacity to effectively model systems with limited data, irregular patterns, and a lack of prior knowledge. Using data from 1949 to 2016, GM (1,1) was found to be the most suitable model for the given dataset, exhibiting the lowest Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) as compared to other statistical models such as Autoregressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM) and Exponential Smoothing. The model also suggested that the current conditions will likely increase turtle landings. This approach will find useful applications in evaluating the conservation status of the species.

Key words: Green sea turtle, grey model, grey system, Sarawak, turtle landing, time series

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INTRODUCTION

Green sea turtles (*Chelonia mydas*) locally known as '*penyu agar*' are the major landers on Sarawak Turtle Islands (STI). They could travel thousands of kilometres to the foraging grounds for food and usually adult females will return to mate and nest at their natal beach. The presence of these majestic creatures enriches both the marine ecosystem and the local heritage.

Sea turtle landings involve the arrival of both male and female turtles onto nesting beaches, with females primarily arriving to lay their eggs in meticulously crafted nests dug into the sand. However, the conservation of these nesting sites faces challenges, including anthropogenic disturbances, climate change impacts, and habitat degradation. Effective conservation strategies necessitate reliable forecasting of turtle landings to inform adaptive management practices and mitigate threats to their survival.

Turtle studies in Malaysia largely focus on nesting biology and its management (Tisen *et al*., 2002; Abd. Mutalib & Fadzly, 2015; Abd. Mutalib *et al*., 2015), ecology (Bali *et al*., 2000; Pilcher, 2010; Tinsung *et al*., 2011; Hassan & Yahya, 2022) as well as genetic studies (Joseph & Shaw, 2011; Yahya *et al*., 2012; Joseph *et al*., 2014; Jensen *et al*., 2016; Joseph *et al*., 2016; Joseph & Nishizawa, 2016; Nishizawa *et al*., 2016; Joseph *et al*., 2017). Minimal attention has been given to the turtle landing pattern and its significance for the population due to limited available data, making modeling and forecasting challenging. Traditional methods of predicting turtle landings often utilize basic statistical techniques that may not account for all relevant factors influencing landing frequencies.

Grey System Theory (GST) or Grey Model (GM) offers a promising framework for modeling systems with limited data (Quartey-Papafio *et al*., 2021) and uncertain dynamics, making it particularly suitable for forecasting ecological phenomena such as sea turtle landing activities. In agricultural science research, GM techniques have been applied to solve problems and contribute to the development of food security early warning prediction by utilizing GM and food quality index (Wang *et al*., 2012.). Numerous researchers have made efforts to enhance the accuracy of grain yield prediction by developing different combined prediction models. These involve merging the GM with the Markov model (Fan *et al*., 2019), support vector machine (Hu & Chen, 2021), and backpropagation neural network (Yang *et al*., 2015). A high prediction accuracy is achieved when utilizing the method. Enhanced GMs also contribute to predicting the occurrence of crop diseases and insect pests, such as the cotton spider mite (Wang *et al*., 2017).

GM has found diverse applications in environmental studies, including the analysis, and forecasting of CO_2 emissions (Wang & Si, 2024). GM offers a robust framework for analyzing historical emission data, identifying trends, and predicting future emission levels. By considering the inherent uncertainties and irregularities in emission data, GM can provide valuable insights into the factors driving CO_2 emissions, such as industrial activities, energy consumption patterns, and land-use changes (Ayvaz *et al*., 2017).

GMs, though not as pervasive in animal analysis as in other fields, offer a versatile and adaptable approach to understanding ecological dynamics, population trends, and species distributions. One significant application lies in fisheries management. By modeling fish population dynamics and catch data, GMs help forecast future fish stocks and assess the sustainability of fishing practices (Li, 2011; Xia *et al*., 2019; Xie & Chen, 2019; Lu & Chen, 2021).

Motivated by the need for accurate forecasting methods to support conservation efforts for Green Sea Turtles in Sarawak, this study utilized the GM approach to model and forecast the number of turtle landings in the region. By comparing the GM methodology and another statistical model, this study aimed to provide insights into the temporal patterns of turtle landings in Sarawak, offering valuable information to guide conservation strategies and protect the nesting habitats of Green Sea Turtles.

MATERIALS AND METHODS

Study site and data collection

The primary nesting area for Sarawak's Sea turtle population is found off the coast of Southwest Sarawak on three islands collectively referred to as the STI (Leh *et al*., 1985). These islands include Talang Talang Besar, Talang Talang Kecil, and Satang Besar (Figure 1).

