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Predicting Beach Profile Changes using Neural Networks with Recursive Add and Repeat Simulation

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Abstract

Accurate prediction of long-term beach profile changes is critical for sustainable coastal management, particularly in the face of climate change, sea level rise, and shifting wave conditions. This study evaluates the performance of two artificial neural network architectures Long Short-Term Memory (LSTM) and Multilayer Perceptron (MLP) in forecasting 15 years of annual beach profile evolution at Narrabeen-Collaroy Beach, Australia. Both models were trained using the Add and Repeat (AdRpt) method, an iterative forecasting approach that extends prediction horizons by incorporating previous outputs as new inputs. Key environmental variables included sea level trends, significant wave height, and wave period. Model performance was assessed across five profiles (PF1, PF2, PF4, PF6, and PF8). Results show that the LSTM consistently outperformed the MLP, achieving RMSE as low as 0.45 m and R^2 values up to 0.97. While LSTM captured temporal patterns effectively, both models struggled with abrupt morphological changes, such as the severe erosion observed at PF2 in 2001. Profiles near the intertidal zone also exhibited greater prediction variability. Furthermore, the study highlights that relying solely on R^2 can be misleading, as high R^2 may coincide with substantial RMSE and MAE values. A multi-metric evaluation approach is essential to ensure reliable model interpretation. These findings support the application of LSTM-based models for data-driven, long-term coastal planning and adaptive nourishment strategies.

Keywords: - Beach profile variation, Artificial neural networks (ANN), Long Short-Term Memory (LSTM), Multilayer Perceptron (MLP)

1. Introduction

Beaches serve as natural buffers, absorbing wave energy and protecting inland areas from hazards like erosion and flooding. They also support marine ecosystems and provide recreational and economic benefits (Stronge, 2005). However, these environments are increasingly threatened by accelerating sea level rise, urban development, and changing wave climates (Hansen et al., 2016 & Barnard et al., 2017). These pressures highlight the urgent need for accurate long-term predictions of coastal change to support adaptation and mitigation strategies (Nicholls & Cazenave, 2010).

Traditional methods for predicting beach profile evolution, such as the Bruun Rule, process-based models, and behavior-oriented approaches, often struggle to capture the complexities of long-term coastal dynamics. While process-based tools like Delft3D can simulate detailed interactions, they require extensive data and high computational resources. Empirical models, in contrast, oversimplify by assuming equilibrium conditions and often overlook critical drivers such as wave variability and storm events.

Artificial Neural Networks (ANNs) provide a data-driven alternative, capable of modeling nonlinear relationships and learning from historical patterns. Although ANNs have been widely applied for short-term coastal predictions, their use in long-term forecasting, especially when accounting for sea level rise and wave transformations, remains limited. Prior studies using

Multilayer Perceptrons (MLPs) and Long Short-Term Memory (LSTM) networks show promise but often focus on short time horizons (Hashemi et al., 2010; López et al., 2018 & Kim & Aoki, 2021).

This study builds on recent work by Khan et al. (2024), who introduced the Add and Repeat (AdRpt) method, a novel approach that improves long-term prediction accuracy. By iteratively feeding predictions back into the input set, this method allows the model to "learn forward," refining outputs without requiring large training datasets. When paired with LSTM and MLP architectures, the approach has demonstrated improved performance in forecasting beach profile and wave parameter changes over multi-decadal scales.

Here, we apply MLP and LSTM models trained with the AdRpt method to predict 15-year beach profile changes at Narrabeen-Collaroy Beach, Australia, incorporating projected sea level rise, wave height, and wave period. These predictions are essential for informed coastal planning, sediment management, and climate resilience.

2. Study Area

The study area is Narrabeen-Collaroy Beach (see Fig. 1), a 3.6 km stretch on Sydney's northern beaches, composed of fine to medium quartz sand and influenced by dynamic coastal processes. The beach morphology varies from a wide, flat profile at the exposed northern end to a narrower, steeper profile at the sheltered southern end. Known for complex dynamics such as storm surges, erosion, and sandbar migration, the beach has been extensively studied for over 30 years, offering a valuable long-term dataset on beach profiles and wave characteristics (Harley et al., 2011).

This site provides an excellent opportunity to study coastal evolution due to comprehensive, freely accessible data (http://narrabeen.wrl.unsw.edu.au/). As described by Turner et al. (2016), the dataset includes monthly beach profile surveys since 1976 across five profiles (PF1, PF2, PF4, PF6, PF8), alongside wave, tidal, and bathymetric data. Advanced methods such as Argus coastal imaging, airborne Lidar, UAV surveys, and bathymetric mapping complement traditional surveys, enabling detailed coastal process analysis.

Offshore wave data have been recorded since 1992 by the Sydney directional wave rider buoy, measuring significant wave height (Hs), peak period (Tp), and direction (Dir). Gaps were filled using hourly hindcast data, with a high-resolution hindcast (1979–2014) extending the record. The SWAN model transformed offshore waves to near-shore conditions at 10 m depth, accounting for wave growth and breaking.

