UMT PRESS

Journal of Sustainability Science and Management
Journal Homepage: https://jssm.umt.edu.my
eISSN: 2672-7226
DOI: http://doi.org/10.46754/jssm.2026.05.006

SPATIAL MODELLING OF DOLPHIN MOVEMENT IN LOVINA, BALI: A MULTI-METHOD APPROACH FOR SUSTAINABLE MARINE CONSERVATION AND TOURISM MANAGEMENT

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ARTICLE INFO

Article History:
Received: 5 May 2025
Revised: 29 December 2025
Accepted: 4 January 2026
Published: 15 May 2026

Keywords:
Dolphin movement, HSI, AHP, multivariate analysis.

ABSTRACT

Dolphins in Lovina, Bali have become a significant marine tourism attraction; however, tourism activities and changing environmental conditions exert considerable pressure on their populations. This study aims to evaluate environmental factors influencing dolphin movement pathways using the Analytic Hierarchy Process (AHP), Habitat Suitability Index (HSI), multivariate analysis, and model accuracy assessment using Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). AHP was employed to assign weights to oceanographic variables, identifying sea surface temperature and salinity as dominant factors. The HSI model was subsequently used to map habitat suitability based on these weighted variables. Multiple regression analysis yielded an R^2 value of 0.872, indicating that Chlorophyll-a concentration, sea surface temperature, and ocean currents significantly influence dolphin movements. The HSI-regression model produced an MSE of 4.74×10^{-5} and an RMSE of 0.0069, indicating good predictive accuracy, although further refinement is recommended. These findings highlight the substantial influence of sea temperature variability and tourism activities on dolphin distribution. Future research should incorporate broader spatial and temporal datasets, including in situ data such as satellite tagging or acoustic surveys. Additionally, the application of non-linear statistical models such as Random Forest is suggested to enhance predictive accuracy.

Introduction

Dolphins (family *Delphinidae*) are marine mammals that play a vital role in maintaining the balance of marine ecosystems and serve as key indicators of aquatic environmental health (Erbe *et al*., 2019; Bhagarathi *et al*., 2024). One prominent species found in the coastal waters of Lovina, North Bali is the Indo-Pacific bottlenose dolphin (*Tursiops aduncus*), which has become a central attraction in the marine tourism industry, providing significant economic benefits to local communities (Mustika, 2011; Wiarti, 2017; Mustika *et al*., 2018). However, the rapid expansion of tourism in the region has raised serious ecological concerns for dolphin populations, including increased underwater noise pollution, risk of vessel collisions, and disruption of natural behaviours (Putland *et al*., 2018; Sequeira *et al*., 2019; Santos-Carvallo *et al*., 2021; Westerlaken *et al*., 2022, 2022a).

Recent studies have shown that unregulated tourism activities can alter dolphin movement patterns, reduce their foraging efficiency, and elevate stress levels, with long-term implications for their health (Constantine *et al*., 2004; Bejder *et al*., 2006; Adikampana *et al*., 2019; Stack *et al*., 2021). Bejder *et al*. (2006) reported in

Western Australia that tour boat disturbances reduced dolphin resting time by up to 30% and increased their energy expenditure by up to 25%. Similar impacts are likely occurring in Lovina, where the number of tour vessels has been steadily increasing (Kasuga *et al*., 2022; Westerlaken, 2024; Wiramatika *et al*., 2024). Furthermore, underwater acoustic disturbances generated by boat engines disrupt dolphins' echolocation systems, which are essential for navigation and prey detection, and may result in habitat displacement (Putland *et al*., 2018); Erbe *et al*., 2019; Williams *et al*., 2020).

Simultaneously, global climate change is altering oceanographic parameters in the Bali region such as sea surface temperature and primary productivity, leading to shifts in prey distribution that consequently affect dolphin movement patterns (Bearzi *et al*., 2007; Sambah *et al*., 2020; Bhagarathi *et al*., 2024; Septiani *et al*., 2024). These overlapping pressures exacerbate the ecological vulnerability of dolphins in Lovina. A comprehensive understanding of dolphin movement pathways is essential for developing effective conservation strategies and sustainable tourism management (Mustika *et al*., 2015; Reisinger *et al*., 2022). However, existing studies in Lovina predominantly rely on direct observational methods, which are limited in both spatial and temporal resolution, resulting in an incomplete mapping of dolphin movement corridors (Clarke *et al*., 2021; Martino *et al*., 2021).

