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Microplastic Deposit Predictions on Sandy Beaches by Geotechnologies and Machine Learning Models

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Abstract: Microplastics (MPs) are polymeric particles, mainly fossil-based, widely found in marine ecosystems, linked to environmental and public health impacts due to their persistence and ability to carry pollutants. In São Paulo's northern coast, geomorphological factors and anthropogenic activities intensify the deposition of these pollutants. Through multivariate techniques, this study aims to investigate the role of the morphometrical parameters as independent variables in quantifying the distribution of MPs on the region's sandy beaches. Using beach face slope ($\tan\beta$) and orientation (Aspect) derived from remote sensing images, calibrated by in situ topographic profiles collected through GNSS positioning, and laboratory analyses, six machine learning models Random Forest, Gradient Boosting, Lasso and Ridge regression, Support Vector Regression, and Partial Least Squares regression were tested and evaluated for performance. The Gradient Boosting model demonstrated the best performance, indicating its superior capacity to capture complex relationships between predictor variables and MPs deposition, followed by Random Forest model. Morphometric analysis revealed, once again, that in this coastal section of São Paulo, beaches with Sloping profiles oriented toward the SSW are more susceptible to MPs accumulation, especially near urban centers. Ultimately, incorporating geomorphological variables into predictive models enhances understanding of MPs deposition, providing a foundation for environmental policies focused on marine pollution mitigation and coastal ecosystem conservation while also contributing to achieve SDG 14.

Keywords: emergent pollution; GNSS position; morphodynamics; multivariate models; orbital remote sensing



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1. Introduction

Considered one of the biggest threats to marine ecosystems [1], microplastics (MPs) are polymeric, mainly fossil-based particles less than 5 mm in diameter [2,3]. They contribute to an estimated 8 million tons of this type of waste reaching the ocean annually, with astonishing quantities of over 4003 million tons produced and discarded until 2022 [4,5]. On sandy beaches, MPs have emerged as key pollutants, diminishing the aesthetic value of these areas and negatively affecting their appeal and recreational quality [6–8]. These pollutants not only reduce the visual and touristic attractiveness of beaches but also reflect broader issues in waste management and the health of marine ecosystems [8–11].

Chemically, MPs can absorb and concentrate organic contaminants, such as polychlorinated biphenyls (PCBs), dichlorodiphenyltrichloroethane (DDT), and polycyclic aromatic hydrocarbons (PAHs), transferring these substances to many marine species and eventually to us through consumption [12,13]. That is why the increasing presence of MPs in coastal regions raises significant concerns due to their durability, ability to carry harmful substances, and potential entry into the food chain (via bioaccumulation and subsequent biomagnification), affecting both marine organisms and human health [14]. Additionally, by altering the composition of coastal habitats, MPs directly impact ecosystems and the species that rely on them [15]; once MPs are degraded by UV radiation or mechanical abrasion, change the porosity of sediments, affecting water retention capacity and potentially releasing greenhouse gases (GHG) like methane and ethylene [16,17].

In Brazil, a review by Escrobot et al. [18] highlighted that between 2018 and 2023, most studies focused on beaches and marine biota, identifying tourism, fishing, and river discharge as the primary sources of MPs. The São Paulo coast, particularly the Santos Estuary, is a critical pollution hotspot due to industrial activities (mainly production and transportation) and inadequate plastic waste management in densely populated urban areas [2,19–21]. Although some studies have addressed this issue, there is still a need for more comprehensive research to understand MPs deposition and accumulation patterns better. These challenges have driven international initiatives such as the elaboration of the United Nations Sustainable Development Goal 14 (SDG 14—Life Below Water) and the G20 Osaka Blue Ocean Vision, aiming to reduce marine pollution by 2025 and eliminate ocean plastic waste by 2050, respectively [22,23]. Furthermore, since 2022 efforts have been made to design a global legally binding agreement among most countries in the UN system [24], but significant advances in this area have not yet been achieved.

Studies by Ferreira et al. [2,20] show that beach slope and orientation directly influence MPs accumulation due to their relationship with hydrodynamic and morphodynamic processes. These variables enhance model accuracy by capturing complex relationships that traditional geomorphological methods, such as grain size distribution studies, often fail to detect. Particularly in regions with high spatial and temporal variability, as observed on the northern coast of São Paulo. In this context, machine learning (ML) algorithms have become a widely adopted approach in environmental studies because they can process large datasets and model complex nonlinear interactions between different variables [25–27]. Moreover, linear methods are sensitive to multicollinearity and struggle to model complex phenomena, whereas ML techniques demonstrate greater precision and robustness when handling large volumes of heterogeneous environmental data [2,26,28,29].

Algorithms such as Artificial Neural Networks (ANN), Random Forest (RF), Support Vector Machines (SVM), and Gradient Boosting (GB) have shown success in capturing these interactions, generating robust predictive models for issues like water quality, land use, and pollutant dispersion [30,31]. In addition to offering greater accuracy, these models can be programmed to automatically select the most relevant variables, enhancing their efficiency [32]. These features are crucial in such research, where data is often collected across different temporal and spatial scales involving multiple interdependent factors [33]. However, the success of these algorithms depends on the quality of the input data and the appropriate model selection, requiring careful evaluation of the applied methodologies [28].

As remote sensing (RS) technologies and in situ surveys evolve alongside computational capacity, ML in environmental studies is expected to expand, delivering increasingly reliable and deeper insights into complex phenomena [2,20,34–36]. This study applies ML algorithms to model and quantify the distribution of MPs/m², using beach face direction and slope as independent variables, both derived and calibrated from orbital RS images and topographic profiles obtained via the Global Navigation Satellite System (GNSS). This

approach innovatively provides an efficient tool for mapping critical areas of MPs pollution, capturing complex deposition patterns, and can be replicated globally. It supports more effective environmental policies and contributes to global plastic waste management in coastal environments, in line with SDG 14 targets, which aims to conserve and promote the sustainable use of oceans, seas, and marine resources [23].