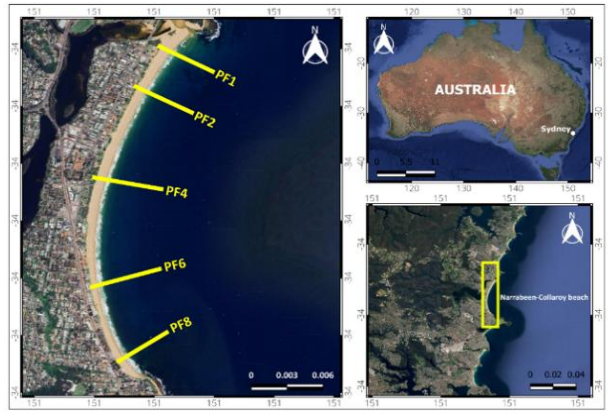

Fig. 1: Location map of Narrabeen-Collaroy Beach, Sydney, Australia

Wave rose analysis (see Fig. 2) reveals varied wave exposure: PF1, PF2, and PF4 face southeast waves, while PF6 and PF8 are influenced by easterly waves. PF1 experiences the highest wave heights (up to 5.7 m), followed by PF4; PF8 has the lowest (max 4.4 m). These patterns are key to understanding the beach's long-term evolution.

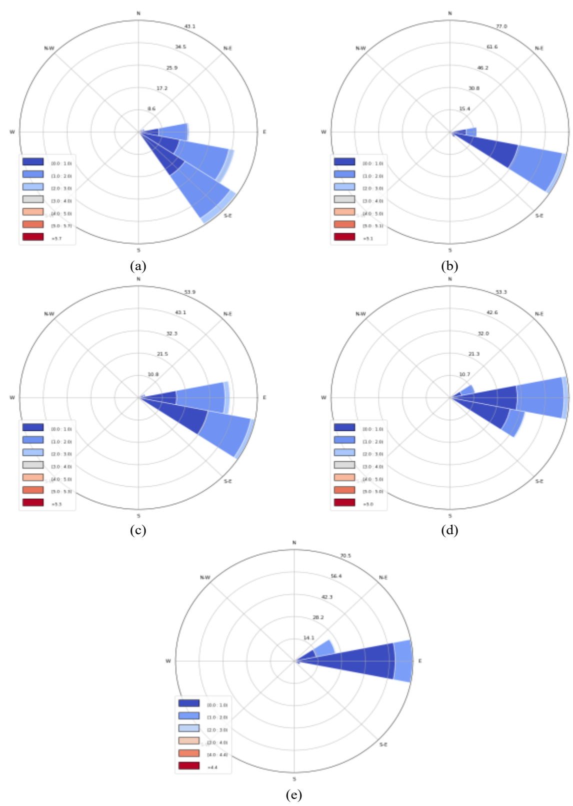

Fig. 2: Wave rose plots for the profiles at Narrabeen-Collaroy Beach are shown. Panels (a) through (e) display the wave rose plots for PF1, PF2, PF4, PF6, and PF8, respectively.

Sea level data for Narrabeen-Collaroy Beach was sourced from NOAA's Sea Level Trends website (https://www.tidesandcurrents.noaa.gov/sltrends/sltrends.shtml). These local Relative Sea Level (RSL) trends combine sea level rise and vertical land motion, measured relative to a fixed land point.

Fig. 3 shows the monthly sea levels with seasonal variations removed (accounting for temperature, salinity, winds, pressure, and currents), along with the long-term linear trend and its confidence interval.

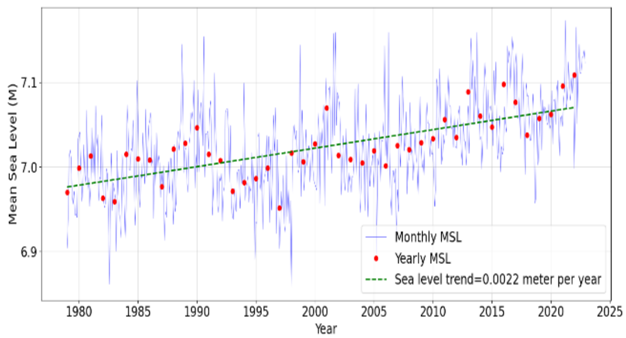

Fig. 3: Relative sea level trend of Narrabeen-Collaroy Beach, Sydney, Australia

The data comes from the Sydney, Fort Denison tide gauge, about 16.5 km away, showing an RSL rise of 2.2 mm/year with a 95% confidence interval of ±0.1 mm/year. This is based on monthly mean sea levels from 1979 to 2022 and equals roughly 0.73 feet per 100 years.

3. Methodology

This study employs advanced machine learning techniques to predict long-term changes in beach profiles over a 15-year horizon, specifically Long Short-Term Memory (LSTM) networks and Multilayer Perceptron (MLP) networks. Long-term predictions will utilize the 'Add and Repeat' methodology proposed by Rehman et al. (2023). This novel approach addresses the challenge of predicting time series data beyond the size of the training dataset by producing predictions in smaller, manageable increments. These increments are systematically added back to the training dataset, allowing the model to iteratively refine its forecasts until the desired forecasting horizon is achieved. This iterative process enhances the model's capability for extended predictions.

The methodology section includes detailed explanations of data preparation, the proposed models, and model performance evaluation. These subsections collectively outline the approach taken for modeling and evaluating the predictions.