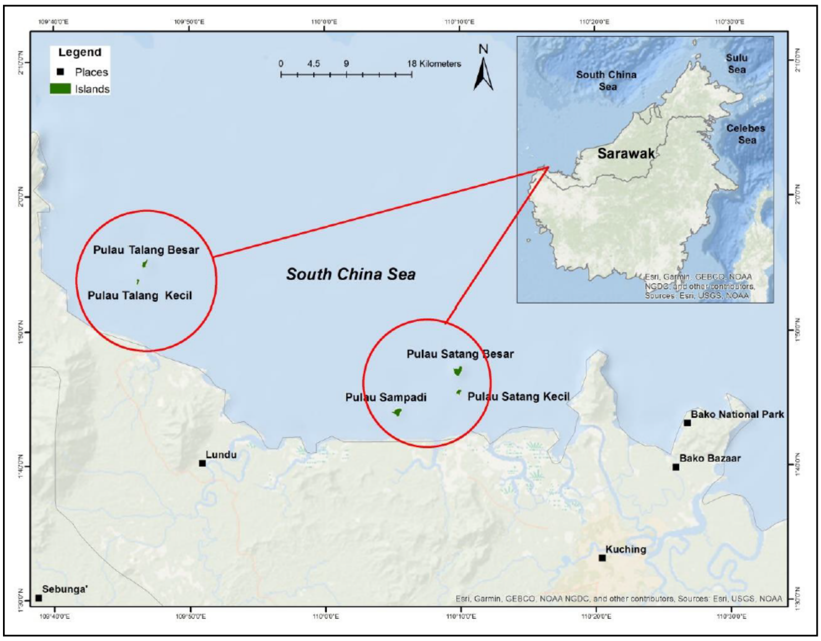

Fig. 1. Location of turtle foraging ground in Sarawak.

This study utilized secondary data from two distinct sources. The annual turtle landing figures spanning from 1980 to 2016 were acquired from the Turtle Board of Sarawak Museum, while the landing data preceding 1980 was retrieved from Mortimer *et al*. (1990).

Grey Model

The Grey Model (GM) is a forecasting model for time series data that consists of three fundamental steps: accumulated generation, inverse accumulated generation, and grey modeling. The grey forecasting model utilizes accumulation operations to create differential equations, which reduces the amount of data required for modeling the series.

Let the initial time series be

$$X^{(0)} = \left\{ x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(i), ..., x^{(0)}(n) \right\} \qquad \text{- Equation 1}$$

Where $x^{(0)}(i)$ is the time series at time *i* and $n \geq 4$

A new sequence $X^{(1)}$

$$X^{(1)} = \left\{ x^{(1)}(1), x^{(1)}(2), ..., x^{(1)}(i), ..., x^{(1)}(n) \right\} \qquad \text{- Equation 2}$$

is first-order accumulation generation of $X^{(0)}$ where

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), \qquad k = 1, 2, 3, ...\ n \qquad \text{- Equation 3}$$

The first-order differential equation is then

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = b \qquad \text{- Equation 4}$$

and its difference equation is

$$X^{(0)}(k) + aZ^{(1)}(k) = b \qquad k = 2, 3, ...\ n \qquad \text{- Equation 5}$$

where $Z^{(1)}(k)$ is the mean generation sequence of $X^{(1)}$. Then, utilizing the initial condition

$$\hat{x}^{(1)}(1) = x^{(0)}(1) \qquad \text{- Equation 6}$$

the approximate equation becomes

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a} \right) e^{-ak} + \frac{b}{a} \qquad k = 0, 1, 2, 3, ... \qquad \text{- Equation 7}$$

Finally, the predicted value of $x^{(0)}(k+1)$ at time $k+1$ can be expressed as

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \qquad k = 0, 1, 2, 3, ... \qquad \text{- Equation 8}$$

Benchmark models and evaluation metrics

Autoregressive Integrated Moving Average Model (ARIMA) model

The ARIMA (p, d, q) model is comprised of the order of autoregressive terms (p), the degree of differencing (d), and the order of moving average terms (q). An ARIMA model can be expressed by the following formula:

$$(1-\phi_1 B-\cdots-\phi_p B^p)(1-B)^d y_t=\delta+(1-\theta_1 B-\cdots-\theta_q B^q)a_t$$ - Equation 9

The ARIMA model involved 3 stages. The initial stage is to identify data attributes, such as trends, seasonality, and irregular patterns. The model's parameters p, d, and q were then estimated by utilizing the autocorrelation function (ACF) and the partial autocorrelation function (PACF) plots. Finally, a few suggested models are obtained, and the model's goodness of fit is assessed by observing the Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC).