Based on the geomorphological influence on MPs deposition, as highlighted in previous studies, this research hypothesizes that beach face slope and orientation are key predictors of MPs accumulation patterns on São Paulo's northern coast. Specifically, beaches with lower slopes and orientations toward the SSW are expected to show higher MPs deposition due to their reduced sediment transport dynamics and greater exposure to storm waves and anthropogenic inputs.

2. Methodological Approach

To identify locations susceptible to MPs deposition, data collection and analysis can be divided into four stages: (1) acquisition of RS images for the generation of the modified normalized difference water index (MNDWI) [37,38], binary mask (BM), beach face direction ($\text{Aspect}_{\text{sat}}$), and slope parameter ($\tan\beta_{\text{sat}}$) derived from the horizontal distance obtained from satellite images (HD_{sat}) and vertical tidal amplitude (VD_{tide}); (2) fieldwork, involving sediment collection and beach morphometric parameters (orientation, slope, and altitude) via GNSS altimetry; (3) laboratory analysis, including sieving (mesh size 1–5 mm); and (4) supervised machine learning models (ML) (Figure 1).

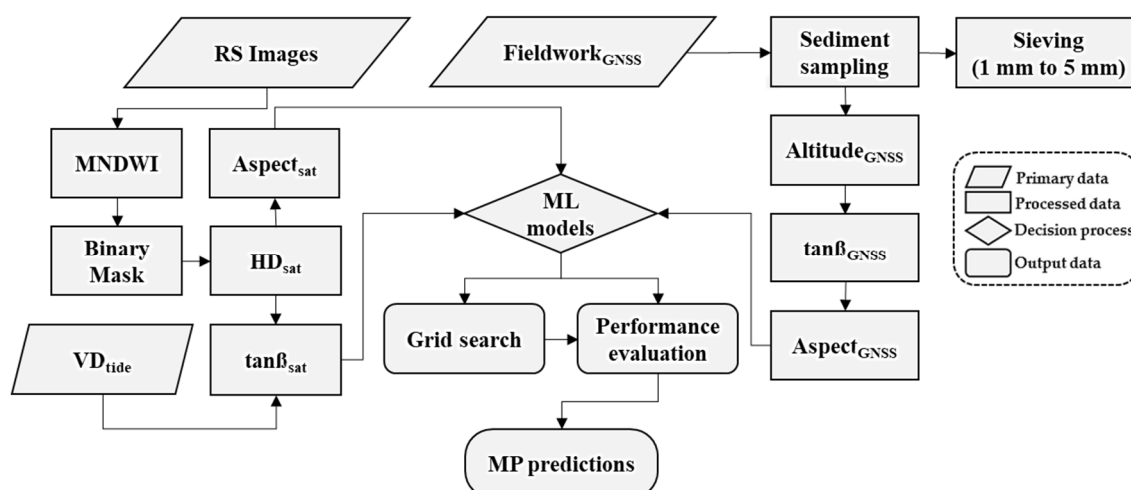


Figure 1. Flowchart of the steps in the methodology used in this research. RS: orbital remote sensing images; MNDWI: modified normalized difference water index; HD_{sat} : horizontal distance derived by satellite; VD_{sat} : vertical distance derived by satellite; $\tan\beta_{\text{sat}}$: slope derived by satellite; GNSS: global navigation satellite system; $\tan\beta_{\text{GNSS}}$: slope derived by GNSS; ML: machine learning models; MP deposits: microplastic deposits.

2.1. Study Area

The coast of São Paulo can be divided into six compartments: (C1) Ilha do Cardoso–Serra do Itatins; (C2) Cananéia–Praia Grande; (C3) Santos–Bertioga; (C4) Bertioga–Toque-Toque; (C5) Toque-Toque–Tabatinga; and (C6) Tabatinga–Picinguaba [39,40]. In the northernmost portion (C4, C5, and C6), the Serra do Mar range gradually approaches the coast, resulting in a narrower coastal plain and smaller drainage basin compared to the southern coast of São Paulo. This section of the coast is geomorphologically more irregular, with smaller pocket-beaches in the form of coves, separated by Precambrian rocky promontories [2,40].

The circulation along the Brazilian continental margin is dominated by the Brazil Current, which flows southward in deeper waters, while the Brazil Coastal Current moves from S-NE over the continental shelf during spring and winter [41–43] (Figure 2). The predominant winds are from the ENE, generating NE-SW coastal currents. However, under the influence of cold fronts, frequent during winter, winds from the SSE produce stronger currents and waves, primarily from the southern quadrant [2,20,35,44–47].