Therefore, research that integrates satellite data and oceanographic parameters to model dolphin movement spatially is crucial for informing environmentally responsible tourism and conservation policies (Hastie *et al*., 2005; Bailey *et al*., 2009; Arida *et al*., 2019; Verutes *et al*., 2021). Based on this context, the present study aims to evaluate the relationship between environmental variables and dolphin movement pathways in the waters of Lovina. Specifically, it seeks to map dolphin distribution by integrating satellite-derived data and key oceanographic parameters, and to develop a predictive spatial model representing dolphin distribution patterns as influenced by environmental drivers such as sea surface temperature, primary productivity, and bathymetry. The results of this study are expected to provide a robust scientific foundation for dolphin conservation policy and sustainable marine tourism management in Indonesia and to serve as a methodological framework for similar coastal studies elsewhere (Reisinger *et al*., 2022; Westerlaken, 2024).

Materials and Methods

Study Area

The study area is located along the coastal region of Lovina, North Bali, Indonesia (Figure 1), a site well known for dolphin-watching tourism activities. The study encompasses nearshore to shallow marine zones surrounding Lovina, situated approximately between 8°7'–8°10' S and 115°0'–115°5' E (Figure 1). This area was selected for its high intensity of interactions among dolphins, tourism activities, and local oceanographic dynamics. Additionally, the coastal environment of Lovina is increasingly subject to ecological pressures from tourism development, making it a suitable location for examining the spatial relationships between oceanographic variables and dolphin movement patterns.

Field Survey

Field surveys were conducted in the coastal waters of North Bali using small traditional boats (Figure 1). Observation sites were selected based on Mustika (2011), who identified areas with a high likelihood of dolphin occurrence. Surveys followed standard cetacean visual observation protocols (Hammond *et al*., 2021), adapted for small-boat operations. Visual monitoring was complemented with GPS tracking and organised into four observation groups. Surveys were conducted daily over three weeks, with repeated coverage of the same location to ensure temporal consistency and comparability. Observers recorded dolphin sightings, including time of occurrence, group location, and movement direction. These data were used to

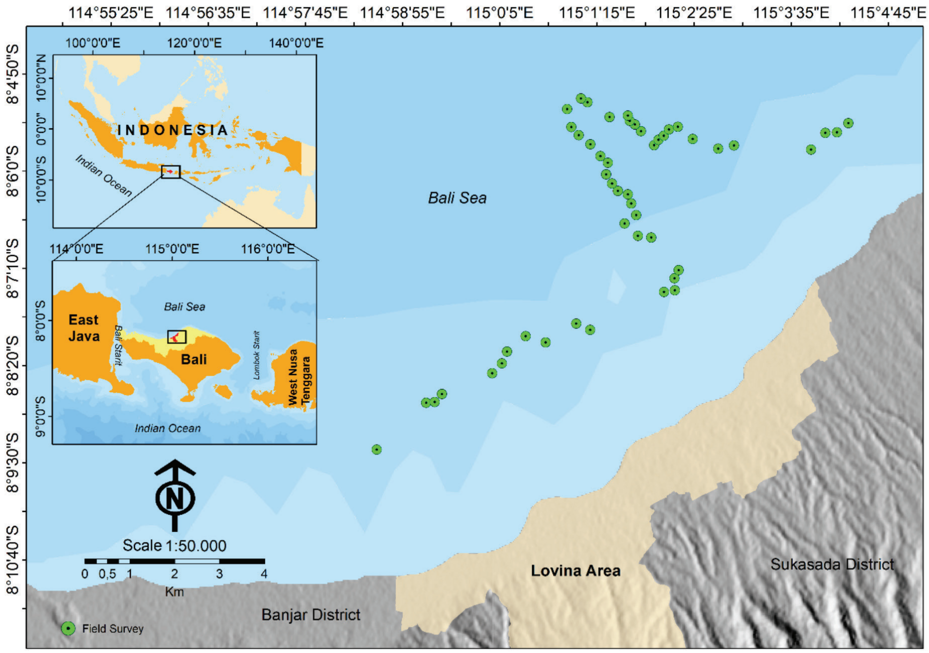

Figure 1: Research location

characterise spatial and temporal movement patterns, which subsequently informed model validation. The survey approach is consistent with established methods for assessing small cetacean distribution and habitat use (Becker *et al*., 2020; Hammond *et al*., 2021).

Data Collection

This study primarily utilised remote sensing imagery as the main data source, acquired from multiple platforms. The selected variables are based on those commonly employed in previous research (Table 1). Additionally, field surveys were conducted to monitor dolphin movement directions and validate the analytical results. Table 2 provides detailed information on the types and sources of remote sensing data utilised in this study.

Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) was employed to assign weights to the environmental variables used in the analysis. The weighting system in AHP applies to the pairwise comparison scale developed by Saaty (1980, 2012), commonly referred to as the Saaty scale (Table 3). These weights were then applied in a weighted overlay analysis using the Habitat Suitability Index (HSI) approach. The HSI method, developed by the U.S. Fish and Wildlife

Table 1: Variable data

Variable	Range Optimal	Source
Sea Surface Temperature (SST)	24°C–28°C	Bearzi *et al*. (2007)
Chlorophyll-a (Chl-a)	0.3–0.8 mg/m^3	Lee *et al*. (2019)
Sea surface salinity	32–34 PSU	Shi *et al*. (2024)
Ocean currents	0.2–0.5 m/s	Shi *et al*. (2024)
Bathymetry	10–100 m	Shi *et al*. (2024)

Table 2: Remote sensing data

Data Types	Data Source	Format	Performance
Sea Surface Temperature (SST) https://oceancolor.gsfc.nasa.gov/	NASA	Raster	Identification of thermal fronts of dolphin habitat
Chlorophyll-a (Chl-a) https://oceancolor.gsfc.nasa.gov/	NASA	Raster	Prediction of primary productivity areas
Sea surface salinity https://www.catds.fr/	ERDAPP	Raster	Habitat preference analysis
Ocean currents https://coastwatch.noaa.gov/erddap/index.html	ERDAPP	Raster	Migration path modelling
Bathymetry https://download.gebco.net/	GEBCO	Raster	Depth mapping
Dolphin sighting locations	Field survey	Vector	Ground truthing

Table 3: Saaty scale

Value	Level of Interest	Description
1	Both elements are equally important	There is no significant difference between the two variables.
3	Slightly more important	One element is slightly more dominant than the other.
5	Much more important	One element has a clearly stronger influence.
7	Very more important	One element is very dominant and the supporting evidence is strong.
9	Absolutely more important	One element is absolutely dominant.
2, 4, 6, 8	Midpoint	Used when the assessment is between two levels (e.g. 2 = between 1 and 3).

Service (1981), generates suitability values ranging from 0 to 1, where 0 indicates unsuitable habitat and 1 indicates optimal suitability. HSI is effective in integrating multiple environmental variables into spatially explicit information (Brooks, 1997; Morrison *et al*., 2006). The HSI formula adopted in this study follows the methodology proposed by Hirzel *et al.* (2006), as shown in Equation (1).

$$HSI = \sum (\omega_i \; x \; X_{i,norm}) \quad (1)$$

Furthermore, data normalisation is a critical step in the HSI processing workflow. This procedure ensures that all variables are scaled appropriately to enable accurate assessment of habitat suitability. Normalisation is essential for generating reliable spatial distribution values within the HSI framework. Table 4 presents the classification scheme used to normalise each variable.

Multivariate Analysis

Multivariate analysis was conducted using multiple linear regression to determine the weight coefficients of the selected variables. This method served as a predictive tool to complement the previously applied HSI model. The use of multiple regression was justified by the inclusion of several environmental variables to estimate the presence and movement patterns

Table 4: HSI normalisation data

Variable	Normalisation	Scale
Sea Surface Temperature (SST)	Min-max (24°C–28°C → 0-1)	Linear
Chlorophyll-a (Chl-a)	Sigmoid (> 0.3 mg/m³ = 1)	Non-linear
Bathymetry	Gaussian (peak 50 m)	Non-linear
Ocean currents	Triangular (0.3 m/s = 1)	Non-linear
Sea surface salinity	Binary (32–34 PSU = 1)	Threshold

of dolphins in the Lovina region. The formula for the multiple linear regression model is presented in Equation (2).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \epsilon \quad (2)$$

In this context, β_i represents the coefficient obtained from the multivariate analysis, while X_i denotes the environmental variables used to model dolphin movement pathways. The multivariate analysis was performed using the SPSS software to facilitate statistical computation and interpretation of the results. Additionally, an accurate assessment was conducted to evaluate the predictive performance of the HSI model derived from both multivariate regression and AHP approaches. The accuracy testing employed the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) methods. These metrics were used to quantify the degree of error and validate the predictive accuracy of the models through 1:1 scatter plot. Equations (3) and (4) present the formulas for calculating MSE and RMSE, respectively, where X_i represents the observed field data and $\bar{x}_i$ denotes the predicted value.

$$MSE = \frac{\sum_{i=1}^{n} |x_i^* - \bar{x}_i|^2}{n} \quad (3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} |x_i^* - \bar{x}_i|^2}{n}} \quad (4)$$

Results and Discussions

The study area for analysing dolphin movement pathways was delineated based on locations covered during field surveys. Accordingly, the coastal region of Lovina selected for this research corresponds to the area through which dolphins are known to migrate. Field surveys were conducted three times over separate weeks to track dolphin movement. As illustrated in Figure 2, the first, second, and third survey tracks exhibited relatively similar patterns of dolphin movement as observed in situ. However, further investigation is necessary to determine whether these consistent movement patterns result from fixed migratory routes or are influenced by varying environmental factors. The detailed field observation results are presented in Table 5.

