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What, where, and when: Spatial-temporal distribution of macro-litter on the seafloor of the western and central Mediterranean sea☆

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ABSTRACT

The progressive increase of marine macro-litter on the bottom of the Mediterranean Sea is an urgent problem that needs accurate information and guidance to identify those areas most at risk of accumulation. In the absence of dedicated monitoring programs, an important source of opportunistic data is fishery-independent monitoring campaigns of demersal resources. These data have long been used but not yet extensively. In this paper, MEDiterranean International Trawl Survey (MEDITS) data was supplemented with 18 layers of information related to major environmental (e.g. depth, sea water and wind velocity, sea waves) and anthropogenic (e.g. river inputs, shipping lanes, urban areas and ports, fishing effort) forcings that influence seafloor macro-litter distribution. The Random Forest (RF), a machine learning approach, was applied to: i) model the distribution of several litter categories at a high spatial resolution (i.e. 1 km^2); ii) identify major accumulation hot spots and their temporal trends. Results indicate that RF is a very effective approach to model the distribution of marine macro-litter and provides a consistent picture of the heterogeneous distribution of different macro-litter categories. The most critical situation in the study area was observed in the north-eastern part of the western basin. In addition, the combined analysis of weight and density data identified a tendency for lighter items to accumulate in areas (such as the northern part of the Tyrrhenian Sea) with more stagnant currents. This approach, based on georeferenced information widely available in public databases, seems a natural candidate to be applied in other basins as a support and complement tool to field monitoring activities and strategies for protection and remediation of the most impacted areas.

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1. Introduction

The mass of human-made materials on our planet has recently overweight the total living biomass (Elhacham et al., 2020) and one of the consequences is that human-generated waste is consistently being dispersed in the environment, with oceans ahead (Jambeck et al., 2015). Global waste doubled every ~20 years over the last century and it is forecasted to reach 53 million tons year^{-1} in 2030, for plastic alone (Borrelle et al., 2020), which numerically accounts for ca. 60% of the whole amount of litter dispersed in the marine environment (https://litterbase.awi.de/litter_graph; Bergmann et al., 2017). Marine macro-litter accumulates on the seafloor, which is regarded as the ultimate sink for macro-litter dispersed in the environment (Woodall et al., 2014).

According to recent scientific literature, it is widely recognized that litter-free seas represent a *utopia*; however, more realistic targets (set to tackle plastic contamination but still applicable to all macro-litter) suggest the use of multiple mitigation measures, that should act synergically to meet ambitious goals (Borrelle et al., 2020; Lau et al., 2020). One of these measures is the removal of the fraction of macro-litter already accumulated in the ocean, which should be coupled with a cap on production of ecologically impacting materials like plastic (Bergmann et al., 2022; Rochman, 2016; Rochman et al., 2013). Consequently, understanding distribution patterns and monitoring of accumulation hotspots becomes crucial steps to drive future remedial actions.

A proper assessment of the distribution and effects of macro-litter on the seafloor is primarily challenged by reduced data availability and comparability, especially in deep-sea environments. However, data is accumulating and studies dealing with spatio-temporal variability of macro-litter on the seabed are becoming available (Buhl-Mortensen et al., 2022; Canals et al., 2021; Galgani et al., 2021; Parga Martínez et al., 2020), thus providing useful information to identify distribution and accumulation patterns and hotspots (Cau et al., 2022; Garofalo et al., 2020; Tubau et al., 2015). This is particularly relevant within the Mediterranean basin, which is globally recognized as a litter hotspot due to its features of semi-enclosed and highly anthropized basin (Canals et al., 2021; Galgani et al., 2000; Pierdomenico et al., 2019); however, only few studies developed models to identify and predict possible locations where macro-litter might accumulate (e.g., Cau et al., 2022; Franceschini et al., 2019; Spedicato et al., 2019).

From a technical point of view, detection and characterization of macro-litter on the seafloor relies mainly on different approaches, including litter collection with bottom trawlers (Melli et al., 2016; Mifsud et al., 2013; Strafella et al., 2015) and optical and acoustic mapping of the seafloor (Angiolillo et al., 2015; Cau et al., 2017; Madricardo et al., 2020). Due to their high costs, these latter approaches can often be performed over a limited spatial and temporal scale. Considering the few and scattered data available and that the distribution of waste is essentially determined by its release and passive transport (unlike nekton organisms that move autonomously), machine learning techniques can be a useful tool to profitably use the already available, yet limited, information collected in the field to possibly infer about macro-litter distribution over large areas for which direct observations are not available.

In this study, we used a machine learning method (i.e., Random Forest; RF - Breiman, 2001), to model the temporal and spatial distribution of seafloor macro-litter in the western and central Mediterranean macro-region. A series of spatial layers, corresponding to the main sources and/or drivers of waste contamination at sea, were gathered from various sources, including the Copernicus Marine Service and the MEDiterranean International Trawl Surveys (MEDITS), across six General Fisheries Commission for the Mediterranean (GFCM) Geographical Sub-Areas (GSA). These layers were used to train a set of RF models with very high spatial resolution (i.e. 1 km square grid), devised to predict the abundance of each typology of macro-litter. Our results confirmed the power of machine learning techniques in capturing the relationships between predictors and the spatio-temporal distribution of different types of marine litter. Furthermore, it is possible to distinguish some important differences within the vast study area examined and to highlight the importance of some anthropogenic forcings.

2. Materials and methods

2.1. Study area

The study area (Fig. 1) belongs to the western and central Mediterranean Sea, covering a total surface of 125,000 km^2 and incorporates FAO GSA 7 (southern France), 8 (Corsica), 9 (Ligurian and northern Tyrrhenian), 10 (south and central Tyrrhenian), 11 (Sardinian Seas, considering GSA 11.1 and GSA 11.2 as a single unit) and 16 (south Sicily). This area encompasses different environments of the western Mediterranean basin such as the Sardinia channel, the strait of Sicily, the Gulf of Lyon, and the Tyrrhenian Sea. Whose geological morphologies and local circulation features cumulatively affect water masses circulation within the basin (Millot, 1999), thus representing a relevant and interesting case study to investigate seafloor macro-litter distribution and accumulation patterns. The detailed description of each GSA is available in a dedicated section of Supplementary materials.

2.2. Data collection

Data used in the present study were collected in the framework of the MEDITS survey conducted from 2013 to 2019, in the above-mentioned GSAs. The MEDITS is the main bottom trawling survey conducted in the whole Mediterranean Sea, aiming at collecting data on demersal resources and, since 2013, it has also become a valuable source of information about seafloor macro-litter (MEDITS working group, 2012).

The data series used in this study was built taking advantage of 495 hauls performed yearly across the six GSAs considered, for a total of 3465 hauls covering 7 years (Supplementary Table 1). In the MEDITS protocol, hauls are located according to a depth-stratified random design with the following *strata*: A [0–50m); B [50–100m); C [100–200m); D [200–500m) and E [500–800m). For the implementation of the RF model, MEDITS hauls were assigned to cells of a 1 × 1 Km square grid. The cells of the grid were then considered as statistical units of the applied model. Given that, in five of the six GSAs considered and throughout the temporal period inspected, dozens of hauls per year were associated with cells belonging to the [800–1000m) *stratum* (the depth of each cell was computed as the average of the NOAA ETOPO1 records - see Supplementary Materials), this additional *stratum* was considered in the model.

Onboard operations include the separation of seafloor macro-litter from the catch and its classification according to nine major categories (i.e., L1: Plastic; L2: Rubber; L3: Metal; L4: Glass/Concrete; L5: Cloth; L6: Processed wood; L7: Paper and cardboard; L8: Other; L9: Unspecified) and relative sub-categories, according to the MEDITS handbook (MEDITS working group, 2012). Within each category, items were counted, and wet weight was measured; in the case of containers, water and sediment contents were washed/removed prior to weighting. The total weight and the number of items collected per each sub-category were standardized according to the swept area, expressed as the number of items and weight km^{-2}. For the purposes of this paper, five out of the nine categories of macro-litter were used in the analysis (L1, L2, L3, L4, L5). Plastic litter (L1) was further divided in two sub-categories, distinguishing objects that are 'related' to fishing activities (i.e., fishing nets, lines, ropes, etc.) and 'non-related' (i.e., plastic bags, bottles, wraps, etc.; Table 1).