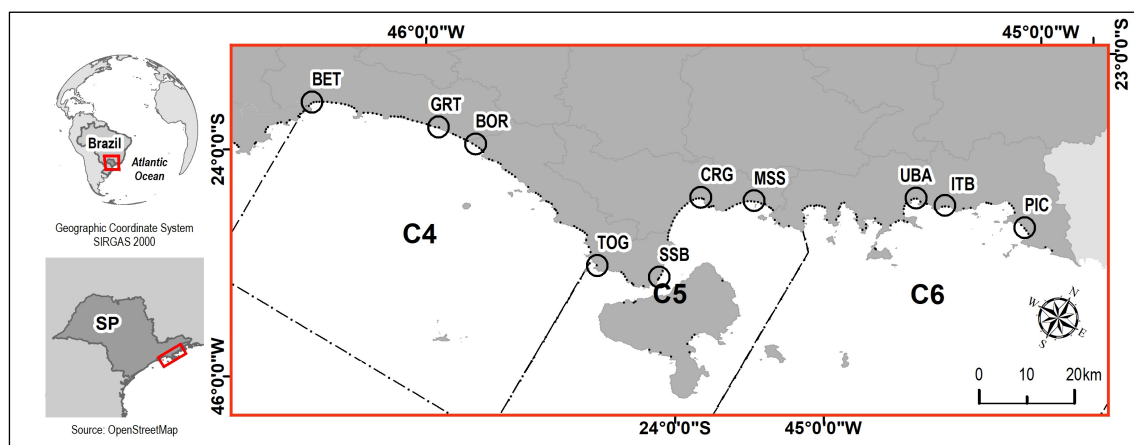


Figure 2. Location of the compartments on the São Paulo coast: (C4) Bertioga–Toque-Toque; (C5) Toque-Toque–Tabatinga; and (C6) Tabatinga–Picinguaba [39,40]. The circles are the sampling locations distributed within the compartments of the northern coast of São Paulo.

2.2. Orbital Remote Sensing Images

The orientation of the beach face ($\text{Aspect}_{\text{sat}}$) was established based on the direction of the transect relative to the geographic north [2,35,48]. Else slope model ($\tan\beta_{\text{sat}}$ in Equation (1)) was calculated using the horizontal (HD_{sat}) and vertical (VD_{sat}) distances between the high and low tide coastlines derived by satellite images, as well as the range of the spring tide [35]. For instance, around the Port of Santos, the average spring tide range is 1.58 m, based on the Mean Sea Level (MSL) from the Imbituba/SC reference point in the Brazilian Geodetic System (BGS) [20,35,49].

$$\tan\beta = \text{atan}(\text{VD}/\text{HD}) \quad (1)$$

HD_{sat} was derived from multispectral remote sensing (RS) data, harmonized between Landsat 8 and Sentinel-2 (HLS) imagery, with a spatial resolution resampled to 30 m for 2019 and 2021. This approach offers up to 7 satellite scenes per month for the same location [35,50]. The median HSL images were captured synchronously during satellite overpasses (~10:30 A.M.) and both high and low spring tide phases, using data from the WXTIDE32 v.4.7 software [51]. As a result, two High Tide (HT) and Low Tide (LT) images were generated, each derived from the median of 26 HT and 27 LT images. Slope information extracted from satellite data provides a quick empirical analysis of the beach morphodynamic stage trend, categorized as steeper ($0.12 < \tan\beta$), intermediate ($0.05 < \tan\beta < 0.12$), and sloping ($\tan\beta < 0.05$) [2,35,52,53].

2.3. Fieldwork Samples

Fieldwork was conducted between April and September 2023, analyzing 10 representative beach profiles (with varying slopes and orientations of beach faces) coinciding with the spring tide period. During this period, cold fronts generated waves of up to 4 m high, approaching the coast from the south and southeast quadrants [47]. These conditions intensified sediment transport, altered beach morphology, and contributed to both the

deposition and remobilization of MPs [2,20,35]. Thus, ten distinct beach profiles were selected to represent this portion of the São Paulo coastline, covering urban and non-urban areas. Sediment samples and beach morphometric data were collected along the profiles, as shown in Table 1 and Figure 2.

Table 1. List of sandy beach profiles per compartment.

Compartment	Profiles ID	Sample Points
C4 Bertioiga–Toque-Toque	BET, GRT, BOR	3
C5 Toque-Toque–Tabatinga	TOG, SSB, CRG, MSS	4
C6 Tabatinga–Picinguaba	UBA, ITB, PIC	3
Total		10

Sampling points along each beach profile were strategically chosen based on environmental factors influencing litter distribution on sandy beaches [3], particularly to water levels (strandline elevations), as noted by [20]. At each beach, sediment samples of approximately 1500 g were collected at a specific higher level (Figure 3): storm surge strandline (P1) [2,20]. These samples were then homogenized and divided into 500 g portions to ensure consistency and enable potential repeat analyses. The surface layer of sediment (~2 cm depth) was collected over a 1 m² area (Figure 3) at each of the 40 sampling points, resulting in the identification of 272 microplastic items in total, ranging from 1 to 5 mm in size [2,3].

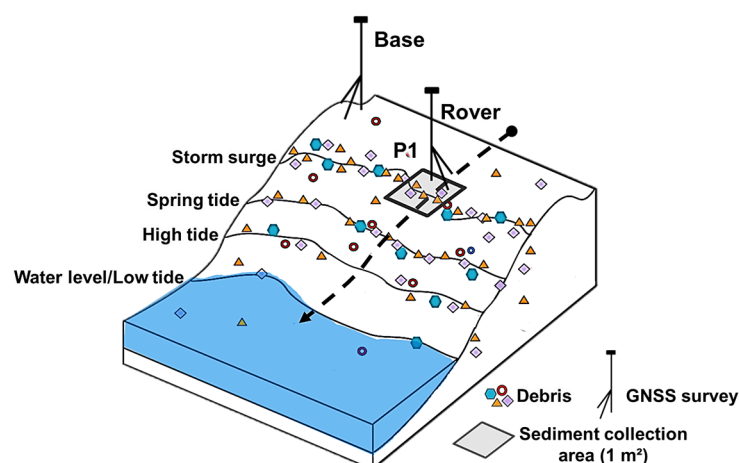


Figure 3. Beach sampling point (P1), modified from [3]. Examples of GNSS base, rover surveys, and area (1 m²) of superficial sediment collection.