Dolphin observations were conducted daily over three weeks. The temporal scale of the survey was informed by previous research in Lovina (Mustika, 2011; Westerlaken *et al*., 2021), which demonstrated that this area consistently serves as a transit corridor and supports daily dolphin occurrences. The three-week duration was further justified by the relatively limited spatial extent of the study site, unlike broader regions that require longer temporal coverage and segmented survey designs (de Jager *et al*., 2019; Mazzoil *et al*., 2020).

All field activities followed standardised assessment protocols for coastal monitoring to ensure compliance with environmental protection and conservation principles (Matias *et al*., 2022; Nita *et al*., 2022). This survey effort was considered sufficient to generate reliable data for modelling dolphin movement patterns.

Analytic Hierarchy Process (AHP) Analysis

Dolphin movement in coastal waters is closely associated with oceanographic parameters that support their optimal habitat such as Sea Surface Temperature (SST), Chlorophyll-a (Chl-a) concentration, bathymetry, ocean currents, and

Table 5: Summary of dolphin field surveys off Lovina

Information	Sampling Type	Sampling Unit	Result
Movement direction	GPS track	Day	Dolphins consistently travelled east to west during morning hours, continuing until midday. This directional movement was observed on 19 of 21 survey days (90.5%).
Occurrence period	Scan sampling	Day	Dolphins were first sighted at 07:00 local time, with occurrences extending until approximately 10:25. Mean surfacing duration was ±2 minutes. A decline in surfacing frequency was recorded during westward movements compared with other directions.
Travel routes	GPS track	Day	Throughout the three-week survey, dolphins followed consistent routes. Variation in movement was not associated with environmental barriers but coincided with the presence of dolphin-watching vessels.
Environmental conditions	Scan sampling	Day	Sea surface temperature remained stable at ~ 31°C (mean daily variation < 1°C), indicating minimal thermal variability during the observation period.
Observation points	GPS plot	Day	Observations from four survey groups confirmed that dolphins travelled in pods, with no solitary individuals recorded. A total of 57 sighting events were documented, with a mean frequency of 2.7 ± 0.6 sightings per day. Pods were generally small, averaging ~ 10 individuals (range: 6 to 12), as determined by direct counts of surfacing animals.

Source: Processing data field survey (2024)

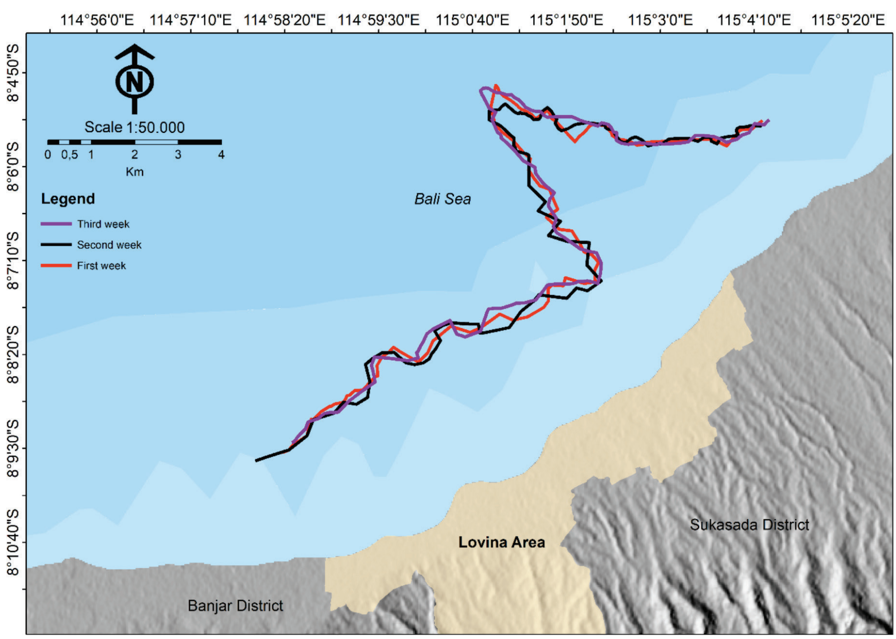

Figure 2: Field survey results for dolphin movement routes
Source: Processing data field survey (2024)

sea surface salinity. Based on the results of the AHP analysis (Figure 3), the most influential variable contributing to suitable dolphin habitat was chlorophyll-a (0.490), followed by sea surface temperature (0.246), ocean currents (0.160), bathymetry (0.069), and salinity (0.035) (Table 6). These findings highlight that primary productivity, as represented by chlorophyll-a concentration, plays a key role in determining habitat suitability. This aligns with the results of Lee *et al.* (2019), which indicated that higher levels of chlorophyll-a correlate with greater prey availability, particularly small fish that constitute the primary food source for dolphins.