Several environmental and anthropogenic variables were considered and used as predictors in the models (Table 2). These variables were considered as reliable proxies for the main sources and drivers of the distribution of marine macro-litter. Sea bottom depth was estimated, for each cell of the grid, querying the NOAA ETOPO1 Global Relief Model

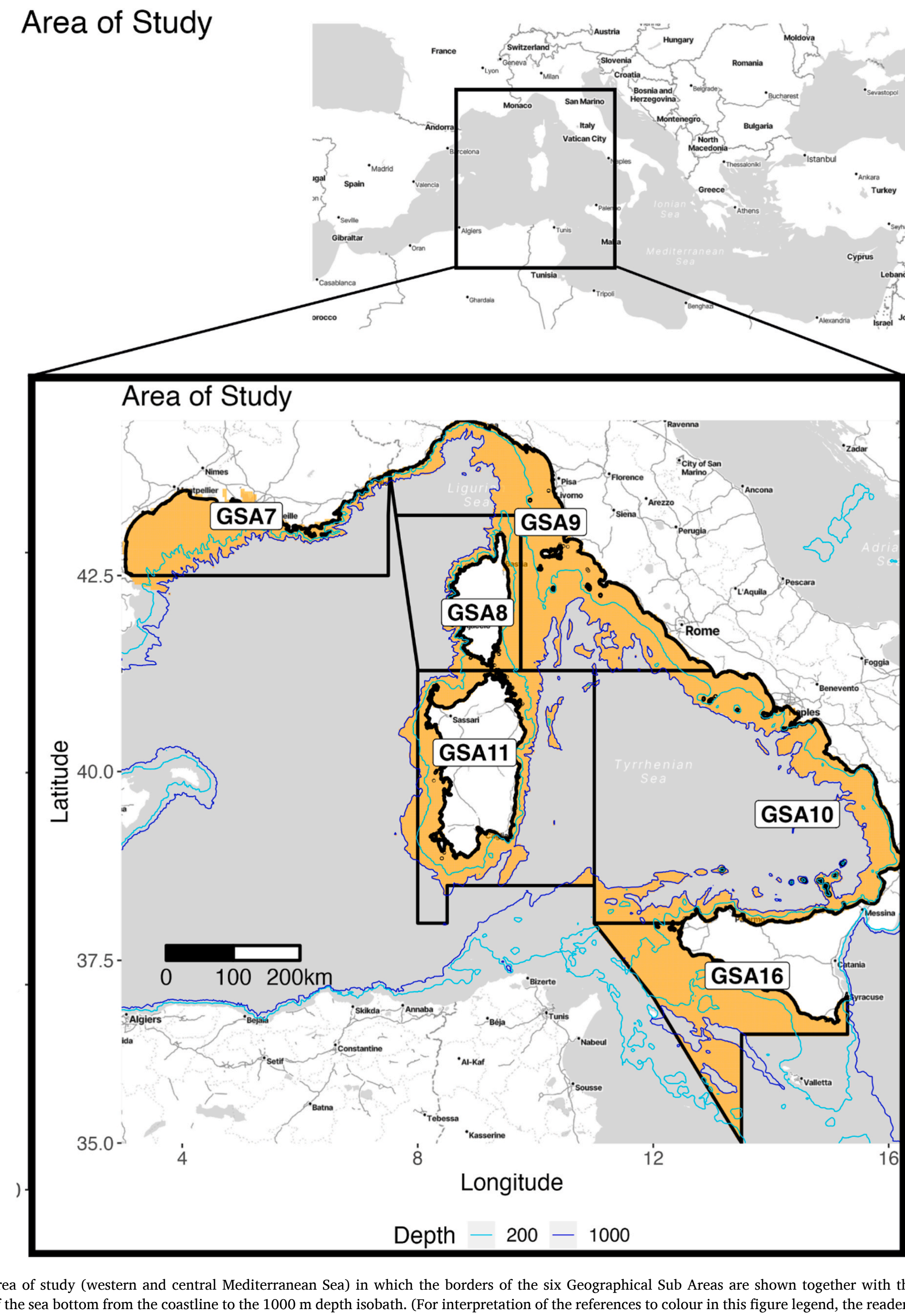

Fig. 1. Area of study (western and central Mediterranean Sea) in which the borders of the six Geographical Sub Areas are shown together with the portion (in orange) of the sea bottom from the coastline to the 1000 m depth isobath. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 1
Classification scheme of marine litter categories and sub-categories applied in the present study.

Category	Sub-category	Type	Source	Groups
L1		Plastics	Mixed	
	L1a	Bags	Non Fishing-related	L1-Non Fishing-related
	L1b	Bottles	Non Fishing-related	L1-Non Fishing-related
	L1c	Food wrappers	Non Fishing-related	L1-Non Fishing-related
	L1d	Sheets	Non Fishing-related	L1-Non Fishing-related
	L1e	Hard objects	Non Fishing-related	L1-Non Fishing-related
	L1f	Fishing nets	Fishing-related	L1-Fishing-related
	L1g	Fishing lines	Fishing-related	L1-Fishing-related
	L1h	Other fishing-related	Fishing-related	L1-Fishing-related
	L1i	Synthetic ropes	Fishing-related	L1-Fishing-related
	L1j	Others	Others	
L2		Rubber	Others	L2
L3		Metal	Others	L3
L4		Glass/Ceramic/Concrete	Others	L4
L5		Cloth(textile)/Natural fibres	Others	L5

using the R package "marmap" (Pante and Simon-Bouhet, 2013). Distance from the coastline was computed for each cell of the grid, using the 'dist2Line' function of the R package "geosphere" (Hijmans et al., 2021). Rivers' mouth positions and catchment area (in km^2) were obtained from the European Environmental Agency https://www.eea.europa.eu/data-and-maps/data/european-river-catchments-1) and used to compute, for each cell of the grid, an index of the Impact of River Basins defined as the average of catchment areas weighted by the distance of the cell centre from the river mouths. The positions of the main shipping lanes were downloaded from (Halpern et al., 2008) (https://knb.ecoinformatics.org/view/doi:10.5063/F1S180FS) and used to compute, for each cell of the grid, the Mean Distance from Shipping Lanes. The positions and the surface (in km^2) of the Urban areas were downloaded from the Efrain Maps Website (https://www.efrainmaps.es/english-version/free-downloads/europe/) and used to compute an index of the Impact of Urban Areas defined as the average of urban areas weighted by the inverse of their distance from the cell centre. Positions and size class of the port areas were downloaded from the National Geospatial-Intelligence Agency website (https://msi.nga.mil/Publications/WPI) and used to compute an index of the Impact of Port Areas, defined as the average of port classes weighted by the inverse of their distance from the cell centre. The Northward and Eastward Sea water velocities in m^{-s}, the Northward and Eastward Sea surface wave stokes drift in m^{-s} the Mean Sea Level in m, the Northward and Eastward wind speed in m^{-s} and the Mean Sea Wave Height in m were downloaded from the Copernicus Marine Service (https://marine.copernicus.eu/) for the period of interest and average to obtain single values for the cells of the grid. Rugosity (RUG) (i.e. the roughness of the seafloor), an indicator of the occurrence of hard-bottom habitat, was derived from the bathymetry layer using the Benthic Terrain Modeller tool in ArcGIS 10.1. RUG is quantified as the likelihood of hard-bottom habitat presence and ranges from zero to one. Finally, three different variables were generated from the analysis of Vessel Monitoring System (VMS) data, according to the procedures described in (Russo et al., 2014) and Russo et al. (2016). The spatial representation of considered environmental and anthropogenic variables is reported in Supplementary Figs. S1 and S2a-b.

Table 2
Environmental and anthropogenic factors collected and processed in order to train the random forest model for the distribution of seafloor litter in the western Mediterranean Sea.