3.1 Data Preparation

Accurate data preparation is critical for successful machine learning modeling, especially when dealing with diverse datasets. For this study, wave data were transformed into significant wave heights and periods at the 1/3 and 1/10 levels. These metrics were chosen due to their strong influence on coastal erosion. Hs at 1/3, representing the average of the highest one-third of waves, captures both moderate and extreme events and has been used effectively in previous studies (Hashemi et al., 2010 & López et al., 2018). Conversely, Hs at 1/10 emphasizes high-frequency extreme wave conditions that can intensify shoreline erosion by concentrating wave energy near the beach (Ruggiero et al., 1998). Kuznetsova et al. (2017) further demonstrated that increasing wave heights and longer wave periods significantly influence bottom profile deformation, justifying their inclusion as input predictors. These parameters were selected to improve the understanding of the wave–profile relationship and enhance erosion risk assessments.

To ensure model accuracy, annual beach profile data for Narrabeen-Collaroy Beach was prioritized over monthly data, avoiding inconsistencies caused by missing or overlapping entries within certain months. Additionally, while most profiles extended to 100 meters, a few were shorter. To standardize input lengths, missing values beyond the last recorded point were estimated using linear forecasting. Although this completed the dataset for model training, it excluded deeper sections beyond the closure depth, which are important for sediment transport and long-term coastal change. Using the cleaned and standardized annual dataset, the model was trained on a 16-year period (1979–1995) and used to generate beach profile forecasts for the following five years (1995–2000) across five profiles. These initial predictions were then added to the training set, allowing for model retraining in successive five-year intervals (2000–2005 and beyond) up to 2010. This iterative approach enabled assessment of the model's ability to predict future profile conditions over time. The selected data period is based on continuous, high-quality measurements and the need to capture long-term morphological patterns. As ANN models learn trends rather than depend on exact timing, this period supports effective pattern recognition. Combined with the Add and Repeat method, it allows predictions to extend into future years without affecting performance.

3.2 Proposed model

To predict beach profile changes, this study used Long Short-Term Memory (LSTM) networks and Multi-Layer Perceptron (MLP), chosen for their effectiveness in time series forecasting and pattern recognition both essential for understanding dynamic coastal systems. LSTMs, a type of recurrent neural network (RNN), are particularly suited for sequence prediction due to their ability to capture long-term dependencies. The models were trained through extensive manual tuning and analysis. Over 52 simulations were conducted, systematically varying hyperparameters to test different configurations and ensure robustness in modeling beach profile dynamics. Both the LSTM and MLP models featured two hidden layers with 64 neurons each, as shown in Fig. 4.

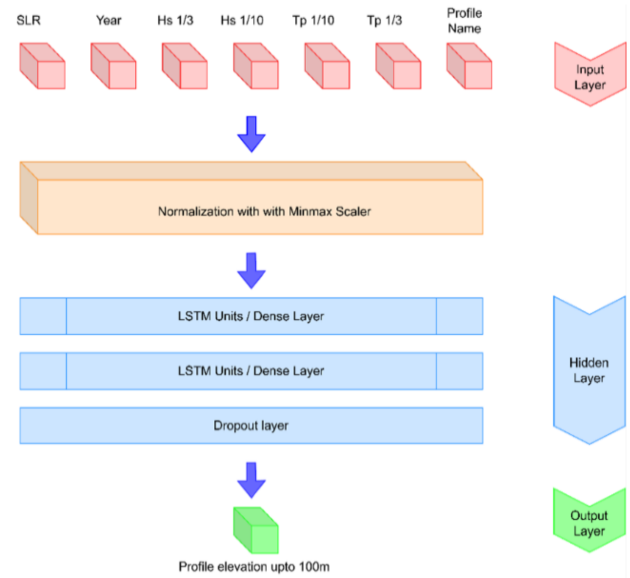

Fig. 4: Proposed LSTM and MLP model

This architecture is designed to effectively capture temporal patterns in the beach profile data. Model tuning involved adjusting batch size (16–64), learning rate (0.001 or 0.01), training epochs (2500–7500), and dropout rates (10%–40%) to prevent overfitting. The final model setup 0.001 learning rate, 20% dropout, and batch size of 32 produced the best performance.

a) LSTM Layer

LSTM networks outperform traditional RNNs in preserving long-term temporal information without complex tuning. Unlike standard RNNs, which often lose long-term dependencies due to gradient issues, LSTMs use gates forget, input (memory), and output to control information flow. As shown in Fig. 5, each LSTM cell has four layers that maintain and update the cell state (Ct), a memory that holds useful information over time. The forget gate controls retention of old data, the input gate adds new information, and the output gate produces the final output. This gating mechanism helps the model keep important dependencies across time steps, crucial for capturing beach profile changes.