The integration of the AHP results with the HSI analysis (Figure 4) demonstrates consistency between the weights of key variables and the actual habitat suitability. The HSI values were calculated based on membership functions that account for the optimal range of each oceanographic variable. In the analysed case, all parameters fell within their optimal ranges, yielding a total HSI of 1.0, indicating that the habitat is highly suitable for dolphins. Chlorophyll-a concentrations ranging from 0.32 to 1.35 mg/m³ reflect primary productivity conditions that support the food web (Shi *et al.*, 2024), while sea surface temperatures between 26°C to 30°C align with the thermal preferences of dolphins, as noted in studies by Pirotta *et al.* (2011).

Bathymetry also plays an important role, although its weight in the AHP analysis is lower than that of other variables. Dolphins are known to be more active in waters with depths ranging from 50 to 200 m, where depth gradients are often associated with areas where ocean currents converge, enhancing food availability (Bailey & Thompson, 2010). Ocean currents with speeds between 0.2 and 0.5 m/s create dynamic conditions that benefit dolphins, both by distributing plankton and by shaping their hunting strategies. Additionally, sea surface salinity in the range of 33 to 35 PSU supports osmotic balance, which is crucial for the physiological health of dolphins (Wells *et al.*, 1999).

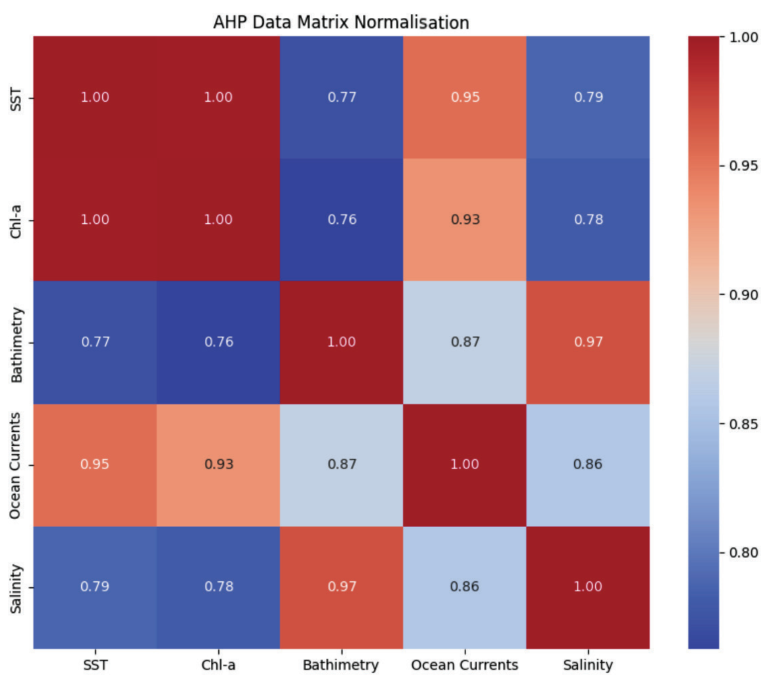

Figure 3: AHP data matrix normalisation
Source: Processing data (2024)

Table 6: Weight value of each variable

Variable	Weight of AHP	Consistency
Sea Surface Temperature (SST)	0.246	λmax = 5.297
Chlorophyll-a (Chl-a)	0.490	CI = 0.07
Bathymetry	0.069	CR = 0.066
Ocean currents	0.160	(CR < 0.1)
Sea surface salinity	0.035	

Source: Processing data (2024)

Considering the spatial and temporal patterns of these variables, it is predicted that dolphin movement paths will follow water areas with high chlorophyll-a concentrations, warm water temperatures, moderate currents, and medium water depths. A study by Robinson *et al*. (2012) supports this finding, indicating that cetaceans often exploit oceanographic frontal zones characterised by temperature gradients and high chlorophyll-a concentrations to forage. Therefore, the integration of AHP and HSI results in this study provides a robust approach to more accurately map potential habitats and dolphin movement pathways.