Environmental variable	Reference	Anthropogenic variable	Reference
Sea bottom depth	NOAA ETOPO1 Global Relief Model using the R package 'marmap' (Pante and Simon-Bouhet, 2013)	Impact of River Basins	(https://www.eea.europa.eu/data-and-maps/data/european-river-catchments-1)
Distance from the coast	'dist2Line' function of the R package geosphere (Hijmans et al., 2021)	Mean Distance from Shipping Lanes	(https://knb.ecoinformatics.org/view/doi:10.5063/F1S180FS)
Northward sea water velocity	(https://marine.copernicus.eu/)	Impact of Urban Areas	(https://www.efrainmaps.es/english-version/free-downloads/europe/)
Eastward sea water velocity	(https://marine.copernicus.eu/)	Impact of Port Areas	(https://msi.nga.mil/Publications/WPI)
Northward Sea surface wave stokes drift	(https://marine.copernicus.eu/)	Mean Fishing effort (bottom otter trawling)	Russo et al. (2014) and Russo et al. (2016)
Eastward Sea surface wave stokes drift;	(https://marine.copernicus.eu/)	Average effort in neighbouring cells	Russo et al. (2014) and Russo et al. (2016)
Mean Sea Level	(https://marine.copernicus.eu/)	Delta effort inside/outside	Russo et al. (2014) and Russo et al. (2016)
Eastward wind velocity	(https://marine.copernicus.eu/)		
Northward wind velocity	(https://marine.copernicus.eu/)		
Mean Sea Wave Height	(https://marine.copernicus.eu/)		
Rugosity	Benthic Terrain Modeller tool in ArcGIS 10.1 (Wright, 2011)		

2.3. Random Forest

Classification (or Decision) Trees (CTs) are a non-parametric supervised learning method based on a model that predicts the value of a target variable (which can be qualitative or quantitative) by inferring simple decision rules from the input data. When an ensemble of Classification Trees is combined (into a "Forest") and their predictions are averaged (if the target variable is quantitative) or used to establish the most voted class (if the target variable is qualitative), we are dealing with a RF (Breiman, 2001). The procedure begins by choosing a bootstrap sample from a subset of the training data for each tree in the forest (Breiman, 2001). Out-Of-Bag (OOB) records are those that were not included in the current bootstrap sample of the data. Each tree is then automatically built to its maximum depth and left unpruned for each bootstrap sample. Only a randomly chosen (hence the term "Random") subset of q predictive variables, where p is the total number of predictors, are accessible for binary partitioning at each split in the tree (Breiman, 2001). Usually, the number of Classification Trees in the forest is represented by the number *ntree*, which is how many times this method is repeated. The final step is to average the results of all the trees for regression applications (Breiman, 2001; Cutler et al., 2007; Gislason et al., 2006; Liaw and Wiener, 2002). The performance of RF can be modified using a number of its parameters. The primary variables that significantly impacted the accuracy of this method were the total number of trees in the forest (*ntree*), the number of randomly chosen predictors available at each split for the binary partitioning, known as *mtry*, as well as the minimum number of records contained in each leaf to stop the splitting procedure (*ndsize*) (Cutler et al., 2012; Scornet, 2017). All 3 of these parameters are tuned by means of an iterative procedure in which a wide range of values is explored for each of them. The final values obtained from the tuning procedure and used in this study were: *ntree* = 1000, *mtry* = 7, *ndsize* = 5.

In this study, the RF approach provided in the R package "RandomForest" (Liaw and Wiener, 2002) was applied to predict the spatial distribution of each of the categories and sub-categories, and groups listed in Table 1. All variables described above as well as the MEDITS data about litter density and weight, per each category/sub-category, were standardized over the set of 11,341 cells covering the portion of GSAs from the coastline to the 1000 m isobath. The number of cells in which at least one MEDITS sampling occurred in the period considered was 1048 (around 10% of the total domain of 11,341 cells). This set of 1048 was used to train and test the RF models, as described in the next section.

The applied procedure can be summarized as follows:

- For each of these litter typologies, the set of 1048 cells containing the MEDITS records was split into two subsets: the *training set* and the *test set*, including 70 % and 30%, respectively, of the total cells. This splitting procedure, repeated 100 times, was pseudo-random as we forced the sampling to guarantee that the 70/30% proportion occurred for each of the bathymetric *strata* of the MEDITS (see Section 2.2).
- 10 RFs models were trained and tested for each of these pairs of training and test sets. Namely, the adjusted R^2 and the root-Mean-Square Error (rMSE) indexes were used to compare the observed *vs* predicted values of litter categories and sub-categories in the number of objects and weights by cell. For each RF model, the relative importance of each predictor was internally assessed by the *randomforest* function in R, using the approach described in (Breiman, 2001). This approach was devised to assess how much removing or noising each variable reduces the accuracy of the model prediction (on the training dataset). Finally, the trained RFs were used to predict the amount of litter over the whole domain (11,341 cells), to obtain a series of spatial maps of litter categories and sub-categories in the study area.

2.4. *Relationship between number and weight of objects: Generalized additive models*

The visual inspection of the results (see next section) suggested a further analysis of the relationship between the number and weight of objects in the original MEDITS data (which are actual observations). This was done by fitting Generalized Additive Model (GAM - Hastie and Tibshirani, 1986) model in which:

Where $W_{Year,\ cell}$ is the weight of objects (kg km^{-2}) in a given cell in a given year, N is the corresponding number of objects km^{-2}, and category is one of the six groups represented in Table 1. GAMs are non-parametric regression models allowing to model the associations between variables without defining the exact shape of the underlying regression function. Compared to parametric (including linear) forms of models, GAMs provide more flexibility when smooth functions are used as regressors. GAMs were applied using the R package "mgcv" (Wood, 2023).

This "naive" modelling approach was devised to assess whether the average weight of waste is significantly different across different GSAs and litter categories. In particular, the Davies' approach (Davies, 1987) was applied to test for statistical differences between regression parameters related to the GSAs, eventually supporting the existence of statistical differences between the slopes of the regression between GSAs (different mean weight of litter categories in different areas). All the analyses described above were carried out in the R environment (R Core Team, 2023).

3. Results and discussion

3.1. *Data exploration, areas of accumulation and hotspots*

The mean distribution of seafloor macro-litter collected from 3465 hauls in the period 2013–2019 is shown in Fig. 2, for both number (2A) and weight (2 B) of objects. In all GSAs, the main group of litter is non-fishing related plastics, followed by fishing related plastics, whereas the other groups contribute with lower, often marginal, percentages to the total. The northern part of the west Mediterranean, which includes northern Tyrrhenian Sea (Italy; GSA9), southern Tyrrhenian Sea (GSA10), and the Gulf of Lion (France, GSA7) consistently appeared to be the most impacted region, with mean densities that sometimes reaches ~ 10^5 items km^{-2} in the case of fishing-related or non-fishing-related plastic, being three orders of magnitude (10^2 to 10^5) more impacted than e.g. the strait of Sicily (Fig. 2). The pattern described above is consistent with previous findings that reported an accumulation of macro-litter along the eastern coast of Corsica (Gerigny et al., 2019). Moreover, this section of the Western Mediterranean hosts important active fisheries and it is close to significant commercial routes. Further environmental drivers are local wind and water velocity that cumulatively could provide clues on the observed patterns, as already documented by Spedicato et al. (2019), who documented a similar pattern of plastic accumulation in this region and attributed this *phenomenon* to the peculiar local circulation pattern.

When considering the total amount of litter in terms of weight of the objects is more balanced (Fig. 2B). Rubber (e.g. tires) is present in large quantities in all GSAs, as for fishery-related plastics and metals. Only GSA07 shows high values of weight for non-fishery plastics. The kernel densities (Supplementary Fig. S3) report unimodal distributions for almost all the categories and sub-categories across the GSAs. The distributions show skewness near zero, but in the GSA16, they are often platykurtic, which means that litter items are, on average, heavier than in other areas. Results indicate that rubber accounted for a small portion in terms of the number of items; however, it was among the most abundant in terms of weight, being mostly composed of dumped car tires (i.e., fewer but heavier objects). Car tires and rubber in general do not decompose easily and can remain on the seafloor for a long time (Kole et al., 2017). Car tires, for instance, slowly degrade into micro-sized rubber fragments. As they break down over time, they release harmful chemicals and pollutants into the marine environment, including heavy metals and toxic compounds (Halsband et al., 2020). Leachates from different plastics and car tire rubber contain a variety of metals and organic additives that cumulatively can affect fish behaviour, gamete fertilization, embryonic development, larvae motility and survival of different species (Capolupo et al., 2021; Halsband et al., 2020; Gorule et al., in press).

3.2. *Random Forest performance and main drivers of litter accumulation*

The results of the application of RF (Supplementary Fig. S4) indicate that the corresponding models largely have a value of median R^2 on the test sets higher than 0.8. The exceptions, represented by L1-Plastics, L1e-Hard objects, L1j-Others and L6-Others, when quantified as weight, have median R^2 values around 0.25, which indicates a low predictive ability of the trained RF models. The median rMSE is always below 0.15 and often below 0.1. Overall, the RF models showed great efficacies for all categories of macro-litter, particularly when the number of items per category was used as a response variable rather than weight. Considering also how the model output showed low values for rMSE, the lower predicting power of the model for those categories could be ascribed to the fact that some relevant categories of predictive factors were not included in the model.