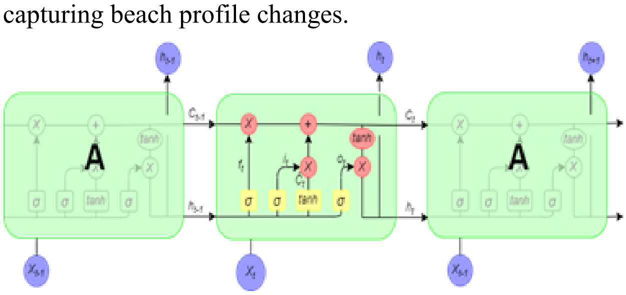

Fig. 5: Schematic concept of a standard LSTM containing four interacting layers

b) Dense Layer

In the MLP model, dense (fully connected) layers play a central role in learning complex patterns. Each neuron in a dense layer performs a weighted sum of inputs followed by an activation function, typically ReLU, sigmoid, or tanh to introduce non-linearity (Goodfellow et al., 2016). Non-linear transformations are crucial for modeling the intricate relationships between wave conditions and beach profile changes. Stacked dense layers help the model learn both simple and complex features. In this regression task, the final dense layer outputs continuous values representing profile elevation, thereby enabling detailed prediction of beach morphology.

c) Dropout Layer

To address overfitting, dropout was applied during model training. This method randomly disables a subset of neurons and their connections, forcing the model to learn more generalized features instead of memorizing the training data. Dropout is particularly useful for regularizing deep learning models in medium-sized datasets. Studies by Lv et al. (2019) & Jeon et al. (2020) show that dropout increases model robustness and improves generalization by reducing over-dependence on specific neurons. It also slows the learning process slightly, which helps avoid convergence to suboptimal solutions and encourages more thorough learning of underlying data patterns.

c) Add and Repeat Method

To extend the forecasting horizon beyond the training data, this study adopts the *Add and Repeat* method introduced by Khan et al. (2023). This iterative approach involves predicting in shorter increments (e.g., 5 years), then appending these predictions to the training dataset. The model is retrained after each step, using its previous outputs as inputs for the next cycle, until the full forecast period is reached. This method enables long-term predictions with limited historical data and allows the model to adapt gradually to evolving patterns. However, it can also lead to error accumulation, particularly in models like the MLP that are less capable of capturing long-term dependencies compared to LSTM networks.

3.3 Model Performance Evaluation

Three evaluation metrics were used to assess model performance: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2).

RMSE measures the square root of the average squared differences between predicted and observed values, making it sensitive to large deviations. MAE calculates the average magnitude of errors without considering their direction, providing a straightforward interpretation of average prediction error. R^2 indicates the proportion of variance explained by the model. Each metric serves a distinct role: MAE is robust against outliers, RMSE penalizes large deviations, and R^2 shows overall model fit.

Together, these metrics provide a balanced view of model accuracy. The most reliable model was identified based on low RMSE and MAE values and an R^2 close to 1.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(x_i - y_i)^2}{n}} \quad (1)$$

$$R^2 = 1 - \sqrt{\frac{\sum_{t=1}^{n}(x_i - y_i)^2}{\sum_{t=1}^{n}(x_i - \bar{x})}} \quad (2)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i| \quad (3)$$

where n is the total number of cases, x_i is the targeted/observed value, and y_i is the output/predicted value and $\bar{x}$ is the mean value.

4. Results and Discussion

This study assessed the predictive performance of LSTM and MLP models in forecasting 15 years of annual beach profile changes at Narrabeen-Collaroy Beach, using the Add and Repeat (AdRpt) method to iteratively extend forecasts. The analysis focused on five representative profiles (PF1, PF2, PF4, PF6, and PF8), with model accuracy evaluated using R^2, RMSE, and MAE. This combination of deep learning and iterative forecasting represents a novel contribution to long-term coastal morphodynamic modelling.

For PF1, characterized by its exposure to high wave energy, the LSTM model demonstrated a strong alignment with observed beach profile changes (see Fig. 6). Its predictions adeptly captured the complex profile dynamics with smaller errors, showcasing its adaptability to high-energy environments. In contrast, the MLP model, while following similar overall trends, exhibited more pronounced deviations, especially in later years, suggesting a degradation in accuracy with iterative predictions. The R^2 values for both models consistently showed LSTM closer to 1, underscoring its superior ability to replicate observed profiles. Notably, the largest prediction discrepancies for PF1 occurred between 70 m and 100 m, a highly dynamic zone prone to significant morphological changes due to energetic wave activity, sediment transport, and storm impacts. The LSTM model's inherent strength in capturing temporal dependencies allowed it to perform better in these volatile regions, whereas the MLP's simpler architecture struggled.