Long Short-Term Memory (LSTM) model

The LSTM model is a recurrent neural network that can learn order dependence in sequential data. Recurrent neural networks have a series of repeating modules. As depicted in Figure 2, a typical LSTM unit is composed of a cell, an input gate, an output gate, and a forget gate. The forget gate can be found in the first part of the cell and is used to control the extent to which the hidden state of the previous cell can be forgotten. Following that, the input gate governs how much new information will be retained in the current cell state. Finally, the output gate is used to show the output of the current cell.

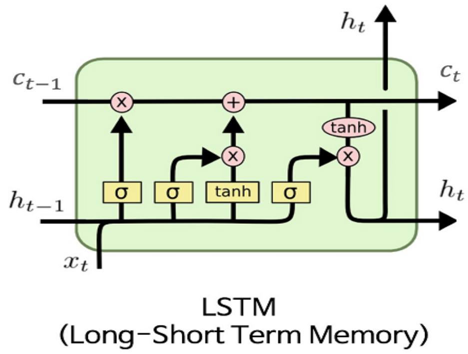

Fig. 2. Structure of the LSTM cell.

Unlike traditional models such as autoregressive models (AR) or moving average models (MA), which typically consider a fixed number of lagged observations, LSTMs dynamically learn which past observations are important. By feeding the model sequences of historical data, LSTMs can extract both short-term variations (captured in the hidden state) and long-term trends (captured in the cell state). As new time steps are added, the LSTM updates its internal state to make predictions about the next time step, utilizing its learned temporal dependencies.

The equations involved in the LSTM are listed below:

Equations 10-15:

$$i_t=\sigma(W_i\cdot[h_{t-1},x_t]+b_i)$$
$$\widetilde{C}_t=\tanh(W_c\cdot[h_{t-1},x_t]+b_c)$$
$$f_t=\sigma(W_f\cdot[h_{t-1},x_t]+b_f)$$
$$C_t=f_t\odot C_{t-1}+i_t\odot\widetilde{C}_t$$
$$o_t=\sigma(W_o\cdot[h_{t-1},x_t]+b_0)$$
$$h_t=o_t\odot\tanh(C_t)$$

where i_t is the value of the input gate, $\widetilde{C}_t$ is state value, f_t is the value at forget gate, C_t is updated cell state value, o_t is the value of the output gate and h_t is the value of a hidden state. W_i, W_c, W_f and W_o represent four distinct matrix weights, b_i, b_c, b_f and b_o represent the offset, σ is the sigmoid function. The symbol $\odot$ represents the vector outer product.

Exponential smoothing

Exponential smoothing is a simple forecasting method that emphasizes more recent observations by applying exponentially decreasing weights to past data points. This technique is particularly useful for time series that exhibit level trends or seasonality, as it adapts to changing patterns by adjusting the weight placed on past values. Holt's Linear Trend Model, a variant of exponential smoothing extends simple exponential smoothing by incorporating both a level and a trend component, making it ideal for time series data that exhibit a trend over time.

The equations for Holt's Linear Trend Model are as follows:

Equations 16-18:

$$l_t = \alpha y_t + (1 - \alpha)(l_{t-1} + b_{t-1})$$
$$b_t = \beta(l_t - l_{t-1}) + (1 - \beta)b_{t-1}$$
$$\hat{y}_{t+h} = l_t + hb_t$$

In Equation 16 (Level Equation), l_t is the estimated level at time *t*, *α* is the smoothing parameter for the level, and b_{t-1} is the trend from the previous period. In Equation 17 (Trend Equation), b_t is the estimated trend at time *t*, and *β* is the smoothing parameter for the trend. In Equation 18 (Forecast Equation), *h* is the number of steps ahead to forecast.

Evaluation metrics

Two metrics were used to assess the forecasting models' performance: the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

Equations 19 & 20:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_t - \hat{Y}_t\right|$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_t - \hat{Y}_t\right)^2}$$

Here, *n* is the number of observations, Y_t is the actual value and $\hat{Y}_t$ is the forecasted value. These metrics will be used on the forecasted value obtained from each model for our sample data.