The in situ morphometric parameters ($\text{Aspect}_{\text{GNSS}}$, beach slope— $\tan\beta_{\text{GNSS}}$, and $\text{Altitude}_{\text{GNSS}}$) were obtained similarly to what is described in subitem “Section 2.2. Orbital Remote Sensing Images”, where the orientation of the beach face ($\text{Aspect}_{\text{sat}}$) was established based on the direction of the transect relative to geographic north, and $\tan\beta_{\text{GNSS}}$ derived by VD and HD are the vertical and horizontal distances (VD_{GNSS} and HD_{GNSS}) between sampling points P1 and water level/low tide, respectively (Equation (1); Figure 3). The slope can be used as a proxy of the beach morphodynamic stage [52]. Orthometric altitudes (H_i) were determined using the GNSS positioning obtained using the fast static relative GNSS surveying method, referenced to the mean sea level at Imbituba-SC, calculated based on the SIRGAS2000 ellipsoid (h_i) and the MAPGEO2015 geoid height model (N_i) [2,20,54,55] (Equation (2)).

$$H_i = h_i - N_i \quad (2)$$

The calibration between satellite-estimated variables ($\tan\beta_{\text{sat}}$ and $\text{Aspect}_{\text{sat}}$) and in situ GNSS measurements ($\tan\beta_{\text{GNSS}}$ and $\text{Aspect}_{\text{GNSS}}$) uses the Random Forest model [30] and performance indicators such as the coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) to ensure accuracy [35]. The selection of $\tan\beta$ and Aspect is justified by the efficiency of GNSS, which enables the rapid, accurate, and cost-effective acquisition of morphometric parameters in the field. In contrast, alternative variables, such as granulometric analysis, are more time-consuming, require significant investment in laboratory facilities and specialized equipment, and have limited applicability in large-scale studies. Integrating $\tan\beta$ and Aspect with RS techniques provides a practical approach to capturing geomorphological patterns at a synoptic scale [56], making the method more accessible and effective for machine learning-based predictive modeling of MPs deposition.

2.4. Machine Learning Models

ML models were employed to predict MPs distribution and deposition on sandy beaches, using $\tan\beta_{\text{GNSS}}$ and $\text{Aspect}_{\text{GNSS}}$ as key variables. The use of ML models for modeling MPs was developed, for example, in the studies by Su et al. [57]; Lin et al. [58], Chaczko et al. [59]. Data from 10 sampling profiles were expanded to 14 and split into 70% for training and 30% for validation to ensure model reliability. The models used include Random Forest (RF), Gradient Boosting (GB), Lasso and Ridge regression, Support Vector Regression (SVR), and Partial Least Squares Regression (PLS). These models are robust, resistant to overfitting, and perform well with datasets containing multicollinearity and high variability, which are common in environmental contexts. Their combined use ensures strong and accurate predictions, addressing the challenges posed by environmental datasets with diverse and interdependent variables [29–32,60–68].

Grid Search was applied for hyperparameter optimization, and model performance was evaluated using the coefficient of determination (R^2), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). The R^2 measures the proportion of the variance in the dependent variable explained by the model, with values close to 1 indicating high explanatory power. The AIC and BIC assess model quality by penalizing its complexity; lower values indicate a better balance between model fit and simplicity, with BIC being more conservative in penalization. The MAE quantifies the average magnitude of errors in absolute terms and is less sensitive to outliers, while the RMSE penalizes larger deviations due to squaring the errors, making it more sensitive to extreme values [28,61,69]. This comprehensive evaluation framework ensures accuracy and generalizability in environmental datasets [70].

SHapley Additive exPlanations (SHAP) were used to visualize variable contributions to the predictions [71]. After transforming quantitative data into qualitative variables, Correspondence Analysis (CA) was applied to unsupervised models. This technique examines associations between the variables of interest using the chi-square test (X^2 ; p -value < 0.05). Adjusted Standardized Residuals (ASR) verify significant dependency relationships between each variable based on the critical reference value ($+1.96 \leq \text{good ASR}$) of the standard normal curve at the 5% significance level [70,72,73]. Slope and aspect were standardized (Equation (3)), and MP deposition results were transformed into a Likert scale (Table 2). All statistical analyses were conducted in Python (version 5.4.3) using the Anaconda/Spyder platform.

$$\text{Standardization} = \frac{(\text{observed value}) - (\text{minimum value})}{(\text{maximum value}) - (\text{minimum value})} \quad (3)$$

Table 2. Standardized qualitative data based on the total microplastic (MP/m²).

Ranking	Qualitative Data
0.80–1.00	Very High (VH)
0.60–0.79	High (H)
0.40–0.59	Moderate (M)
0.20–0.39	Low (L)
0.00–0.19	Very Low (VL)

3. Results

3.1. Morphometric Parameters and Microplastic Distribution In Situ

In Table 3, the in situ data show $\tan\beta$ values ranging from 0.0166 (BET) to 0.1262 (CRG), with beach face orientations varying from 119° (SSB) to 259° (TOG). Among MPs, fibers constitute the most significant proportion (54%), with the highest concentration recorded in BET (38 fibers). Films account for 29% of MPs, with notable amounts in GRT and BET, showing 31 and 45 plastic films, respectively. Pellets comprise 13% of MPs, with the highest count observed in GRT (19 pellets). Fragments represent only 3% and are more evenly distributed across locations. Foam is nearly absent, with only one occurrence noted in BOR. BET and GRT stand out with the highest values of MP/m², at 88 and 56 MPs per square meter, respectively, suggesting that these areas may serve as hotspots for MPs deposition. In contrast, TOG exhibits the lowest concentration of MPs, with only 2 MPs/m².

Table 3. Distribution (quantities and percentages) of MPs types and morphometric parameters on São Paulo's northern coast beaches.