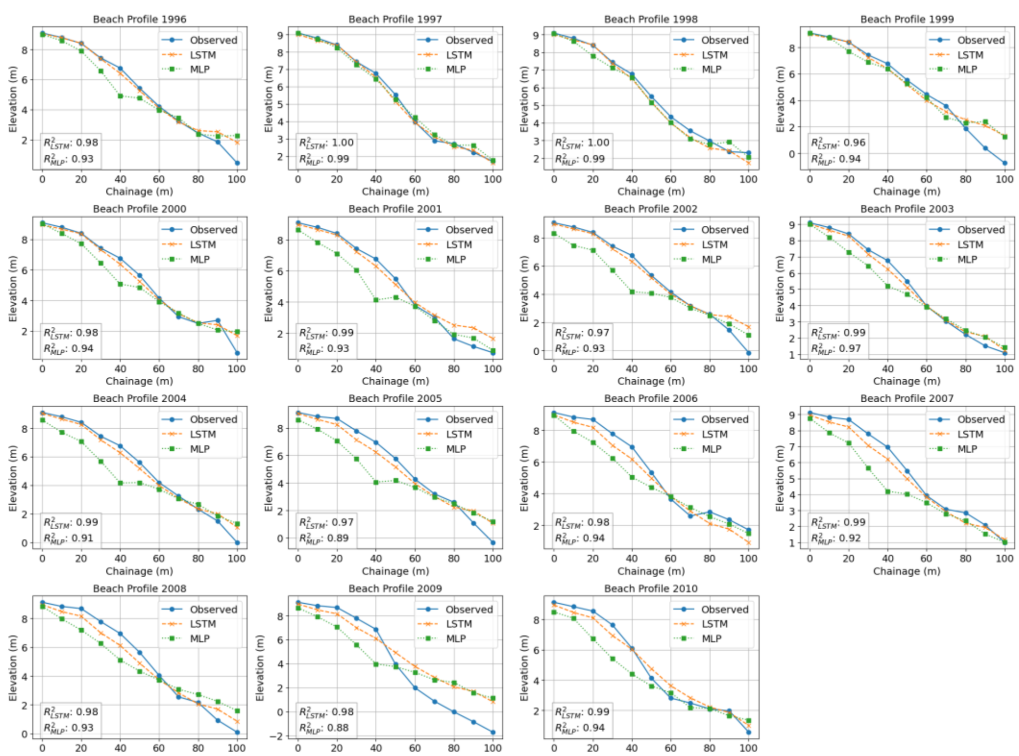

Fig. 6: Comparison of observed beach profiles with LSTM and MLP model predictions for PF1 (1996–2010)

In the case of PF2, both models yielded similar predictions, though the LSTM model generally performed better, evidenced by R^2 values closer to 1 as shown in Fig. 7. However, the MLP model showed a slight advantage in specific years like 1997, 2001, and 2005. A significant deviation for both models from observed data was prominent in 2001, where the observed profile underwent substantial erosion exceeding 2 meters in some areas. This discrepancy highlights a challenge for both ANN architectures in handling abrupt, large-scale changes, potentially linked to storm events. Such sudden changes were also noted in other profiles, particularly PF2 and PF4, possibly due to their central locations making them more susceptible to multi-directional wave energy and sediment transport. Interestingly, PF2 appeared to recover by 2002, reverting to a pattern like 2000, suggesting a dynamic system capable of adjusting to disturbances. The substantial deviation at the lower part of the PF2 profile might also be influenced by the reliance on linear regression forecasting for data beyond the 80-meter mark in the observed dataset, which may not accurately represent actual conditions.

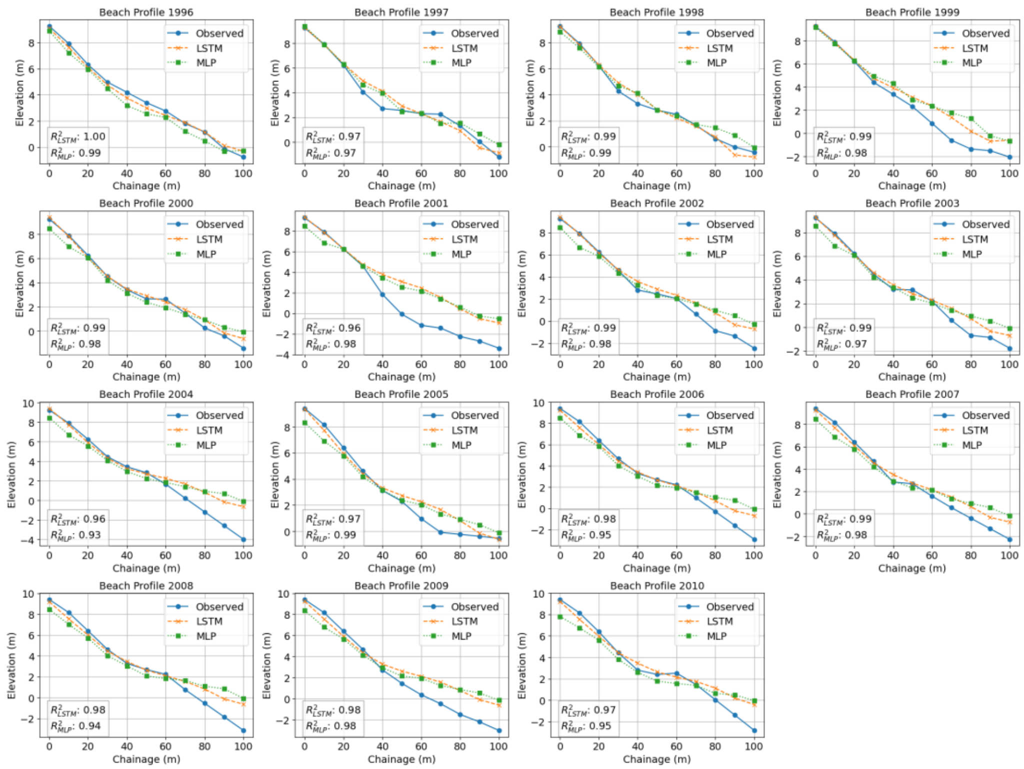

Fig. 7: Comparison of observed beach profiles with LSTM and MLP model predictions for PF2 (1996–2010)

PF4 exhibited trends like PF2, with LSTM and MLP predictions generally aligning with observed data, as shown in Fig. 8. However, predictions for PF4 showed closer agreement across the profile compared to PF2. Like PF2, PF4 also experienced a sudden variation in 2001, though more moderate (around 1 meter). Notably, the LSTM predictions for PF4 closely matched the observed data, even during this period of abrupt change. Improved alignment at the bottom of PF4's profile might be attributed to the availability of actual measurements up to 100 meters.

