ARTIFICIAL INTELLIGENCE ASSISTED SELECTION OF CORAL NURSERY SITES

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Abstract: Coral reefs play a crucial role in contributing towards the global economy, improving livelihood in coastal regions and maintaining the marine ecosystem. Regardless, coral reefs are being rapidly degraded creating the need for restoration methods, such as the establishment of coral nurseries. Site selection for coral nurseries remains a critical challenge considering the complex interplay of environmental factors, but accurate selection of the best site determines the survival rate of corals in the nursery. This study applies a Neuro Evolution of Augmented Topologies (NEAT) model to predict suitable locations for coral nurseries in the waters around Mauritius. Environmental predictors mean temperature, water current and salinity were selected based on their relevance to coral growth and survival. The model achieved a high overall accuracy of 96.05%, Area Under the Receiver Operating Characteristic Curve (AUC-ROC) of 0.95, and a strong recall (92.86%) for suitable sites, indicating its potential as a robust preliminary tool for site identification. Location based analysis identified a concentration of suitable sites near Snake Island and Round Island, characterized by high mean currents. The NEAT model offers a scalable and accurate method to streamline the process of site selection from large datasets.

Keywords —Coral nurseries, Restoration, Environmental predictors, NeuroEvolution of Augmenting Topologies (NEAT), Site selection, Mauritius

I. INTRODUCTION

The coral ecosystem is a crucial component of marine life, providing refuge, spawning grounds, and food for a wide range of species, while also protecting shorelines from strong currents and waves [1]. Corals also play a key role in regulating carbon dioxide balance in oceans, ensuring the survival of over 500,000 aquatic species [1]. Despite their importance, coral reefs are deteriorating at alarming rates. This decline is driven by rising ocean temperatures and acidification caused by increasing greenhouse gas emissions [2][3]. Such changes threaten marine biodiversity and global sustainability.

In Mauritius, coral ecosystems have become increasingly vulnerable to changing environmental and human pressures. Between 1971 and 2020, the rise in sea surface temperature was recorded at 0.216 °C per decade, significantly higher than the global average of 0.17 °C per decade [4]. Sea levels have also risen by approximately 0.12 mm annually, altering lagoon depth and circulation patterns. In addition to thermal stress, coral degradation has been accelerated by anthropogenic factors such as boating, sailing, scuba diving, and sand mining along the east and southeast coasts. Anchors, snorkelling in shallow waters, and nutrient enrichment from sewage outflows have all contributed to coral bleaching and physical damage [5][6]. These environmental and human-driven changes have reduced the number of sites suitable for coral nurseries, emphasizing the need for efficient, data-driven restoration planning.

Conventional methods for coral conservation and reef restoration are increasingly inadequate [7]. Alternative methods need to be found or the efficiency of existing techniques needs to be increased. For instance, the process of reef restoration, which involves aquaculture of corals in ocean-based nurseries and transplanting the grown corals to damaged reefs, is widely employed around the world. However, the efficiency of the technique still needs to be improved for a higher success rate. Site selection, when setting up a nursery, is a critical step in a restoration project and accurate selection of the best site will increase the survival rate of corals in the nursery and determine the overall success of the project. However, manually determining the best sites for coral nurseries is both time consuming and also makes it difficult for such a huge number of sites to be considered.

In recent years, machine learning has been especially useful in analysing data for determining site suitability. Studies have shown its effectiveness in coral conservation with MaxEnt and other algorithms being used to model coral habitat distribution [8][9].

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In the present study, we aim to develop an artificial intelligence program that aims at assisting reef restoration professionals to predict the best location for setting up a coral nursery by analyzing physical parameters of potential nursery sites while taking into account optimum environmental conditions required by corals for optimum growth and survival. In this era of Big Data, the program can prove particularly useful in predicting best nursery sites from large volumes of data from satellites. This can considerably increase efficiency of the coral restoration process.