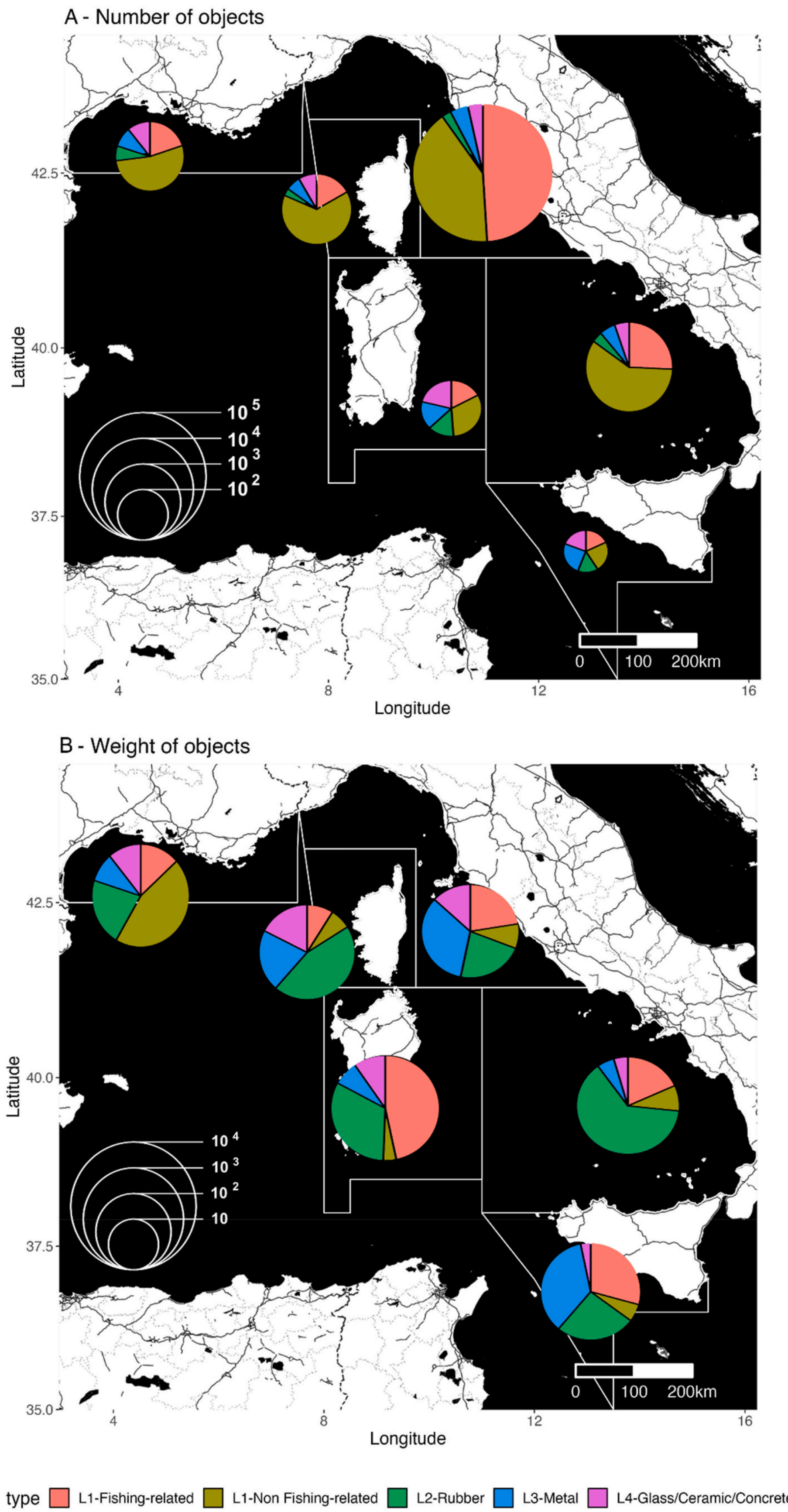

Fig. 2. Maps with pie charts showing the mean total amount (radius of the pie) and the mean composition (with respect to the main categories) of marine litter, by GSA, as number of objects km^{-2} (A) and weight of objects kg km^{-2}; (B).

With respect to the relative importance of predictors (Supplementary Figs. S5a and S5b), it is possible to notice that, for most of the categories/sub-categories, only one or a few predictors tower above the others. Interestingly, trawl effort influences the distribution of fishing related categories (i.e., hard objects [L1e] and other fishing related [L1h]), while the distance from the coast (dCoast) is associated with fishing lines (L1g). In contrast, a large set of predictors influences the amount of litter in terms of the weight of the objects (Supplementary Fig. S5b). It is interesting to notice that single use plastics (i.e., bags [L1a], bottles [L1b], and food wrappers [L1c]) are mainly influenced by their relative position with respect to urban areas, and by the distance from the coast and shipping, while fishing lines (L1g) are associated with trawling. This resulted in scattered accumulation hotspots for the two different categories, with the former being more abundant in areas closer to the coastline and, likely, to their source point, while the latter was more concentrated on fishing grounds far from the coastline (Fig. 3a).

However, the Year is by far the most important variable when modelling all the categories and sub-categories in terms of the number of objects. The temporal pattern of the absolute amount of seafloor macro-litter in the study area shows interannual fluctuating trends (Fig. 4); still, an overall increase is detectable in most of the GSAs. Observed trends become more fluctuating when the weight of objects is considered. Nonetheless, our results further highlight how the standing stock of marine macro-litter is highly unstable due to variations in inter-annual dynamics of both natural events (e.g., flooding, heavy rain, storms) or human activities that modulate macro-litter leak into aquatic environments. On top of these, the fraction of macro-litter already accumulated in the environments can possibly get dislocated by trawling activities (Franceschini et al., 2019), resuspended in case of lighter objects, or even buried in case of proximity to peculiar hydrological and/or geomorphological settings (e.g., Pierdomenico et al., 2023). These documented but still poorly understood patterns could play a role in explaining the sharp increase or decrease (i.e., in the order of ~30–50%) that was observed for some categories of macro-litter such as glass (L4) or Rubber (L2; Fig. 4) over certain years.

3.3. Predicted spatio-temporal distribution of seafloor macro-litter

Trained RF was used to forecast the amount of litter for each category and sub-category within the spatial domain considered in the study (11,341 cells), on a yearly basis from 2013 to 2019. The averaged spatio-temporal patterns are proposed in Fig. 3a and b. Fig. 3a provides clues on the predicted density and abundance of macro-litter towards the 6 bathymetric *strata* depth gradient. It appears that single use items, or more generally lightweight objects, tend to be consistently more abundant in the shallower depth range and consistently decrease with depth across all GSAs (Fig. 3a_A). Indeed, a significant proportion of land-based litter is composed of single use objects. When litter originates from the mainland or areas close to the coast, most of them are found to be stranded quickly and a significant portion remains in coastal waters near their point of origin. (Critchell and Lambrechts, 2016).

On the contrary, heavier objects are predicted to be more abundant in the deepest *strata* or at least as abundant as in shallower ones. This is the case of plastic subcategories such as L1h - Other fishing-related objects, L1i - Synthetic ropes, L1j - Others, or other heavier categories such as L2 Rubber and L3 Metal. These items are expected to increase with depth in GSA 07, 08, 11, and 16. The increase of small or light objects on the seafloor at high depths relies essentially on two mechanisms: i)

temporal changes in the weight of floating litter due to biofouling (Amaral-Zettler et al., 2021) and/or ii) local features of water circulation and geomorphologies such as submarine canyons, which are known to funnel huge quantities of macro-litter to the deep ocean (Hernandez et al., 2022). On the other hand, heavy objects are likely to be dropped directly into the sea and proximity to major trade routes may have been a contributing factor. The "other" category of L1j is a subcategory that is especially important in the deepest depths. Overall, any object that does not fall within a specific category or subcategory in the classification list is to be classified under the 'other' category: e.g. as regards its size or quantity of material. Therefore, it is not easy to know which type of objects are covered by the particular category and any speculation on those patterns cannot be substantiated. Unfortunately, this aspect does not vary from one classification scheme to the other and becomes even more important for protocols such as the MEDITS survey that proposes a rather limited number of subcategories. In this view, we emphasize the need for waste monitoring protocols to propose a workflow for the correct use of the "other" category.

The main spatial results were simplified by focusing on the different degrees of accumulation of the various types of macro-litter across various areas. To achieve this, a trade-off was made between the heterogeneity of the litter, its origin in relation to human activities, and the heterogeneity of the spatial distribution.

Spatial patterns for macro-litter sub-categories are represented in Fig. 3b. This is because spatial patterns are of particular interest since they allow the identification of the main hotspots, which are the most relevant areas to be identified and, eventually, where mitigation actions should be prioritized. Moreover, the temporal persistence of accumulation areas can be a further diagnostic tool to give relevance to a certain hotspot. This aspect has never been tested so far and the present study provides the first insights into the temporal pattern, based on a yearly basis, of accumulation hotspots.