COD	$\tan\beta$	Aspect	Pellet	Fragment	Fiber	Foam	Film	MP/m ²
PIC	0.0316	191	5	1	7	0	15	28
ITB	0.1242	138	0	0	4	0	4	8
UBA	0.1019	162	0	0	0	0	3	3
MSS	0.1001	171	0	1	9	0	12	22
CRG	0.1262	150	1	0	7	0	8	16
SSB	0.0950	119	1	0	4	0	8	13
TOG	0.1030	259	1	0	0	0	1	2
BOR	0.0227	187	5	3	6	1	21	36
GRT	0.0281	167	19	2	4	0	31	56
BET	0.0166	136	4	1	38	0	45	88
Total			36	8	79	1	148	272
%			13	3	29	0	54	100

3.2. Models Calibration and Validation Metrics

The calibration of morphometric data between $\tan\beta_{\text{GNSS}}$ (measured in situ) and $\tan\beta_{\text{sat}}$ demonstrated the strong predictive capability of the Random Forest (RF) model, with a coefficient of determination (R^2) of 0.6776. This result indicates that the model explained approximately 68% of the variability in slope values estimated from satellite data. The accuracy of the predictions was confirmed by low MAE (0.0071) and RMSE (0.0080) values. For the $\text{Aspect}_{\text{sat}}$ variable, the RF model performed even better, achieving an R^2 of 0.8478, which accounted for 85% of the variability. Furthermore, the model obtained an MAE of 8.9779 and an RMSE of 11.8824, highlighting its effectiveness in identifying and capturing patterns among the morphometric variables in the training dataset.

Table 4 compares six machine learning models (RF, GB, Lasso, Ridge, SVR, and PLS) used to predict MP deposition. The GB model achieved the best performance, with the highest R^2 value (0.9771) and the lowest MAE (1.3343) and RMSE (2.3081), indicating

high predictive accuracy. Additionally, this model exhibited low values in AIC (52.0372) and BIC (47.6642) information criteria, suggesting a favorable balance between model fit and complexity. The other models also performed satisfactorily, with R^2 values ranging from 0.7283 (RF) to 0.7836 (PLS), although with more significant prediction errors than GB. Among these models, PLS distinguished itself by achieving the lowest AIC (33.5268) and BIC (32.4856), suggesting an equilibrium between fit and simplicity. Furthermore, all models were classified as “Good Fit”, indicating that none suffered from significant overfitting or underfitting. Thus, while GB proved superior in accuracy, the PLS model also stands out as a viable alternative, depending on model simplicity requirements.

Table 4. Performance metrics of machine learning models for predicting MP deposition. The best model is highlighted in bold.

Model	R^2	MAE	RMSE	AIC	BIC	Overfit/Underfit
RF	0.7283	5.7158	7.9583	60.8906	57.1423	Good Fit
GB	0.9771	1.3343	2.3081	52.0372	47.6642	Good Fit
Lasso	0.7361	6.6844	7.8436	44.7164	42.6340	Good Fit
Ridge	0.7546	6.6514	7.5641	40.2810	38.6151	Good Fit
SVR	0.7347	5.6361	7.8641	46.7477	44.4571	Good Fit
PLS	0.7836	6.2130	7.1033	33.5268	32.4856	Good Fit

The SHAP plots in Figure 4 show the impact of the variables $\tan\beta$ and Aspect on predicting MP deposition. In the RF plot (Figure 4a), $\tan\beta$ shows the most significant positive impact, with high values significantly contributing to an increase in predictions, while Aspect has a less pronounced impact. For GB (Figure 4b), the effect of $\tan\beta$ is even more prominent, with a precise distribution of values reinforcing its critical role in the model, indicating that high values of this variable considerably increase predictions. In the Lasso model (Figure 4c), $\tan\beta$ remains the most influential variable, although the overall impact is more distributed across low and medium values, suggesting a more linear relationship. The Ridge plot (Figure 4d) is similar to Lasso’s. However, it shows a smoother impact variation, indicating that both variables contribute in a balanced way, though $\tan\beta$ still plays a more dominant role. In the SVR model (Figure 4e), $\tan\beta$ again stands out, with high values associated with a more pronounced positive impact. At the same time, Aspect has a less significant and more scattered effect, suggesting a less consistent contribution to predictions. In the PLS model (Figure 4f), the impact of $\tan\beta$ is visibly more considerable and well-distributed across values, reinforcing its importance in the model’s structure. At the same time, Aspect maintains a less significant yet relevant effect. These results indicate that $\tan\beta$ is the most important variable in modeling MPs/m² deposition on sandy beaches, regardless of the model used. At the same time, the aspect has a smaller influence, except in specific situations, such as during storm surges caused by cold fronts [2,20,35].

3.3. Morphometric Parameters and Microplastic Distribution Models

Table 5 and Figure 5 provides the statistical summary of beach slope ($\tan\beta$), beach face direction (Aspect), and MP deposition (MP/m²) for compartments C4, C5, and C6. For $\tan\beta$, compartment C5 had the highest mean value of 0.0719 with a standard deviation (SD) of 0.0235, indicating more significant variability than compartments C4 and C6. Compartment C4 had the lowest mean slope (0.0578) and a relatively low SD (0.0129), suggesting a more uniform slope in this area. Compartment C6 presented an intermediate mean slope of 0.0604 with a low SD (0.0107), indicating less variability than C5 but slightly more than C4. The Aspect variable shows that compartment C4 had an average direction of 147° with an SD of 16°. Conversely, compartment C5 had a lower average direction (129°) with a slightly higher SD (18°), while C6 showed the lowest average direction (127°) with the highest

variability ($SD = 23^\circ$). For MP deposition, compartment C4 recorded the highest total values (1709 MP/m^2) and a mean of 24 MP/m^2 , with an SD of 10 MP/m^2 . Compartments C5 and C6 had similar mean values, with 24 and 22 MP/m^2 , respectively, but lower total deposition values (1434 MP/m^2 for C5 and 1349 MP/m^2 for C6).