II.METHODOLOGY

2.1 CASE STUDY, THE ISLAND OF MAURITIUS

This study was carried out for the Island of Mauritius. Located around 2000 km off the southeastern coast of Africa, Mauritius is an island nation located in the Indian ocean known for its rich marine biodiversity and coral reef ecosystems. The island has a coastline that is about 200 km and possesses 240 km^2 of reef habitats [10]. The lagoonal depth is relatively shallow, with lagoons mostly being less than 3 meters deep [10], a depth within the suitable range for coral growth [11]. Waves in the lagoon are also typically not more than 1m in height [12]. Mauritius experiences warm temperatures throughout the year. Sea surface temperatures range between 23℃ to 29℃, well within the optimum range of 21.7-29.6℃ for coral growth [13]. Furthermore, the island's relatively clear waters also allow sunlight to easily penetrate through, which is essential for photosynthesis in the marine ecosystem. These conditions are typically ideal for coral growth, but they are increasingly being affected by environmental stressors.

Since, this study primarily focuses on environmental conditions when determining the suitability of locations as coral nursery sites. Specifically, it focuses on some consistent and gradually evolving environmental factors: temperature, salinity and current. Factors such as cyclones are excluded from the analysis as they represent short-term disturbances rather than stable predictors. By concentrating on long-term, steady-state variables, this research aims to identify locations where corals can thrive under sustained environmental conditions, providing reliable insights for coral nursery establishment.

Figure 1: Map of Mauritius in the Indian Ocean [14].

2.2 THE DATASET

The GLOBAL_ANALYSIS_FORECAST_PHYS_001_015 dataset from Marine Copernicus EU (CMEMS-GLO-PUM-001-015) was used for model training. This dataset, with a spatial resolution of 1/4° (1440 × 692 grid points), consists of 500,587 data points collected between 12:00 on 30 December 2015 and 12:00 on 28 July 2018. Data were derived from multiple sources, including satellite observations, in-situ measurements, and auxiliary datasets [15]. The variables included temperature, sunlight, salinity, depth, water flow, wave energy, and wind speed – all factors known to influence coral distribution and health.

The CMEMS dataset integrates observational data with numerical ocean models, which can introduce uncertainties due to model assumptions and interpolation processes. Moreover, the 1/4° spatial resolution may not capture fine-scale oceanic features such as eddies and boundary currents, potentially reducing accuracy in parameters like current and water flow.

For model testing, the Wyoming dataset was used, containing field data from 253 regions across Mauritius. However, this dataset only included three environmental variables: temperature, salinity, and current speed. Consequently, these were the only parameters available for validation. While the trained model incorporates a broader range of predictors to improve generalization, only these three could be used in testing due to dataset limitations. This constraint was carefully considered during analysis to ensure consistent comparison and meaningful evaluation of model performance.

The suitability of locations for coral growth was assessed using the NEAT model, and the test sites are shown in Figure 2.

Figure 2: Locations tested for suitability of coral growth

2.3 THE MACHINE LEARNING MODEL: NEURO EVOLUTION OF AUGMENTED TOPOLOGIES

The AI program was developed using Neuroevolution of Augmenting Topologies (NEAT), an algorithm that evolves both the structure and weights of artificial neural networks through genetic principles [16]. NEAT begins with simple network topologies and gradually increases complexity

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through mutation and crossover operations until an optimal network is evolved to solve the problem.

NEAT works on three main mechanisms: speciation, complexification, and historical marking. Speciation groups similar networks into subpopulations (niches) so that newly mutated networks are protected from immediate competition, allowing innovative structures to mature before being evaluated against other species. Complexification allows the network to grow incrementally by adding new nodes and connections without disrupting existing structure similar to biological gene duplication [17][18]. Historical marking assigns unique identifiers to genes, enabling crossover between networks with differing structures and tracking of genetic lineage through generations [16]. An offspring is built by copying the parent with a higher fitness value.