Regions with moderate to low accumulations of seafloor macro-litter include the coasts of Sardinia (GSA11) and Sicily (GSA16), the two largest Italian islands. In comparison to the accumulation observed along the northern Italian coastline, non-fishing-related plastic items were found to be very scarce. This pattern changes a bit when considering the weight of the objects (kg per km^{-2}) as the response variable and Sicily and Sardinia islands (GSA16 and GSA11, respectively), showed very large values for the weight of L1 - Fishing-related items and L3 - Metal. More in general, those areas in these two GSAs that appear numerically less contaminated with waste, do become among the most contaminated if the weight of waste is considered.

3.4. Number versus weight

Monitoring litter by number or weight can lead to different results, as explained by other authors (Smith & Turrell, 2021). The efficacy of monitoring based on the number is influenced by factors such as the minimum detectable fragment size, the age of the debris, and environmental forcings that can increase the fragmentation processes (Smith & Turrell, 2021). Given that the single presence or absence of mega-litter may constitute a strong bias in weight-based monitoring (Smith & Turrell, 2021), it is important to combine data on the number and weight of objects in order to generate reliable information. The effect of the number of objects on the respective value of the weight of the object is, as expected, close to linear (Fig. 5A). In addition, GAM detected a significant effect of the GSA, with a pattern of the coefficients (Fig. 5B) in which the GSA16 has the highest value and the GSAs 09 and 08 the smallest ones (Table 3). Davie's test also allowed us to reject the null hypothesis that coefficients (slopes) of the number/weight relationship for the different GSAs belong to the same distribution. This demonstrates that, in the Strait of Sicily (GSA16), macro-litter is heavier than in other areas, as observed in the steeper slope of the area (Fig. 5C). The difference between number and weight patterns, represented in Fig. 3a and b, could be justified by the fact that along the southern coast of Sicily, stronger currents prevent the deposition on the seafloor of lighter items. In contrast, the ribs of GSA09 and GSA10 are characterised by greater stagnation, which allows even lighter items to be deposited on the bottom. Indeed, (Collignon et al., 2014) demonstrated that the mean weight of particles in the northwestern Mediterranean Sea is smaller than in other areas, in agreement with the results of this study.

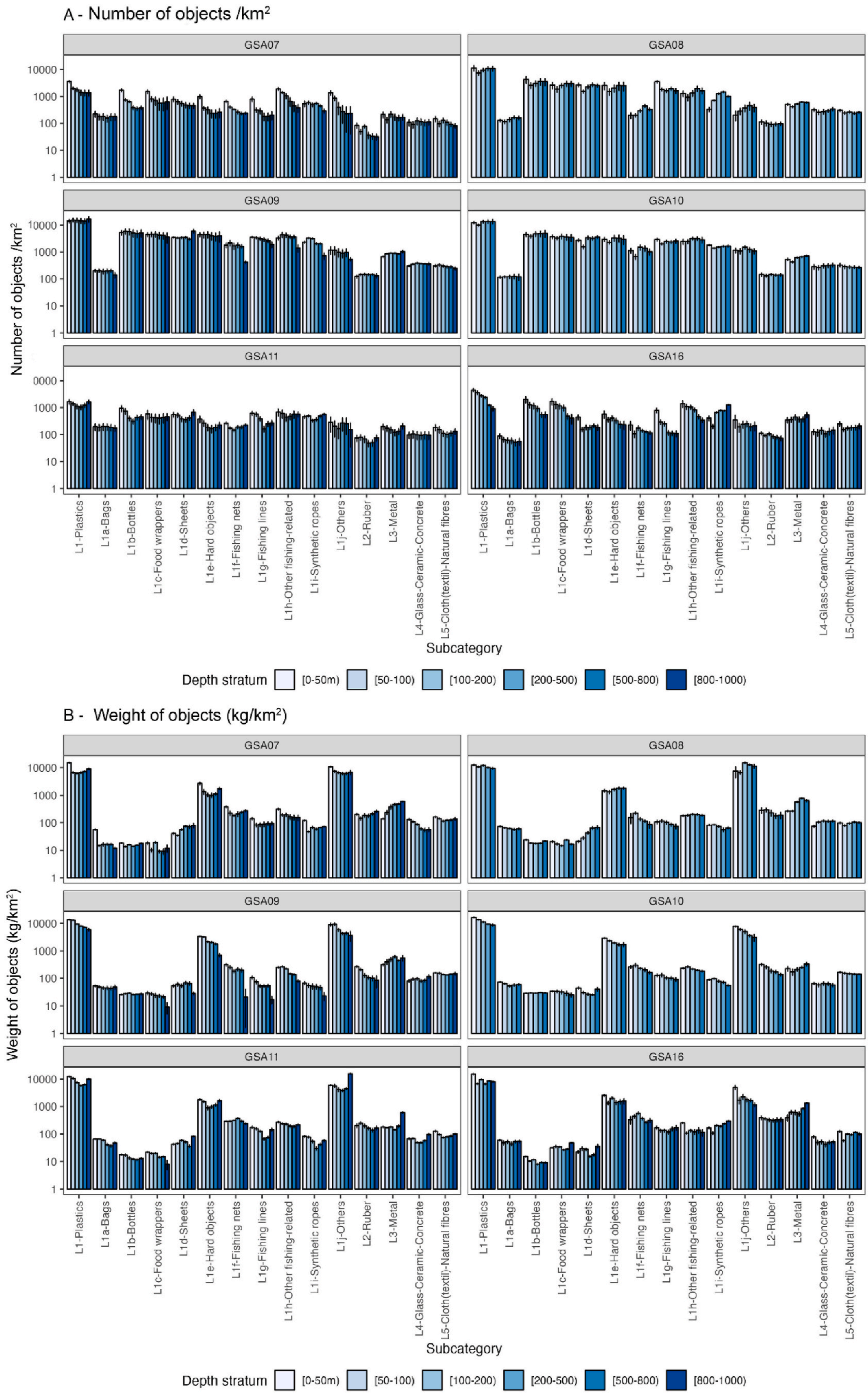

Fig. 3a. Barplots of the predicted seafloor litter abundance in the western Mediterranean Sea, by depth stratum, and Geographical Sub Areas, for all the sub-categories, as (A) mean number of objects km^{-2} and (B) mean weight of objects per ($kg\ km^{-2}$). Bars represent the mean value over the period (years 2013–2019) considered, and the standard deviation is represented by the error bars.