The LSTM model's relatively strong predictive performance, evidenced by a consistent R^2 value of 0.9 across profiles like PF4 and PF2, and comparatively lower RMSE and MAE scores, demonstrates its capacity to identify long-term trends crucial for informing coastal management strategies. The iterative "Add and Repeat" methodology facilitated extended predictions, enabling the identification of temporal patterns in erosion and accretion, which is valuable for anticipating nourishment needs.

PF6, a less elevated profile, is prone to greater variations despite lower wave energy, attributed to its proximity to the intertidal zone where tidal forces and sediment redistribution are more significant. As shown in Fig. 9, the LSTM model performed exceptionally well for PF6, closely matching observed data over 15 years and effectively capturing gradual accretion and minor seasonal variations with high accuracy, reflected in its R^2 values.

The MLP model, while providing similar overall predictions, introduced noticeable deviations, particularly towards the 100m chainage mark, possibly due to its limited ability to capture complex spatial patterns. A profile shift in 2001 was observed in PF6, though less pronounced (<1 meter). A significant deposition of sand (2–3 meters) at the top of PF6's profile between 2009 and 2010 was also noted, the reasons for which are unclear from the dataset. PF6 appeared to be the most active profile, exhibiting substantial inter-annual variation, suggesting that even low-energy environments can experience significant morphological changes.

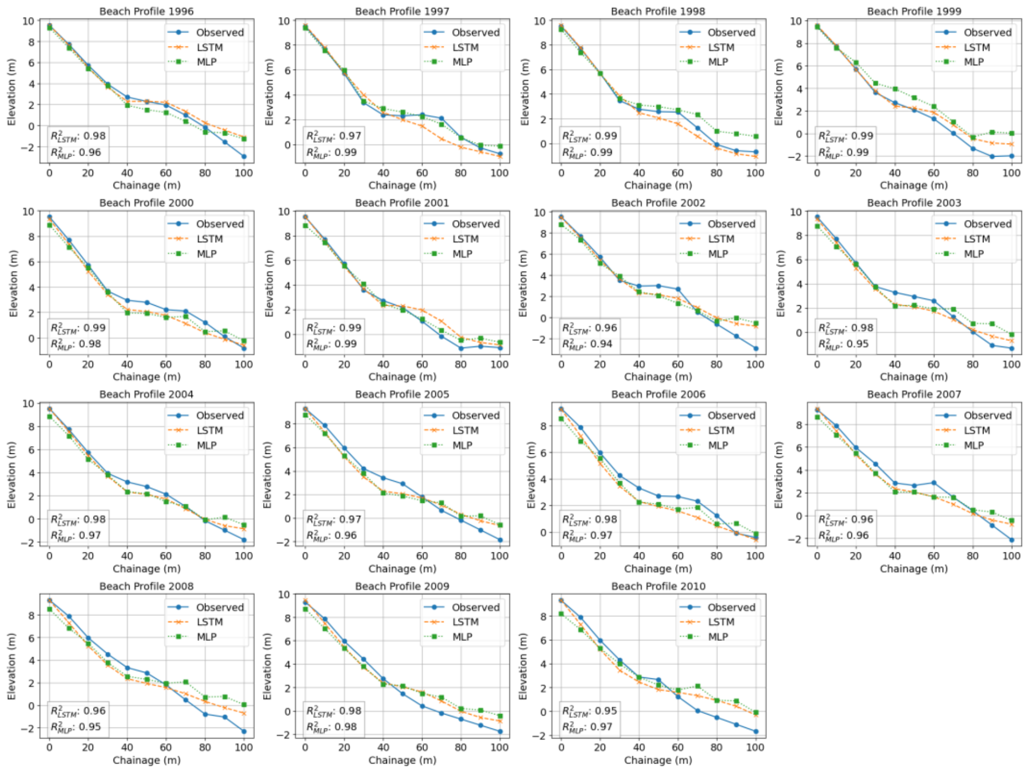

Fig. 8: Comparison of observed beach profiles with LSTM and MLP model predictions for PF4 (1996–2010)