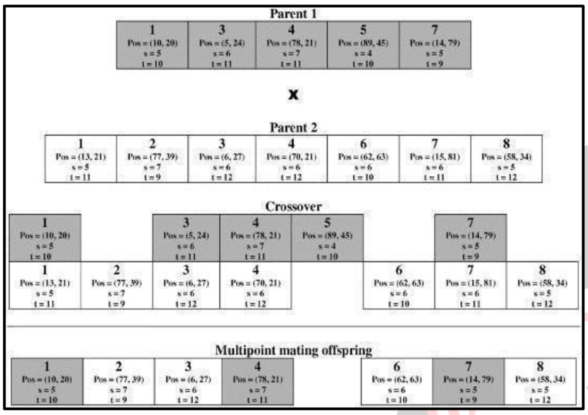

Figure 3. Example of historical marking during the mating of two individuals [16]

In the present study, NEAT was applied to evolve a classifier that predicts coral nursery site suitability. The process began with minimal neural networks connecting the input variables, mean temperature, mean water current velocity, and mean salinity, to a single output node representing suitability (1 = suitable, 0 = unsuitable). Through successive generations, NEAT introduced structural mutations such as new nodes or connections and selected the fittest networks based on classification accuracy against expert-labeled data.

Speciation preserved new network structures long enough for evaluation, while historical marking enabled consistent crossover between differing topologies. A grid search was employed to optimize hyperparameters such as mutation rate, crossover probability, and population size. These mechanisms allowed an efficient search of the solution space and progressive improvement in model performance. This is particularly important because the relationship between environmental variables and site suitability is highly nonlinear.

2.4 MODEL PERFORMANCE EVALUATION

Using a NEAT model for classification purposes requires some criteria for evaluation and hence table 1 displays the performance evaluation metrics used in this study.

Performance Evaluations	Formula	References
Accuracy	□□ + □□ / □□ + □□ + □□ + □	[19]
Precision	□□ / □□ + □□	[20]
Recall	□□ / □□ + □□	[21]
F-Score	2(□□□□□□□□□ / □□□□□□□□□ +	[19]
Specificity	□□ / □□ + □□	[20]

Table 1: Accuracy tests and their formulas, where TN = True Negative, FN = False Negative, FP = False Positive and TP= True Positive.

III. RESULTS & DISCUSSIONS

The NEAT model achieved an accuracy of 0.96 (two significant figures) and an Area Under the Receiver Operating Characteristic curve (AUC-ROC) score of 0.95, indicating strong overall classification performance. The classification matrix in Figure 4 displays the distribution of predictions across classes. The model achieved a recall of 0.93, demonstrating high sensitivity in identifying unsuitable coral nursery sites. However, the precision score was relatively lower at 0.59, indicating that the model occasionally misclassified unsuitable locations as suitable. The area under the precision–recall curve (AU-PR) was 0.76, lower than the ROC value, suggesting reduced robustness in identifying optimal nursery sites. These findings highlight the model's less robust performance in identifying suitable locations as opposed to determining unsuitable locations.

In the context of this study, precision is a more critical metric than recall. The AI model is not intended to replace expert judgment but to reduce the total number of sites requiring human evaluation. A model with higher precision ensures that most of the sites flagged as suitable by the algorithm are genuinely promising, thereby saving time and resources during field validation. Despite the relatively lower precision, the high overall accuracy and recall suggest that NEAT effectively learns the nonlinear relationships between environmental variables and coral site suitability.

Factor	Optimum range	Reference
Temperature	21.7—29.6 °C	[13]
Light	Min : 450 µmol photons m^{-2} s^{-1}	[13]
Salinity	28.7—40.4 psu	[13]

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Depth	2-5m	[11]
Water flow	20 to 70 cm s^{-1}	[22]
Wave/Wave energy	<0.51 N/m2	[23]
Wind speed	10-25cm/s	[24]

Table 2: Optimum conditions for coral growth

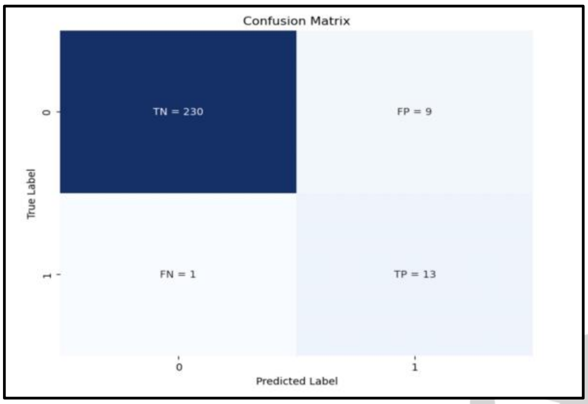

Figure 4: Confusion matrix of model testing results where TN = True Negative, FN = False Negative, FP = False Positive and TP= True Positive.