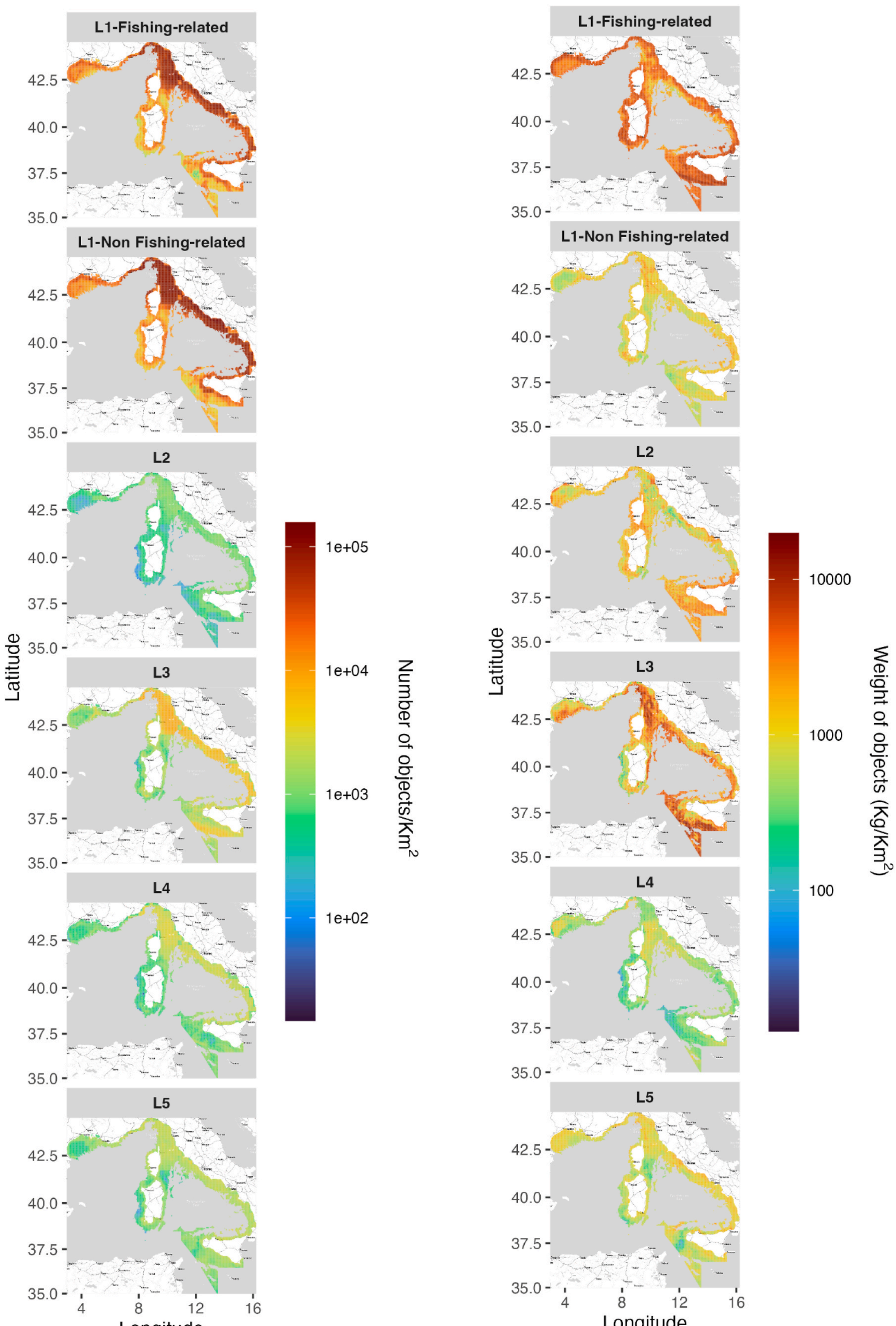

Fig. 3b. Maps showing the average amount of marine litter categories over the period 2013–2019, as total number and weight of objects km^{-2}.

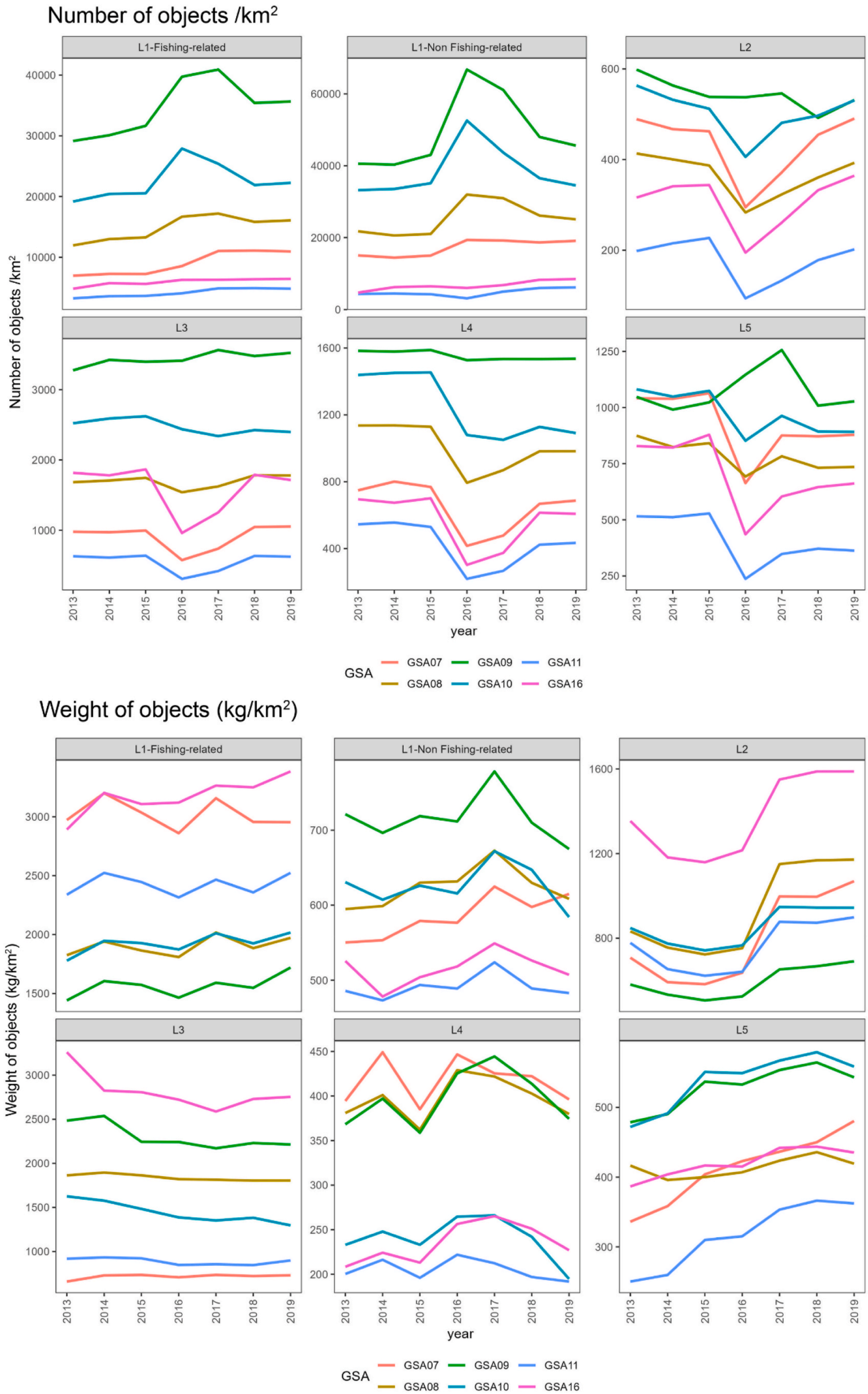

Fig. 4. Temporal trends (2013–2019) for the main litter groups across different GSAs, expressed both as n. of items and kg of objects km^{-2}.

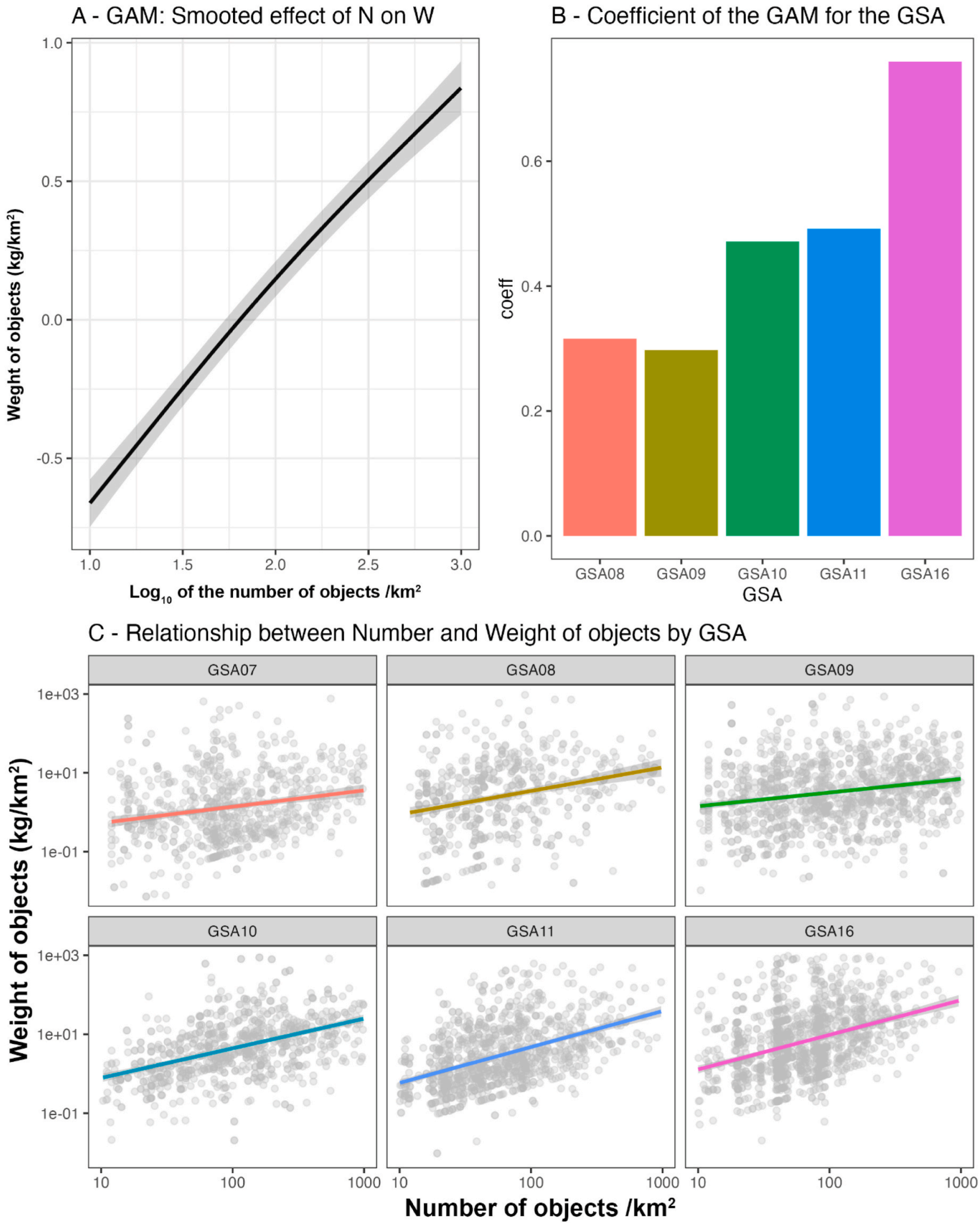

Fig. 5. **A**) General relationship (GAM smoothed effect of the number of objects on the weight of objects, irrespectively of the GSA; **B**) Barplot of the GSA-specific coefficient for the weight of objects; C - GSA-specific relationship between weight and number of object in which the linear trend is represented.