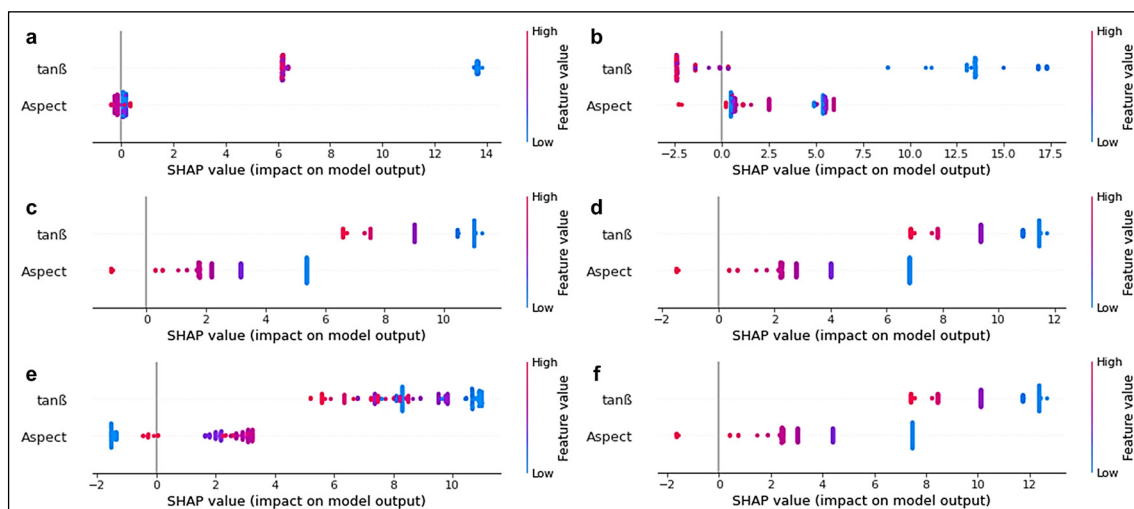


Figure 4. SHAP analysis of variable contributions for predicting microplastic deposition using multiple machine learning models: (a) RF—Random Forest; (b) GB—Gradient Boosting; (c,d) Lasso and Ridge Regression; (e) SVR—Support Vector Regression; (f) PLS—Partial Least Squares. The intensity of each variable varies according to the color (blue and red, indicating low and high values, respectively).

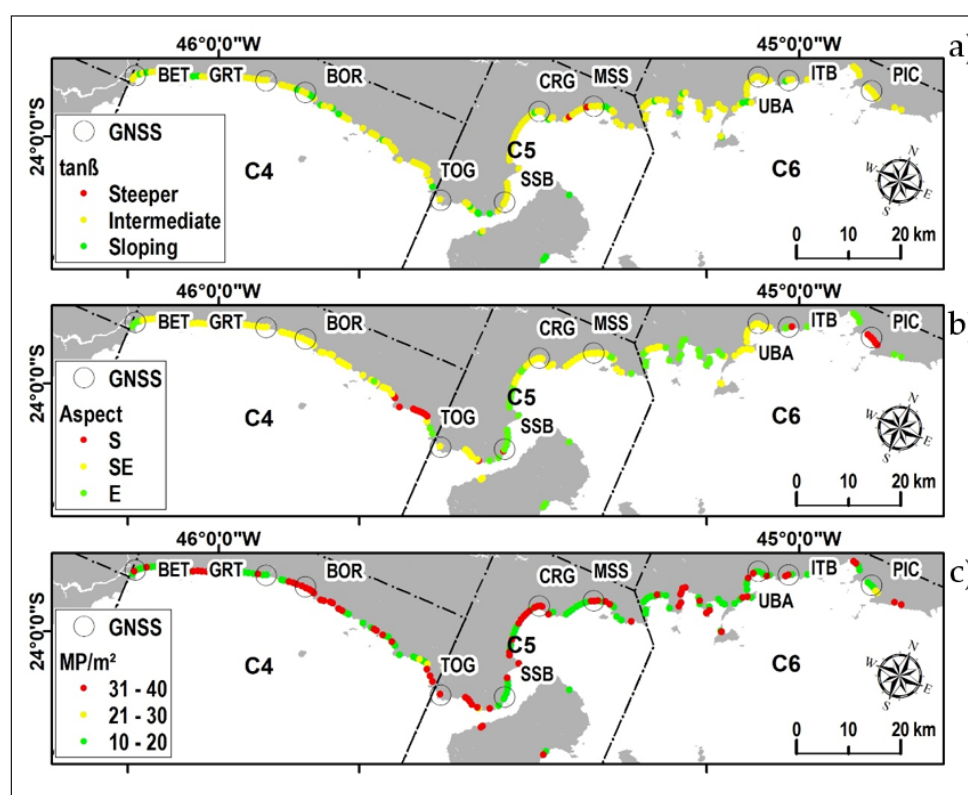
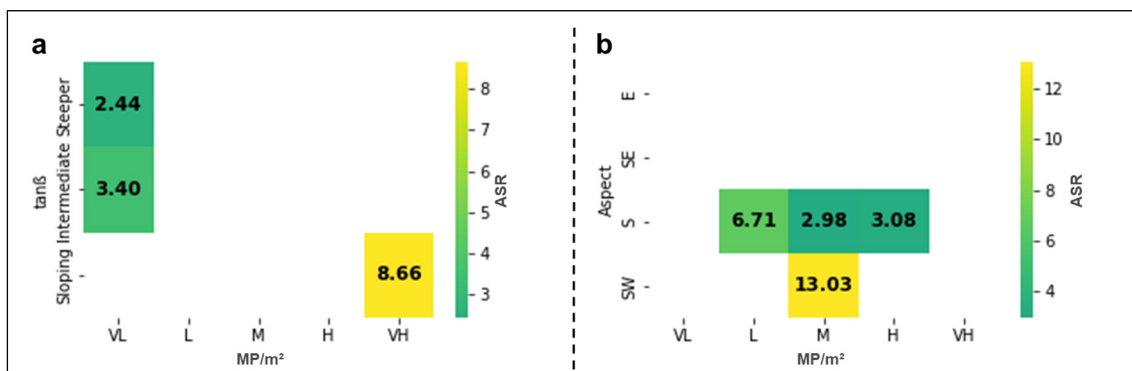


Figure 5. Transect observations of GNSS transects; (a) beach slope ($\tan\beta$); (b) beach face direction (Aspect); and (c) microplastic deposition GB model per square meter (MP/m^2).