Understanding these dynamics is essential for effective marine conservation and management, particularly in light of climate change, which is likely to alter oceanographic patterns (MacLeod, 2009). Employing an Analytic Hierarchy Process (AHP)-based and Habitat Suitability Index (HSI)-supported approach, together with empirical oceanographic data and predictive species-movement models, facilitates the development of adaptive, evidence-based conservation policies. Future research should integrate human activity variables into the identification of dolphin movement to further optimise the HSI model.

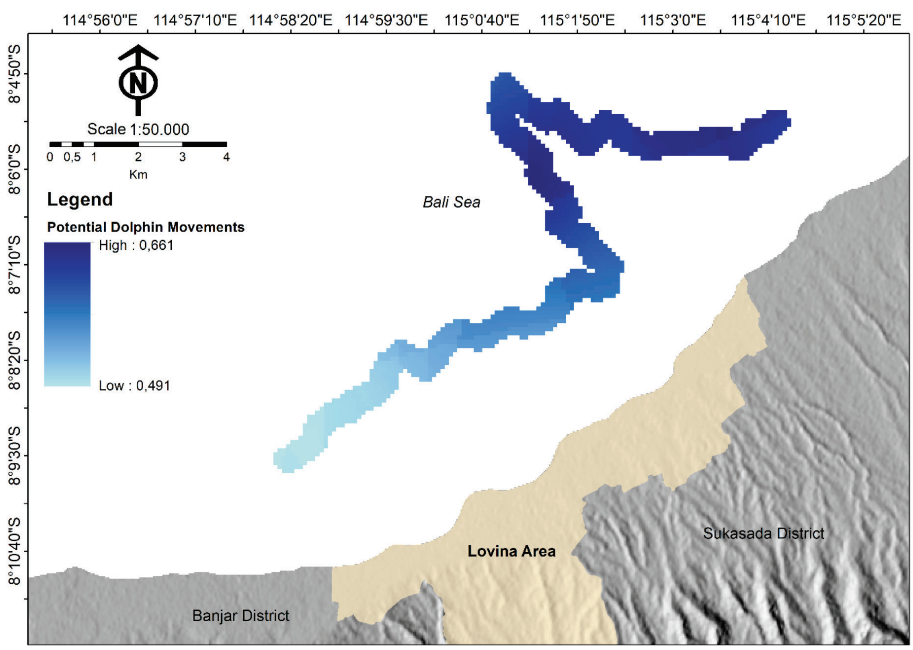

Figure 4: HSI result from AHP
Source: Processing data (2024)

Multivariate Analysis

A multiple linear regression analysis was conducted to evaluate the influence of oceanographic variables on the Habitat Suitability Index (HSI) for dolphins in the studied marine area. The analysed variables include Sea Surface Temperature (SST), Chlorophyll-a concentration (Chl-a), bathymetry, ocean current speed, and sea surface salinity (Table 7). The results of the regression model (Figure 5) indicate that Chl-a, SST, and ocean current make significant contributions to the formation of suitable habitats for dolphins, while bathymetry and salinity have a weaker influence.

The positive regression coefficient for Chl-a ($\beta = 0.486$; $p < 0.01$) suggests that an increase in Chlorophyll-a concentration significantly enhances the HSI. This finding is consistent with previous studies, which indicate that food availability, as reflected in high chlorophyll-a concentrations as a proxy for primary productivity is a key factor in determining important areas for dolphins and other cetaceans (Bailey & Thompson, 2010). Additionally, SST shows a positive relationship with HSI ($\beta = 0.021$; $p < 0.05$), supporting the hypothesis that dolphins prefer waters at optimal temperatures, consistent with this species' thermal preferences across various marine ecosystems (Redfern *et al*., 2006). Ocean Current, with a significant positive coefficient ($\beta = 0.315$; $p < 0.05$), indicates that areas with moderate currents support more suitable habitats, likely through mechanisms such as nutrient enrichment and prey aggregation, which subsequently facilitate dolphin movement and foraging behaviour.

On the other hand, bathymetry shows a small negative coefficient for HSI ($\beta = -0.002$; $p > 0.05$), although it is not statistically significant. This suggests that excessive depth tends to reduce habitat suitability, but its effect is relatively minor within the context of the studied waters. Dolphin preference for medium depths has been reported previously, with individuals tending to inhabit neritic zones with easy access to prey and dynamic oceanographic conditions (Forney *et al*., 2012). Sea surface salinity, despite having a positive coefficient ($\beta = 0.018$; $p > 0.05$), also does not significantly influence HSI, indicating that within the relatively homogeneous salinity range in the study area, this factor is not a primary determinant of dolphin movement corridors. When linked to dolphin movement paths, these results suggest that areas with higher chlorophyll-a concentrations, optimal sea surface temperatures, and moderate ocean current speeds are likely to be the primary movement corridors for dolphins. These paths not only provide a sufficient food supply but also facilitate efficient movement across critical habitats. This concept is supported by previous research demonstrating that dolphin habitat preferences are heavily influenced by spatiotemporal interactions between oceanographic factors and prey species distributions (Torres *et al*., 2008).