Northwestern Mediterranean coasts were also characterised by the presence of high accumulation zones in the near-shore region (Pedrotti et al., 2016). In essence, it seems reasonable to assume that the part north of the Tyrrhenian Sea is the one (within the six GSAs considered in this study) with the highest number of plastic items but with a lower average weight than other areas (such as the southern coasts of Sicily), and this is due to the synergistic effect of two factors: the presence of major rivers (the Tiber, the Arno, the Rhone), and a hydrodynamic regime that favours stagnation and accumulation.

Results here presented are based on a broader geographical scale compared to available studies conducted in single GSAs within the study area (e.g., Alvito et al., 2018; Franceschini et al., 2019; Garofalo et al., 2020); which eventually allowed us to put into a broader perspective some of the results obtained locally; this is the case of GSA11, that appeared less critical once put into a larger spatial scale and perspective, not showing any relevant accumulation hotspot compared to the whole western Mediterranean pattern. This, however, should not divert attention from local peculiarities, since potential mitigation actions

Table 3
GAM coefficients and main statistics for the relationship between number of objects km^{-2} and weight of objects ($kg\ km^{-2}$). The GAM model was fitted on the dataset of 5869 records corresponding to the values of marine litter abundance in 1073 cells (corresponding to the MEDITS sampling sites) monitored over seven years. Asterisks mark significant values (* P-value <0.05, ** P-value <0.01, *** P-values <0.001), which are also highlighted in bold.

Term	Coefficient
GSA08	**0.32*** **
GSA09	0.3***
GSA10	0.47***
GSA11	0.49 ***
GSA16	0.76***
L1-Fishing-related	0.05
L1-Non Fishing-related	−0.11***
L2-Rubber	0.75***
L3-Metal	0.08*
L4-Glass/Ceramic/Concrete	0.57***
Deviance explained of the GAM	47.5%

would mostly act locally, based on the efforts of local fisheries (e.g., fishing for litter initiatives). Still, present results could provide useful insights to define sub-basin spots that would deserve priority for broader, coordinated efforts.

3.5. Replicability and limitations

One of the strengths of the approach proposed in this paper is that it is based on widely and easily accessible information through online portals such as those of NOAA and Copernicus. This could make it possible to expand predictions to other areas of the Mediterranean or, more generally, of European seas and world oceans (considering that initiatives similar to Copernicus exist in other areas of the globe). In addition, future applications of this kind of predictive model could allow for the refinement of predictions in already investigated areas, since machine learning techniques (such as RF) are born precisely to exploit the mass of information (big data) that is progressively accumulated. On the other hand, it will be necessary to supplement direct information, like that from MEDITS but also other forms of data collection such as image-based analysis, on the amount of macro-litter present on the seabed. With this respect, a number of limitations of this work emerge: 1) it is a data-demanding approach; 2) it has so far only been applied to macro-litter, as there is no geo-referenced information for litter of smaller size classes; 3) we do not know whether this kind of approach can also work in 3D (for litter in the water column) and for surface litter. These aspects, however, open the prospect for new work and stimulate the integration of observations from different sources in order to explore the limits of the method itself. Marine litter threat is, indeed, a transboundary issue and the best strategy to tackle it requires close cooperation across geographically close and distant countries.

3.6. Conclusions, implications, and future perspectives

The ecological modelling exercise presented in this study aims to try to answer the question in the title: what, where, and when (and, potentially, why) does litter accumulation occur on the seafloor? From a compositional point of view, the category of non-fishing related objects represents the numerically most abundant component, especially along the continental coasts. By weight, however, the situation is more heterogeneous. Islands (Sicily, Sardinia, and Corsica) are the least contaminated areas, while considering the temporal pattern of hotspots, as anticipated, results here put emphasis on the temporal consistency of hotspots, an overlooked that would deserve consideration. This is of crucial importance since it is well documented how macro-litter can be displaced or buried and a proper identification of hotspots could be compromised. In case of consistent and spatially stable hotspots, stakeholders would have the tool to identify areas where the litter standing stock is stable across time and where: i) mitigation can be prioritized and ii) test for the efficacy of broad transnational litter reduction policies. Indeed, besides a few environmental factors, input from land, in all its forms, represents the main contributor and driver of macro-litter distribution. Our approach, which likely does not allow us to assess local measures' effectiveness could, on the contrary, be very effective in detecting the temporal effects of binding targets foreseen within transnational initiatives such as the plastic treaty of the United Nation (Bergmann et al., 2022).

Mapping the distribution of marine macro-litter is also a key element in assessing the exposure of marine organisms to potential plastic pollution. In the case of plastic ingestion by marine species or just entanglement in ghost fishing gear, the risk assessment must indicate where and when harm may occur. These risks are largely defined by the potential encounter of marine organisms with litter, but also by litter's nature and form. Risk assessment has been used recently to study areas where species may be harmed by the presence of litter and, more specifically, to predict areas where the risk of ingestion is high (e.g., ecological threats to marine biota at the population level are often unclear, as is the geographic extent of impacts). Modelling the likelihood of litter ingestion by cross mapping the distribution of both litter and sea turtles or cetaceans has been proposed as a tool to define areas at risk, in terms of exposure (Darmon et al., 2017; Fossi et al., 2018). This tool was then used to investigate the possible overlap between plastic accumulation maps and microplastics in bioindicator species and ichthyofauna in Mediterranean Marine Protected Areas (Compa et al., 2023, 2022). As the mapping of demersal fish abundance has been recently described in the Mediterranean Sea (Colloca et al., 2015), the same approach could be used, taking advantage of the results of the modelled macro-litter distribution to predict areas where the demersal fish population may be affected, environmentally, but also with possible consequences for the quality of fish as seafood.

Within mitigation initiatives, a good example is the "Fishing for litter" initiative (https://fishingforlitter.org) (García-Hermosa and Woodall, 2023). Indeed, trawls cover the largest total swept area (Haarr et al., 2022) and, most importantly, remain the only available option for reaching greater depths, during the regular working routine of fisheries. However, trawls come at great environmental costs due to their disturbance (and possible destruction) of substrate and *biota* (Canals et al., 2021; Pusceddu et al., 2014). Scientific evidence informs on how trawl-based mitigation action could prioritize macro-litter hotspots to be more effective and how cumulative maps of hotspots could be spatially misleading (Cau et al., 2022); we stress here that the temporal factor can play a crucial role as well. This latter information was missing from available literature and clearly shows how hotspots identified during a survey conducted in a specific year may not be consistent in the following years. The reasons that can explain such temporal changes are ascribable, as anticipated above, to remobilization or burial as major causes, but also to differential riverine input driven by major atmospheric events across years (Laverre et al., 2023), or fluctuations in seasonal anthropic activities such as coastal tourism (Ronchi et al., 2019).

Initiatives that involve fishermen to collect macro-litter are relatively low-cost and efficient, at least considering exclusively fishing grounds, even though several difficulties arise in their execution and implementation (Cho, 2009; Ronchi et al., 2019; Viejo et al., 2023). The effective reduction of marine litter' contamination should begin with a cap on the production, especially of hazardous materials like plastic (Bergmann et al., 2022). However, for that fraction of macro-litter already dispersed in sea bottoms worldwide, mitigation initiatives represent the most realistic and feasible strategy to pursue, still considering the enormous limitations that arise when working at high depths in the marine environment (Canals et al., 2021). Our approach could also provide a benchmark for monitoring the effectiveness of numerous directives that are put in place at both national and international levels. Since macro-litter can be identified and divided into subcategories (i.e. plastics, rubbers, metals, glass, and clothes), the temporal trends of each of these categories could be informative of the actual effectiveness of specific measures, such as waste management policies, bans of certain products or introduction of taxes and charges (Chen, 2015).