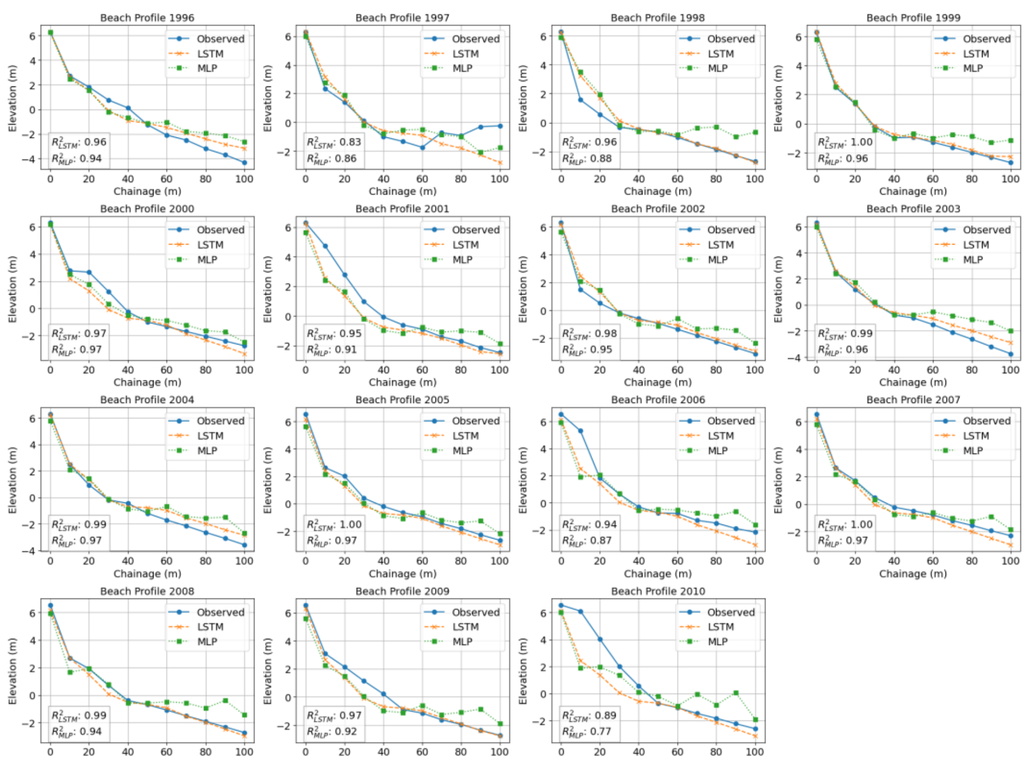

Fig. 9: Comparison of observed beach profiles with LSTM and MLP model predictions for PF6 (1996–2010)

PF8, another relatively lower-elevation profile, proved challenging for both models (see Fig. 10). While the LSTM model outperformed MLP by capturing minor accretion trends and periodic variations with smaller errors and better R² values, both struggled to accurately match observed data. This difficulty can be attributed to PF8's heightened variability due to its proximity to the dynamic intertidal zone, susceptibility to localized morphological processes, occasional storm surges, and minor hydrodynamic changes. The reliance on linear regression forecasting for the last three chainages of PF8 after 1995 likely introduced uncertainties, further impacting predictive performance. The challenges in accurately predicting PF8's behaviour underscore the limitations of the current methodology in addressing localized variability influenced by external or unaccounted factors.

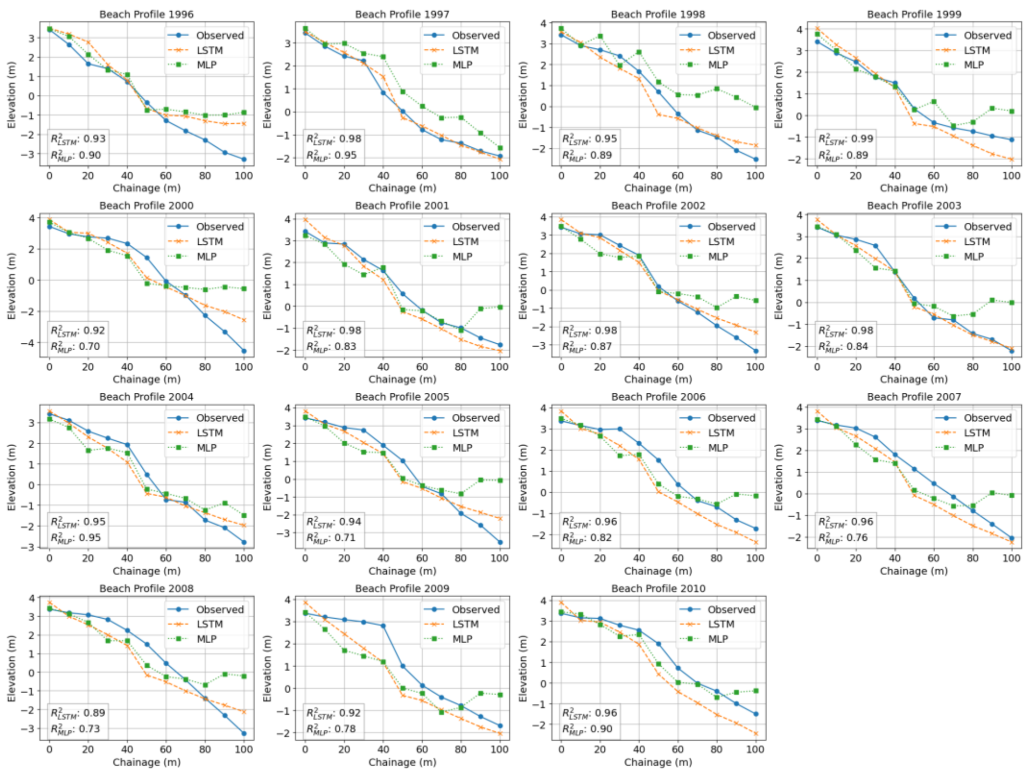

Fig. 10: Comparison of observed beach profiles with LSTM and MLP model predictions for PF8 (1996–2010)

Critically, this study underscores that relying solely on the coefficient of determination (R^2) is insufficient for comprehensive model assessment. As highlighted by Onyutha (2020) & Rose & McGuire (2019), high R^2 values do not always indicate strong performance, nor do lower values necessarily imply poor predictions, especially given R^2's sensitivity to outliers. For example, in PF8, despite visible deviations between observed and predicted values, the LSTM model achieved R^2 values of 0.91 and 0.95 during iterations 1 (1995–2000) and 2 (2001–2005), respectively. While these values may seem commendable, they mask underlying predictive errors that are better reflected in RMSE and MAE metrics. In contrast, the MLP model showed lower R^2 values (0.70 and 0.77) for the same periods, aligning more clearly with its higher error magnitudes.