Table 7: Results of multiple linear regression value analysis

Variable	Coefficient (β)	Std. Error	t-Value	*p*-Value	VIF	Interpretation
Intercept	-0.523					
SST	0.021	0.08	5.25	<0.001	1.8	Significant influence
Chl-a	0.486	0.12	2.58	0.011	2.1	Very significant influence
Bathymetry	-0.002	0.09	-2.11	0.036	1.5	Not significant
Ocean currents	0.315	0.05	1.40	0.162	1.2	Positive and significant influence
Sea surface salinity	0.018	0.04	0.75	0.455	1.3	Marginally significant

Source: Processing data (2024)

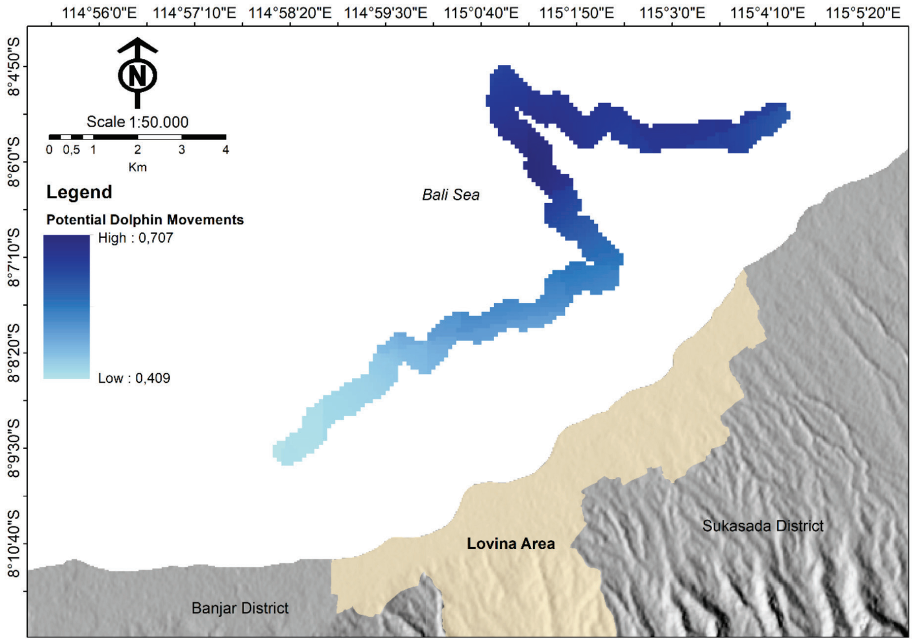

Figure 5: HIS result from multiple linear regression
Source: Processing data (2024)

These findings underscore the need to incorporate oceanographic dynamics into conservation planning and to designate protected zones along dolphin migration routes. This conclusion is supported by results consistent with those derived from the AHP method. Additionally, systematic monitoring of oceanographic variables, including chlorophyll-a concentration and sea surface temperature, is essential for anticipating changes in potential habitats resulting from climate change and anthropogenic influences in marine environments.

Validations

Model validation (Figure 6) through the scatterplot of actual versus predicted values shows a very high degree of agreement, with Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) values approaching zero on the training dataset. However, cross-validation reveals a slight increase in error, suggesting overfitting due to the limited sample size. Nevertheless, the model generally explains 87.2% of the variation in HSI values based on the examined oceanographic factors.

Figures 6 (a) and (b) show that the validation results of both models closely align with field measurements through a 1 x 1 plot. The difference in HSI-Reg indicates a greater distribution and spread of potential dolphin movement paths than in HSI-AHP. Additionally, Figure 6 (c) illustrates the sample distribution between HSI-Regression and HSI-AHP, with an ideal distribution along the plot line. However, values below 0.5 suggest that dolphin movement paths are likely overestimated, possibly influenced by other factors. Both the AHP and Regression models could be used for monitoring dolphin movement along coastal areas, with environmental variables, particularly oceanographic factors, playing a critical role.