RESULTS AND DISCUSSION

Data classification

The data for this study consists of 68 yearly data recorded from 1949 to 2016. As shown in Figure 3, the dataset exhibits a downward trend over the observed period, indicating a consistent decrease in the number of green sea turtle landings. No seasonal patterns were apparent, suggesting that the fluctuations in turtle landings are not influenced by yearly cycles or recurring seasonal events. The dataset was divided into two groups: training (80% of the samples) and testing (20% of the samples). The training set will be used to build the GM (1,1) model, and the testing set will be used to evaluate the model's forecasting ability. This approach mirrors the evaluation methodology applied to the benchmark models.

GM (1,1)

The Grey Model is particularly suitable for this study due to the limited number of data points (68 yearly data), as GM (1,1) is known for its ability to model systems with small sample sizes, overcoming the limitations of other forecasting methods that require larger datasets for reliable predictions. The forecasting equation GM (1,1) was obtained by having parameters $\alpha = 0.07273875$ and $\beta = 18394.5$.

$$\hat{x}(k) = -245560.05e^{-0.7273875(k-1)} + 252855.05 \qquad \text{- Equation 21}$$

Despite the data showing a general downward trend, the positive α suggests that the long-term dynamics are influenced by external factors that may cause periodic rebounds and the overall system still has the potential for minor recovery phases. Given that turtle populations may fluctuate due to various ecological or anthropogenic factors, this parameter helps capture subtle variations in the landing counts that are not strictly linear or consistently declining.

The value of β being relatively large suggests that, historically, there was a significant baseline level of turtle landings. This could be related to favorable environmental conditions in the earlier years or strong conservation efforts. Over time, factors such as habitat degradation, changes in ocean conditions, or human activities might have contributed to a gradual decrease, but the baseline influence remains strong.

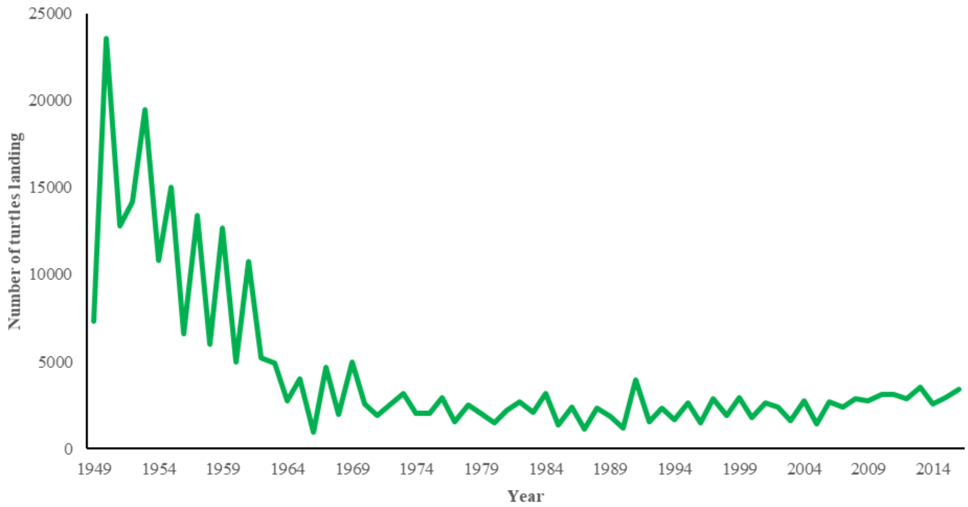

Fig. 3. Turtle landing trend from year 1949 to 2016

ARIMA

Stationary testing was conducted to assess the time series properties of the data, ensuring that the assumptions of the ARIMA analysis were met. An augmented Dickey-Fuller (ADF) test was performed to determine the presence of trends or seasonality in the dataset. The result of the ADF test is shown in Table 1.

Table 1. Stationary test for turtle landing data

	t-Statistic	Prob
Level	-1.7365	0.6806
First difference	-5.3239	0.01*

*Significant at 5% significance level

From Table 1, the data is stationary at the first difference. The ARIMA model parameters were estimated using the maximum likelihood estimate. The Akaike Information Criterion (AIC) and the Ljung-Box test were utilized to determine the adequacy of the model. ARIMA (1,1,2) was chosen as the best model having the lowest AIC values.

$$(1+0.5821)(1-B)x_t = (1+0.6319B-0.7151B^2)\delta \qquad \text{- Equation 22}$$

LSTM

A univariate LSTM model was trained using the input from the original data. The hyperparameter settings were manually tweaked to produce the best model performance throughout the training phase. After several iterations, the hyperparameter settings were identified, as shown in Table 2.