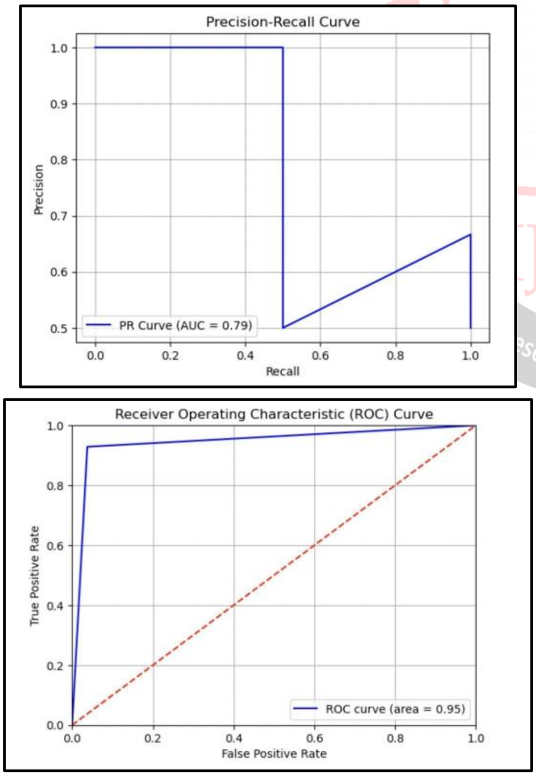

Figure 5: NEAT model performance PR Curve and ROC Curve

Model Evaluation	Mean Temperature (°c)	Mean Water Current (m/s)	Mean Salinity (psu)
0	28.275652	0.135372	35.034276
1	28.265715	0.176091	35.031166

Table 3: The mean water temperature, current and salinity across suitable and unsuitable regions.

Salinity and mean temperature, as indicated in Table 3, varied little among the predicted suitability levels, indicating that they are either largely constant within the study area or only indirectly affect the suitability of nursery sites. It is crucial to remember that temperature can have a significant impact on coral survival at finer spatial and temporal resolutions, especially during seasonal extremes or marine heatwaves. Therefore, local temperature variations that are ecologically important for coral growth may have been obscured by the current dataset's comparatively coarse resolution.

In contrast, mean water current velocity demonstrated clear differentiation between suitable and unsuitable locations. According to Table 1, the mean current speed in suitable locations was higher (0.176 m/s) than in unsuitable ones (0.135 m/s). This implies that within the modeled region, water flow has a significant impact on the suitability of coral nursery sites. Coral health is directly impacted by hydrodynamic conditions, which improve gas exchange, remove sediment, and improve nutrient delivery. Therefore, moderate current velocities can encourage coral growth and larval settlement, while stagnant or excessively strong flows may hinder these processes. Previous studies have found that corals grow and survive better at nursery sites with steady, moderate water flow [24].

Despite the fact that temperature anomalies are commonly acknowledged as the primary cause of coral bleaching, this study found minimal differences in temperature between sites that were suitable and those that were not (Table 3). This suggests that thermal conditions were comparatively uniform within the modelled region, making them a weak differentiator for suitability. Under such circumstances, the primary factor influencing coral health is hydrodynamic processes. By promoting convective cooling, oxygen exchange, and nutrient supply while avoiding sediment buildup, water flow affects how corals react to heat stress. Under the same ambient heat conditions, corals exposed to moderate flow rates maintained lower tissue temperatures and higher photosynthetic efficiency than those in stagnant waters, according to experimental work by Nakamura and van Woesik [21]. Therefore, the model's emphasis on current velocity reflects genuine ecological mechanisms. Currents create localized microclimates that mitigate the physiological effects of heat, even when overall temperature gradients are small. This supports the interpretation that flow dynamics, rather than temperature per se, are the key

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determinant of nursery site suitability in the Mauritius region.