Table 5. Statistical summary of the models: slope ($\tan\beta$) and direction of the beach face (Aspect), as well as the microplastic deposition (MP/m^2).

Var.	Compartment	N	Min	Max	Sum	Mean	SD
$\tan\beta$	C4	71	0.0309	0.0947	-	0.0578	0.0129
	C5	61	0.0309	0.1396	-	0.0719	0.0235
	C6	62	0.0309	0.0951	-	0.0604	0.0107
Aspect	C4	71	108	184	-	147	16
	C5	61	108	184	-	129	18
	C6	62	108	184	-	127	23
MP/m^2	C4	71	13	37	1709	24	10
	C5	61	13	37	1434	24	10
	C6	62	13	37	1349	22	10

The results of the CA between MP/m^2 and $\tan\beta$ indicate a statistically significant relationship, with an X^2 value of 183.4008 and an extremely small p -value (1.9873×10^{-35}), demonstrating a strong dependency between beach face slope and MPs deposition. In the first figure (Figure 6a), the ASR values associated with the Steeper and Intermediate categories are highlighted with values of 2.44 and 3.40, respectively, for VL levels of MPs deposition. The beach faces categorized as Sloping show a higher value (8.66) for the VH level of deposition, indicating that these beaches have a significant association with MP deposits in this coastal region. For the variables MP/m^2 and Aspect, the X^2 value was even more pronounced (275.1023), with a p -value of 7.7873×10^{-52} , confirming a strong statistical dependency between beach orientation and MPs deposition. In Figure 6b, the perceptual map for the Aspect variable examines the ASR for four main beach face orientations: E, SE, S, and SW. Beaches with faces oriented toward the S direction have ASR values of 6.71, 2.98, and 3.08 for L, M, and H levels of MP/m^2 deposition, respectively. The SW categories show a ASR value of 13.03 associated with the M level of MP/m^2 deposition.

**Figure 6.** Perceptual maps showing the Adjusted Standardized Residuals (ASR) values between the microplastic deposition model (MP/m^2), (a) beach slope ($\tan\beta$) and (b) orientation of the beach face (Aspect). The colored cells indicate significant relationships between variables ($+1.96 \leq \text{good ASR}$). VL (very low), L (low), M (medium), H (high), and VH (very high) represent the different levels of MP/m^2 deposition by CA analysis.

4. Discussion

The choice of ML models used in this study (GB, RF, Lasso, Ridge, SVR, and PLS) is justified based on their documented performance in similar environmental studies and their capacity to address the specific characteristics of the dataset. The GB model was selected for its ability to capture complex and nonlinear relationships between predictor variables and the target variable, as demonstrated in environmental predictions involving

high data variability [32,62,63]. RF, known for its robustness and resistance to overfitting, performs well with multicollinear and high-variability datasets, which are common in these same contexts [26,30,74].

The Lasso and Ridge Regression models were included as baseline techniques due to their computational efficiency and effectiveness in handling multicollinearity or reducing irrelevant predictors [28,64,65]. While SVR was chosen for its ability to model nonlinear patterns in complex and heterogeneous datasets, which has proven useful in coastal and environmental studies [31,66,67]. Last, PLS method was applied for its suitability in managing multicollinear variables and small sample sizes while efficiently reducing dimensionality without compromising predictive power [29,68].

The SHAP plots play a crucial role in assessing the relative influence of the independent morphometric variables ($\tan\beta$ and Aspect) on predicting MPs deposition. These plots enabled the identification of each variable's individual contribution to the performance of ML models, assisting in both model selection and interpretation [71]. In this study, SHAP results showed that beach slope exerts a significant influence on MPs accumulation, emerging as the most impactful variable, while beach face orientation exhibited a smaller but still relevant effect during storm surge events [2,20]. Furthermore, the plots highlighted the GB model's ability to capture complex patterns by integrating environmental variables [75–77], providing a holistic understanding of the processes governing MPs distribution (Friedman, 2001 [32]; Ke et al., 2017 [63]).

The results indicate that the GB model achieved the best precision and generalization capability for predicting MPs/m² deposition. This performance suggests that the GB model captured the relationship between predictor variables and the dependent target variable (MPs/m² deposition) more efficiently than other tested models, aligning with previous studies pointing the potential of GB in environmental contexts due to its robustness with noisy data and fine-tuning capability. In this regard, GB demonstrated good fit and lower complexity, reflecting its ability to balance fit and simplicity [28,32,62,63], which is essential given the geomorphological characteristics of São Paulo's northern coast's (irregular, with pocket beaches of various sizes and orientations) [2,40,78].