Table 2. Hyperparameter setting for LSTM model

Hyperparameter	Value
Hidden layer	1
Hidden neuron	64
Batch size	32
Epochs	100
Loss function	MSE
Optimizer	Adam

The choice of a single hidden layer with 64 neurons allowed the model to effectively capture the complexity of the time series data while preventing overfitting. The batch size of 32 facilitated efficient training by balancing the trade-off between computational efficiency and model convergence speed. Training the model for 100 epochs ensured sufficient iterations to minimize the loss function, defined as Mean Squared Error (MSE). Utilizing the Adam optimizer, recognized for its adaptive learning rate capabilities, contributed to faster convergence and improved performance compared to standard gradient descent methods.

Exponential smoothing

Holt's Linear Trend model was applied to the turtle landing data to capture both the level and the trend over time. The model's smoothing parameters, α = 0.1705 and β = 0.0535, indicate moderate adjustments to both the level and trend based on new observations. The initial level was estimated to be 16919.22, with a negative trend of -658.04, suggesting a steady decline in turtle landings over the observed period. For any *h*-step ahead forecast, the equation becomes:

$$\widehat{y}_{t+h} = 16919.2245 - 658.042h \qquad \text{- Equation 23}$$

The model fit was evaluated using metrics such as AIC (1084.51), suggesting a reasonably good fit for this type of model. The decreasing trend observed in the forecasts aligns with the historical data pattern, confirming the appropriateness of using Holt's Linear Trend model to forecast the turtle landings.

Forecasting performance on the dataset

Each model was fitted using the respective training dataset, allowing them to learn the underlying patterns and relationships present in the historical data. Figure 4 shows the forecasted value of each model on the training data.

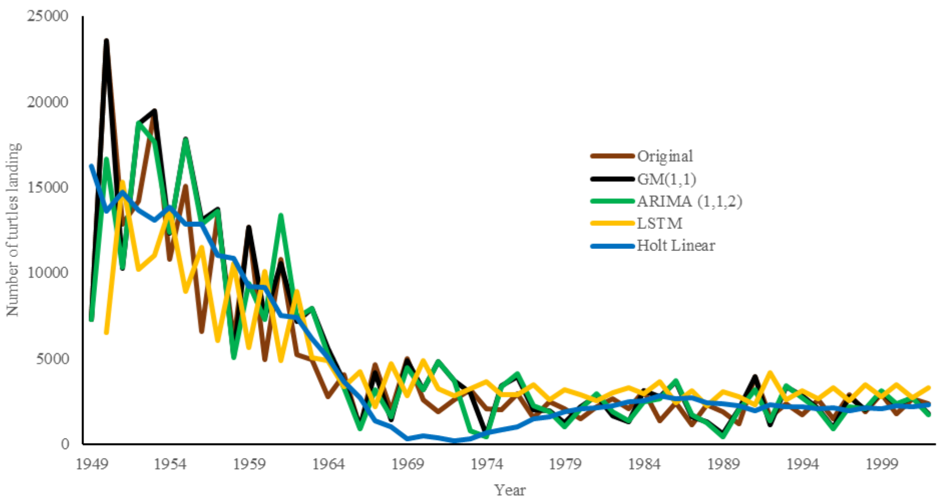

Fig. 4. Forecasted value of different models on the training data period (1949-2002).

Figure 4 illustrates that GM (1,1) effectively captured most of the spike in the data, demonstrating its ability to discern and adapt to sudden changes or anomalies in the data. This capability is attributed to GM's inherent robustness and adaptability, allowing it to respond promptly to variations in the data without overfitting or being excessively influenced by outliers. As a result, GM's forecasts closely align with the observed values during periods of significant deviation, highlighting its reliability in capturing both long-term trends and short-term fluctuations in the time series. The performance of the GM (1,1) was further evaluated using MAE and RMSE as shown in Table 3.