Table 1 presents the average prediction errors for each iteration period, providing a quantitative comparison of RMSE, MAE, and R^2 values for both LSTM and MLP models. These results reinforce the trends observed in the profile plots. The LSTM model consistently outperforms the MLP model, as evidenced by generally lower RMSE and MAE values and R^2 values closer to 1 across most profiles and iterations. Notably, the highest errors for both models occurred in PF2 during iteration 2 (2001–2005), corresponding to the sudden morphological changes in the profile discussed earlier. The table also shows that the MLP model's errors particularly RMSE and MAE increase more significantly in later iterations, indicating reduced effectiveness under the iterative "Add and Repeat" approach. This decline is likely due to its weaker ability to model long-term time-series dependencies. In contrast, the LSTM model maintains more stable and constrained error values over time, highlighting its robustness in capturing temporal dynamics and delivering more accurate long-term predictions.

Overall, these findings highlight that strong R^2 values alone do not guarantee reliable predictions. Higher RMSE and MAE values particularly in dynamic profiles emphasize the need to evaluate models using multiple metrics. The LSTM model consistently demonstrates superior performance and reliability, maintaining lower error rates and effectively capturing temporal patterns. This makes it especially suitable for long-term coastal profile prediction using iterative methods like Add and Repeat. In contrast, the MLP model shows greater sensitivity to temporal complexity and tends to accumulate larger errors over time, limiting its effectiveness in morphologically variable environments.

Table 1: Performance metrics of LSTM and MLP models for beach profile predictions (1995–2010)

Profile	Iter	LSTM			MLP		
		RMSE	MAE	R^2	RMSE	MAE	R^2
	1	0.45	0.30	0.97	0.65	0.50	0.94
PF1	2	0.51	0.38	0.97	1.15	0.93	0.85
	3	0.71	0.60	0.95	1.32	1.09	0.83
	1	0.54	0.42	0.97	0.74	0.61	0.94
PF2	2	1.20	0.89	0.89	1.40	1.13	0.86
	3	1.04	0.79	0.92	1.30	1.07	0.88
	1	0.62	0.47	0.96	0.73	0.61	0.95
PF4	2	0.66	0.53	0.96	0.79	0.67	0.94
	3	0.82	0.72	0.94	1.00	0.89	0.91
	1	0.66	0.48	0.91	0.85	0.68	0.87
PF6	2	0.53	0.41	0.96	0.83	0.70	0.90
	3	0.75	0.53	0.91	1.03	0.79	0.85
	1	0.61	0.48	0.91	1.15	0.87	0.70
PF8	2	0.46	0.38	0.95	1.02	0.74	0.77
	3	0.84	0.73	0.77	0.91	0.71	0.77

*Iter means iteration
RMSE, R^2 and MAE (see equations (1) – (3))

The LSTM model's ability to capture both accretion patterns and inter-annual variations, even under low-energy conditions, is particularly relevant for beach nourishment planning. Accurate predictions of sediment deposition trends can help identify periods when nourishment may be necessary, supporting proactive and cost-effective coastal management (Dean, 1991). However, the model still faces limitations in predicting abrupt morphological changes, such as those observed in PF2 and PF4 during 2001. Addressing these challenges may require incorporating storm-related variables and exploring ensemble modeling approaches. Additionally, uncertainty introduced by linear regression estimates in parts of the profile data may limit model generalization.

Despite these challenges, LSTM-based prediction frameworks hold significant potential to improve coastal planning by enabling forward-looking sediment management strategies and reducing reliance on emergency interventions. Their integration into adaptive management systems, especially when combined with high-resolution inputs from technologies like UAVs and LiDAR, aligns with the goals of sustainable coastal development (Hanson et al., 2003 & Nicholls et al., 2010). In summary, while LSTM models are highly promising for long-term beach profile forecasting, further enhancements are needed to address localized variability and abrupt changes, strengthening their role as data-driven tools in coastal resilience and nourishment planning.

5. Conclusion and Recommendations

This study demonstrates the potential of Long Short-Term Memory (LSTM) models for predicting long-term beach profile variations, offering valuable insights for coastal management and beach nourishment projects. While the LSTM model outperformed the Multilayer Perceptron (MLP) in capturing gradual trends and inter-annual variations, challenges remain in accurately predicting abrupt morphological changes linked to extreme events. The recursive simulation by adopting "Add and Repeat" methodology proved effective for extending prediction horizons, but localized variability and uncertainties in input data highlight areas for improvement. By integrating additional environmental factors and leveraging high-resolution datasets, LSTM-based predictions could be further refined to support proactive, sustainable nourishment strategies and enhance resilience to climate change impacts. Future studies could also explore combining the Narrabeen dataset with limited available Malaysian beach data to assess whether this approach can improve long-term predictions for Malaysian coastlines.

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