Moderate to high flow rates (20–25 cm/s) provide maximum growth and survival for scleractinian and pocilloporid corals, whereas stagnant or very low flow (< 3 cm/s) decreases resilience and increases susceptibility to bleaching [22][24]. Acropora, Pocillopora, and Galaxea, three coral species that are common in Mauritius, appear to do best in this range of flow speeds, according to similar findings. The higher current velocities that the model identified as a feature of appropriate nursery sites most likely correlate with these flow conditions. Thus, under such hydrodynamic conditions, the model's preference for higher current speeds is in good agreement with experimental data demonstrating enhanced coral growth, stress resistance, and decreased algal overgrowth.

Most predictions for suitable locations lie outside Q3 of mean current speeds, with a majority of them being at the maximum current speed. However, a surprising trend was that the model determined more locations with a current speed below Q1 as suitable locations than locations with a current speed between Q1 and Q3. As displayed in figure 7, most of the suitable locations (class 1) seem to be clustered in areas with higher longitude and latitude values. Most suitable locations seem to be located north of the Mauritius island, towards the round island, flat island and snake island with very few suitable locations found at the lower longitude and latitude points of the coast of the main island. The clustering may represent isolated ecological niches where conditions are optimal for suitability. A closer examination of specific regions revealed noteworthy observations that provide deeper insights into the model's performance and the underlying environmental factors influencing suitability predictions.

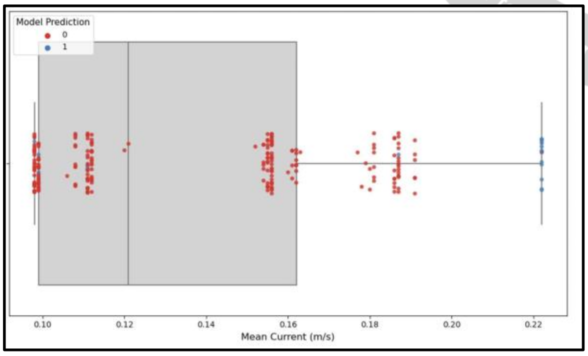

Figure 6: Box-plot showing model predictions at different distributions of mean currents

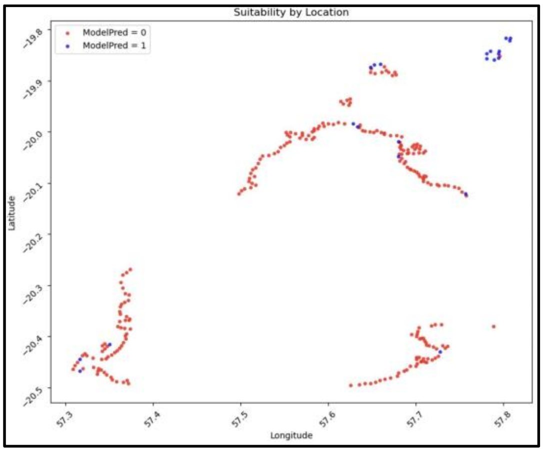

Figure 7: Site suitability by location

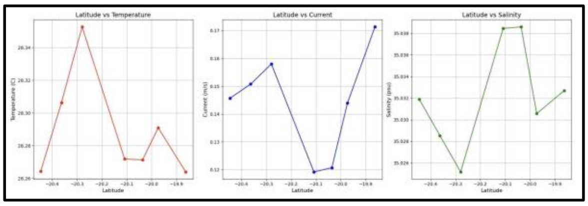

Figure 8: Relationship between longitude and the spatial predictors

The model found a cluster of suitable locations around the coasts of snake island and round island, with 10 out of 11 locations being deemed suitable. As shown in figure 8, these locations exhibit consistently elevated water current values (latitude > -19.9), aligning with suitability thresholds. Despite the higher currents, salinity values remained stable, and temperatures were notably lower compared to other regions, both of which likely contributed to the high suitability classification. In contrast, the region around Mauritius Island presented significant classification challenges for the model. Amongst the data points analysed, 9 locations were misclassified as suitable (false positives). The errors were likely influenced by borderline environment conditions, such as the comparatively medium-high water current between the latitude range of -20.5 and -20.3. The study demonstrates the high accuracy of the proposed NEAT (NeuroEvolution of Augmenting Topologies) model in determining suitable coral nursery in Mauritius, achieving an overall accuracy of 96.05%. The model identified a geographically restricted range of suitable locations, with most locations determined as suitable concentrated around Snake island and Round island, supporting the idea that the North Western regions of Mauritius form the best location for coral growth [25]. These regions exhibited high mean water currents, stable salinity and low temperatures, each of which was within the optimum range for coral growth (table). In contrast, only very few of the locations around the coast of Mauritius island were deemed suitable by the model, a result that was in line with results validated from human evaluation.