Table 3. Performance of GM (1,1) and other models in the training and testing period

Model	Training Period (1949-2002)		Testing Period (2003-2016)	
	MAE	RMSE	MAE	RMSE
GM (1,1)	1407.639	1982.846	288.457	351.5474
ARIMA (1,1,2)	1419.177	1988.404	291.784	355.9078
LSTM	2374.8407	3736.8079	644.8221	855.2097
Holt's Linear	1914.6855	2848.9360	415.0533	493.9596

GM (1,1) outperformed other models in terms of MAE and RMSE in both training and testing periods, indicating its superior accuracy in predicting the observed values. Furthermore, the consistency of GM (1,1)'s performance across both training and testing periods highlights its robustness and generalization ability, further validating its suitability for forecasting the turtle landing frequency. ARIMA, LSTM, and Holt's Linear models struggle with small or noisy datasets, as they require enough data to accurately capture patterns and dependencies. In contrast, GM is specifically designed to handle limited or irregular data, making it more suitable for such scenarios. ARIMA models assume linear relationships and stationarity in the data, which may not always hold for complex or nonlinear time series (Quartey-Papafio *et al*., 2021). Similarly, LSTM models, while powerful in capturing temporal dependencies, are prone to overfitting, especially in the presence of noisy or irregular data. Moreover, Holt's method can be sensitive to outliers, potentially distorting the trend estimation and leading to less accurate forecasts. GM, with its simpler structure and focus on trend and pattern extraction, may be more robust in such cases.

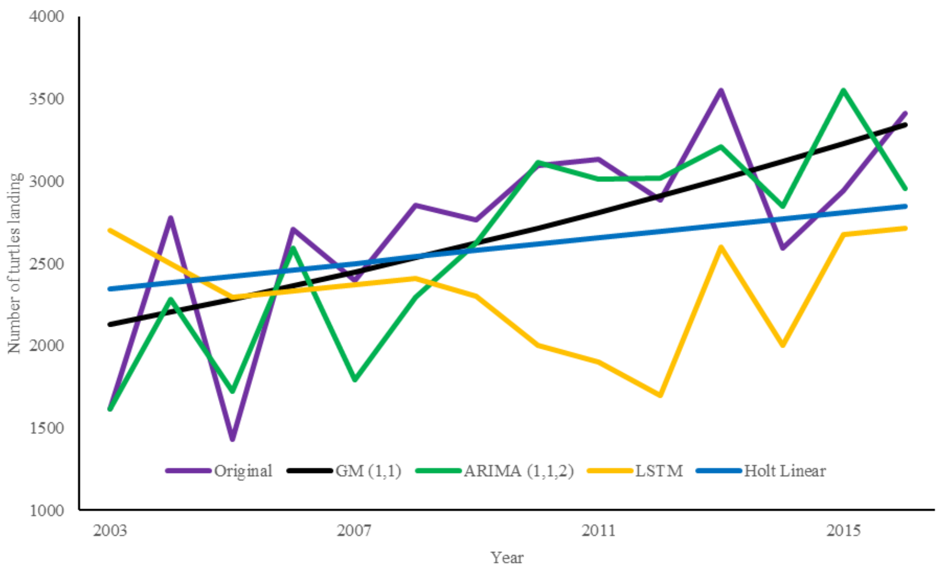

Fig. 5. Forecasted value of different models on the testing data period (2003-2016).

Further exploration of the GM (1,1) model on turtle landing data reveals an upward trend in the next forecasted year, indicating a potential increase in turtle landings compared to previous periods (Figure 5). This insight suggests that environmental factors or nesting behaviors conducive to turtle landings may be influencing the observed trend, highlighting the importance of continued monitoring and conservation efforts to protect turtle habitats and ensure their long-term survival.

CONCLUSION

In conclusion, this study has demonstrated the efficacy of the Grey Model in forecasting Green Sea

Turtle (*Chelonia mydas*) landings in Sarawak. By leveraging GM (1,1) methodology and historical landing data, we have provided valuable insights into the temporal dynamics of turtle nesting behaviors in the region. Our findings reveal GM (1,1) as a reliable forecasting tool, capable of capturing both short-term fluctuations and long-term trends in turtle landings. The model's ability to adapt to irregular and limited data underscores its suitability for predicting turtle populations in data-constrained environments. Through the identification of upward trends in future forecasted years, this research not only aids in the understanding of turtle nesting patterns but also facilitates informed conservation strategies for protecting these endangered species and their habitats. Moving forward, the integration of GM-based forecasting into conservation management frameworks holds promise for enhancing the sustainability of turtle populations in Sarawak and beyond.

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ETHICAL STATEMENT

Not applicable.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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