In turn, although the RF model also demonstrated satisfactory performance, it was inferior to GB, consistent with the literature describing RF as a robust model but with precision limitations when compared to more complex algorithms, especially in highly variable data [30]. Linear models, such as Lasso and Ridge, also showed intermediate performance, demonstrating a lower capacity to capture the non-linearity of variables, a characteristic of MPs deposition conditions [64,65]. The SVR model also presented intermediate performance, indicating a good fit without overfitting. This aligns with studies showing SVR's ability to capture non-linear patterns, especially in complex and heterogeneous data [31,66,67]. In contrast, PLS stood out as a viable alternative when model simplicity is preferable (e.g., in the case of more homogeneous coastlines, considering the beach slope and orientation), confirming its traditional use in scenarios that seek to explain variance in multivariate datasets effectively reducing dimensionality without compromising predictive power [29].

Emphasizing again, the RF, although effective for datasets with high variability, often fails to detect subtle interactions [26,30]. Similarly, Ridge Regression does not adequately represent environmental phenomena characterized by nonlinearity [28,65]. While, GB outperforms RF and Ridge due to its sequential structure, which iteratively adjusts predictions to correct residual errors. This flexibility allows GB to identify intricate patterns that simpler models often fail to capture [28,32,62]. Nevertheless, RF remains valuable in scenarios where interpretability is less critical, and computational efficiency is a priority, as it trains faster and resists overfitting in noisy data [30]. Ridge Regression remains

applicable when linear relationships dominate the dataset, offering a computationally efficient and straightforward solution [65]. Combining RF and Ridge Regression with GB can create a more comprehensive analytical framework. While GB excels in accuracy and generalization, RF and Ridge can serve as complementary tools for baseline analysis or cross-validation [33,79].

In this coastal area, MPs deposition on sandy beaches was found to be strongly influenced by beach slope ($\tan\beta$) and beach face direction (Aspect), corroborating other studies that emphasize the importance of geomorphological parameters in MPs retention [2,20,80–83]. Beach faces oriented toward directions with greater wind and current exposure exhibit higher debris deposition, including MPs [4,84,85]. This finding is consistent with ASR values and with Ferreira et al. [20,35], who observed on the São Paulo coast that beaches facing SSW are particularly susceptible to MP deposition. These observations suggest that adjusting predictive models based on beach slope and orientation could enhance understanding of plastic debris accumulation in coastal zones [2,79,86–88].

In this context, beaches facing SSW are more predisposed to coastal stability and/or accretion processes that make them susceptible to MPs accumulation. This accumulation occurs due to the approximate 90° angle between storm surge waves from the south and the coastline, which reduces sediment transport rates alongshore, thereby promoting the deposition of sediments and anthropogenic debris, including MPs [2,16,20,21,35,89,90]. The SW-NE orientation of this portion of São Paulo's coast also makes SE-facing beaches more vulnerable to erosion, as storm waves strike at an angle of approximately 45° , maximizing sediment transport during the austral autumn and winter [2,20,35,45,89,91]. The seasonal incidence of storms promotes sediment resuspension and increases MPs mobility, especially in areas near estuaries, such as Bertioga (BET), which serve as critical entry points for MPs into the ocean due to urbanization and human activities [92–96].

In compartment C5, near São Sebastião (SSB), high population density and industrial and port activity promote MPs dispersion in the area [21]. Ivar do Sul et al. [19] MPs concentrations correlate with industrial and port activities, particularly in Southeastern Brazil. Although compartments C4, C5, and C6 are not as densely populated as southern portions of the São Paulo coast, their beaches receive many visitors on weekends, holidays, and vacations. As a result, these beaches do not undergo frequent mechanical cleaning, and waste from insulating containers (i.e., Styrofoam and other materials) for storing beverages and/or food left by tourists and street/beach vendors tends to accumulate mainly in the higher beach portions [2,20,97–100].

5. Conclusions

The study highlights the importance of incorporating variables like beach slope ($\tan\beta$) and beach face orientation (Aspect) into predictive multivariate techniques and the central role of ML in better understanding the patterns of MPs pollution on sandy beaches and generating information. GB model emerged as the most efficient in predicting MPs deposition, with the highest coefficient of determination ($R^2 = 0.9771$) and the lowest error values (MAE and RMSE). The SHAP effectively captured complex relationships between predictor and dependent variables, making it suitable for environmental studies involving high data variability. While, the PLS model performed well in simplicity, with low AIC and BIC values, making it a viable option in contexts prioritizing lower complexity.

It is essential to conduct a literature review on the generalization capacity of models under different environmental conditions to deepen the understanding of MPs predictions. The geometric shape, density, and size of MPs were not directly analyzed in this study. Information such as polymer density can be investigated using additional methods, such as Raman spectroscopy. However, the study has other limitations, including the absence of

additional metoceanographic variables, such as waves and winds, which may influence MPs deposition. It is also suggested to expand the study area to cover the entire São Paulo coast, increase in situ sampling points, and explore more advanced ML models, such as deep learning methods.

Expanding the use of these models in other regions can increase understanding of the dynamics of this pollutant. GB has demonstrated a great capacity to capture complex patterns, making it suitable for analyzing large data sets in different environments, demonstrating its potential for broader applications along the coast of São Paulo. Once again, morphometric analysis revealed that beaches with Sloping profiles and facing SSW are more prone to MPs accumulation due to the interaction between storm waves from the south and the south-facing coastline. This angle of incidence reduces sediment transport and promotes debris deposition, including MPs, besides other anthropogenic factors, such as industrial and port activities (near São Sebastião), that also contribute to MPs dispersion.

These results help to create more effective environmental policies that consider local characteristics to mitigate marine pollution, allowing proper management and conservation of coastal ecosystems. It also contributes to achieving SDG 14, precisely 14.1—to prevent and significantly reduce marine pollution, particularly from land-based activities, including marine debris (Indicator 14.1.1—density of plastic debris) by 2025—and Goal 14.a, which seeks to enhance scientific knowledge, develop research capacities, and transfer technology to improve ocean health [23].

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