The high recall 0.93 underscores the models ability to prioritize positive class predictions, making it a robust tool for initial site determination. Furthermore, the minimalist

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structure of the NEAT model makes it particularly suitable for analyzing large satellite datasets, which could be crucial for scaling up site selection efforts in conservation projects. Despite its high accuracy, the model struggled to handle imbalance datasets as evidenced by its lower precision score (0.59). The relatively lower AUC-PR score (0.76) compared to the AUC-ROC score (0.95) underscores the difficulty in maintaining a balance between precision and recall for suitable locations. If applied to a larger scale false positives in the model could potentially lead to misallocation in resources in conservation projects. However, the model's prioritisation of recall over precision could be highly advantageous in the context of setting up coral nurseries considering the already limited number of potential sites identified in Mauritius. As of current the model can be used as a tool to limit the number of locations considered for setting up coral nurseries. The final locations can then be determined using human evaluation. Previous studies have identified water current as a critical determinant as a critical determinant of ecological patterns due to its role in nutrient distribution and habitat suitability, and this research reaffirms its significance as the most influential predictor in the model. The observed clustering of suitable locations in regions with relatively high currents (>0.17 m/s), such as Snake and Round islands supports earlier findings of coral growth in regions of high water current, such as that of Sundahl, Buhl-Mortensen, and Buhl-Mortensen [26] which found corals to prefer a relatively high mean current speed, especially around 0.20 m/s. Temperature and salinity values remained relatively stable across testing locations, reducing their impact on the model's predictions. Near Mauritius island the model showed a high rate of false positives. These false positives occurred at locations around the latitude of -20.3, with mean water currents around that location being close to 0.16 m/s. There is indication of potential overlaps in predictor values between suitable and unsuitable sites, emphasising the need for region-specific adjustments in the model to account for localized ecological factors, to potentially increase precision.

Several limitations must be acknowledged, firstly the significant class imbalance in the dataset with 14 positive and 239 negative cases, might have influenced the precision of the model. Secondly, the restricted geographical distribution of predictions could hint towards potential biases in the model, however, since human validation reflected similar results it is difficult to evaluate the presence of bias in the model. Additionally, the model's limited number of parameters considered could be simplifying complex ecological relationships. However, this was something that could not be addressed given the limitation in the testing set for Mauritius. Since the training of the model has been done considering a larger range of parameters future studies could utilise the same type of on other geographic locations while making sure that the testing dataset contains other important parameters like water depth. Strategies to enhance the model's precision-recall trade-off could also be explored.

IV. CONCLUSION

Through this program we were able to determine that suitable locations for coral nurseries lie towards north-east Mauritius, with most located around Round island and Snake island in Mauritius and some also located around the Flat island. However, only a few sites around the main island were deemed as suitable. This paper is one of the first papers to explore the use of the NEAT for determining coral locations. The model was highly successful showing a greater AUC (0.95) than the MaxEnt models in Yuen et al [9] (0.82) and Hidayah et al. [27] (0.9). The success of the NEAT model could be attributed to its similarity to coral evolution, with both following the process of speciation. This process allows the NEAT model to capture complex relationships within the natural environment, as new variations of the model are each given a chance to reach their full potential. Site selection when starting coral nurseries is essential as poor conditions lead to very low survival rates for corals. The NEAT method proposed by this paper significantly increases the efficacy of site selection for coral nurseries. Accurate sight selection will significantly increase the survival rate in the nurseries and improve project success. The structure of the NEAT model makes it very quick at traversing through large datasets such as satellite datasets. Traditional methods of eliminating sites are slow and tend to overlook a huge portion of possible locations. Hence, this program can considerably speed up the process and with its high recall score, serve as a preliminary step before biologists' field test locations.

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