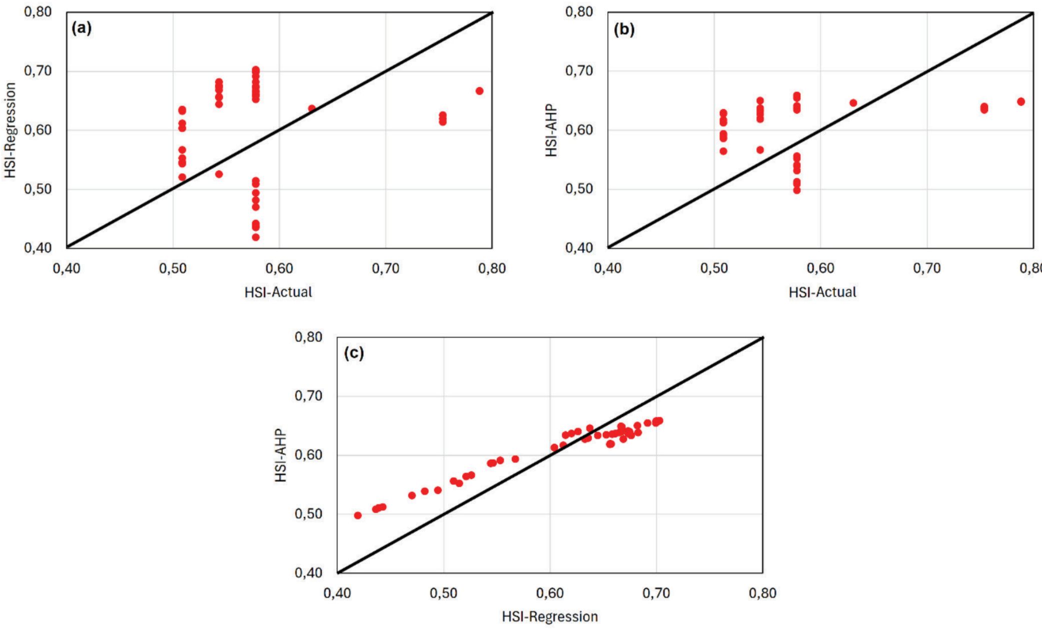

Figure 6: Validation plot 1 x 1 (a) HSI-Actual with HSI-Regression, (b) HSI-Actual with HSI-AHP, and (c) HSI-Regression with HSI-AHP
Source: Processing data (2024)

Conclusions

The results of the Analytic Hierarchy Process (AHP) indicate that chlorophyll-a is the most influential variable in determining dolphin habitat suitability, followed by Sea Surface Temperature (SST) and ocean currents. Meanwhile, bathymetry and salinity have lower weights. Chlorophyll-a plays a crucial role as it is directly related to primary productivity and the presence of prey, which are key factors in determining dolphin locations. SST and ocean currents are also important as they affect the physiological comfort and movement efficiency of dolphins. The Habitat Suitability Index (HSI) model is constructed by combining the AHP weights with the actual values of each variable. The results show that habitats with an HSI value > 0.80, which include Chlorophyll-a > 0.2 mg/m^3, temperatures between 26°C to 29°C, and ocean currents between 0.2 to 0.5 m/s, are highly suitable for dolphins. These areas are strongly suspected to be part of dolphin movement corridors as they offer optimal conditions for foraging and migration. Multiple linear regression was used to test the strength of the relationship between environmental variables and HSI values. The model yields an R^2 of 0.872, indicating that most of the variation in HSI values is explained by the five examined variables. Chlorophyll a has the greatest influence (β = 0.486), followed by ocean currents and SST. The model evaluation yields a Mean Squared Error (MSE) of 4.74×10^{-5} and a Root Mean Squared Error (RMSE) of 0.0069, indicating minimal prediction error. Cross-validation yielded an average RMSE of 0.0145, suggesting the model is relatively stable, though there are indications of potential overfitting due to limited data. These results support previous findings that cetacean distribution is heavily influenced by oceanographic conditions, particularly chlorophyll-a and ocean currents. Dolphin movement corridors tend to follow areas with high productivity and stable environmental conditions. For future research, it is recommended to use broader spatial and temporal data, as well as field data such as satellite tagging or acoustic surveys. Non-linear statistical models such as Random Forest are also suggested to enhance accuracy. These results can support marine spatial planning policies, marine mammal conservation management, and the protection of dolphin migration corridors in the context of marine ecosystem sustainability.

Data Availability Statement or Supplementary Data

No data was used for the research described in the article.

Ethics Statement

All information communicated in this article does not need ethical approval for research or informed consent because human or animal subjects were not involved.

Acknowledgements

The authors would like to thank Department of Tourism at the Faculty of Tourism, Universitas Udayana for providing research facilities, Tourism Office, and Department of Marine and Fisheries on Buleleng Regency for the data and participant. Thanks to all the anonymous reviewers and editors for taking the time to review this article.

Conflict of Interest Statement

The authors agree that this research was conducted in the absence of any self-benefits, commercial, or financial conflicts and declare absence of conflicting interests with the funders.

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