Author statement

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envpol.2023.123028.

References

Alvito, A., Bellodi, A., Cau, A., Moccia, D., Mulas, A., Palmas, F., Pesci, P., Follesa, M.C., 2018. Amount and distribution of benthic marine litter along Sardinian fishing grounds (CW Mediterranean Sea). Waste Manag. 75, 131–140. https://doi.org/10.1016/j.wasman.2018.02.026.

Amaral-Zettler, L.A., Zettler, E.R., Mincer, T.J., Klaassen, M.A., Gallager, S.M., 2021. Biofouling impacts on polyethylene density and sinking in coastal waters: a macro/micro tipping point? Water Res. 201, 117289 https://doi.org/10.1016/J.WATRES.2021.117289.

Angiolillo, M., di Lorenzo, B., Farcomeni, A., Bo, M., Bavestrello, G., Santangelo, G., Cau, Angelo, Mastascusa, V., Cau, Alessandro, Sacco, F., Canese, S., 2015. Distribution and assessment of marine debris in the deep Tyrrhenian Sea (NW Mediterranean Sea, Italy). Mar. Pollut. Bull. 92, 149–159. https://doi.org/10.1016/j.marpolbul.2014.12.044.

Bergmann, M., Almroth, B.C., Brander, S.M., Dey, T., Green, D.S., Gundogdu, S., Krieger, A., Wagner, M., Walker, T.R., 2022. A global plastic treaty must cap production. Science 376, 469–470. https://doi.org/10.1126/SCIENCE.ABQ0082, 1979.

Bergmann, M., Tekman, M.B., Gutow, L., 2017. Marine litter: sea change for plastic pollution. Nature 544, 297. https://doi.org/10.1038/544297a.

Borrelle, S.B., Ringma, J., Lavender Law, K., Monnahan, C.C., Lebreton, L., McGivern, A., Murphy, E., Jambeck, J., Leonard, G.H., Hilleary, M.A., Eriksen, M., Possingham, H. P., De Frond, H., Gerber, L.R., Polidoro, B., Tahir, A., Bernard, M., Mallos, N., Barnes, M., Rochman, C.M., 2020. Predicted growth in plastic waste exceeds efforts to mitigate plastic pollution. Science 1518, 1515–1518.

Breiman, L., 2001. Random forests. Mach. Learn. 45, 5–32. https://doi.org/10.1109/ICCECE51280.2021.9342376.

Buhl-Mortensen, L., Houssa, R., Weerakoon, W.R.W.M.A.P., Kainge, P., Olsen, M.N., Faye, S., Wagne, M.M., Myo Thwe, S., Cudjoe Voado, G., Grøsvik, B.E., 2022. Litter on the seafloor along the African coast and in the Bay of Bengal based on trawl bycatches from 2011 to 2020. Mar. Pollut. Bull. 184 https://doi.org/10.1016/j.marpolbul.2022.114094.

Canals, M., Pham, C.K., Bergmann, M., Gutow, L., Hanke, G., van Sebille, E., Angiolillo, M., Buhl-Mortensen, L., Cau, A., Ioakeimidis, C., Kammann, U., Lundsten, L., Papatheodorou, G., Purser, A., Sanchez-Vidal, A., Schulz, M., Vinci, M., Chiba, S., Galgani, F., Langenkämper, D., Möller, T., Nattkemper, T.W., Ruiz, M., Suikkanen, S., Woodall, L., Fakiris, E., Molina Jack, M.E., Giorgetti, A., 2021. The quest for seafloor macrolitter: a critical review of background knowledge, current methods and future prospects. Environ. Res. Lett. https://doi.org/10.1088/1748-9326/abc6d4.

Capolupo, M., Gunaalan, K., Booth, A.M., Sørensen, L., Valbonesi, P., Fabbri, E., 2021. The sub-lethal impact of plastic and tire rubber leachates on the Mediterranean mussel Mytilus galloprovincialis. Environ. Pollut. 283, 117081 https://doi.org/10.1016/J.ENVPOL.2021.117081.

Cau, A., Franceschini, S., Moccia, D., Gorule, P.A., Agus, B., Bellodi, A., Cannas, R., Carugati, L., Cuccu, D., Dessì, C., Marongiu, M.F., Melis, R., Mulas, A., Porceddu, R., Porcu, C., Russo, T., Follesa, M.C., 2022. Scattered accumulation hotspots of macro-litter on the seafloor: insights for mitigation actions. Environ. Pollut. 292, 118338 https://doi.org/10.1016/j.envpol.2021.118338.

Cau, A., Moccia, D., Follesa, M.C., Alvito, A., Canese, S., Angiolillo, M., Cuccu, D., Bo, M., Cannas, R., 2017. Coral forests diversity in the outer shelf of the south Sardinian continental margin. Deep-Sea Res. Part I Oceanogr. Res. Pap. 122, 60–70. https://doi.org/10.1016/j.dsr.2017.01.016.

Chen, C.L., 2015. Regulation and management of marine litter. In: Marine Anthropogenic Litter. Springer International Publishing, pp. 395–428. https://doi.org/10.1007/978-3-319-16510-3_15/TABLES/2.

Cho, D.O., 2009. The incentive program for fishermen to collect marine debris in Korea. Mar. Pollut. Bull. 58, 415–417. https://doi.org/10.1016/j.marpolbul.2008.10.004.

Collignon, A., Hecq, J.H., Galgani, F., Collard, F., Goffart, A., 2014. Annual variation in neustonic micro- and meso-plastic particles and zooplankton in the Bay of Calvi (Mediterranean-Corsica). Mar. Pollut. Bull. 79, 293–298. https://doi.org/10.1016/j.marpolbul.2013.11.023.

Colloca, F., Garofalo, G., Bitetto, I., Facchini, M.T., Grati, F., Martiradonna, A., Mastrantonio, G., Nikolioudakis, N., Ordinas, F., Scarcella, G., Tserpes, G., Tugores, M.P., Valavanis, V., Carlucci, R., Fiorentino, F., Follesa, M.C., Iglesias, M., Knittweis, L., Lefkaditou, E., Lembo, G., Manfredi, C., Massutí, E., Pace, M.L., Papadopoulou, N., Sartor, P., Smith, C.J., Spedicato, M.T., 2015. The seascape of demersal fish nursery areas in the north Mediterranean Sea, a first step towards the implementation of spatial planning for trawl fisheries. PLoS One 10, e0119590. https://doi.org/10.1371/journal.pone.0119590.

Compa, M., Alomar, C., Deudero, S., 2023. Mapping microplastic overlap between marine compartments and biodiversity in a Mediterranean marine protected area. Sci. Total Environ. 892, 164584 https://doi.org/10.1016/j.scitotenv.2023.164584.

Compa, M., Wilcox, C., Hardesty, B.D., Alomar, C., March, D., Deudero, S., 2022. Quantifying the risk of plastic ingestion by ichthyofauna in the Balearic Islands (western Mediterranean Sea). Mar. Pollut. Bull. 183, 114075 https://doi.org/10.1016/j.marpolbul.2022.114075.

Critchell, K., Lambrechts, J., 2016. Modelling accumulation of marine plastics in the coastal zone; what are the dominant physical processes? Estuar. Coast Shelf Sci. 171, 111–122. https://doi.org/10.1016/J.ECSS.2016.01.036.

Cutler, A., Cutler, D.R., Stevens, J.R., 2012. Random forests. Ensemble Machine Learning 157–175. https://doi.org/10.1007/978-1-4419-9326-7_5.

Cutler, D.R., Edwards, T.C., Beard, K.H., Cutler, A., Hess, K.T., Gibson, J., Lawler, J.J., 2007. Random forests for classification in ecology. Ecology 88 (11), 2783–2792. https://doi.org/10.1890/07-0539.1.

Darmon, G., Miaud, C., Claro, F., Doremus, G., Galgani, F., 2017. Risk assessment reveals high exposure of sea turtles to marine debris in French Mediterranean and metropolitan Atlantic waters. Deep Sea Res. Part II Top. Stud. Oceanogr. 141, 319–328. https://doi.org/10.1016/j.dsr2.2016.07.005.

Davies, R.B., 1987. Hypothesis testing when a nuisance parameter is present only under the alternatives. Biometrika 74, 33. https://doi.org/10.2307/2336019.

Elhacham, E., Ben-Uri, L., Grozovski, J., Bar-On, Y.M., Milo, R., 2020. Global human-made mass exceeds all living biomass. Nature 588, 442–444. https://doi.org/10.1038/s41586-020-3010-5.

Fossi, M.C., Pedà, C., Compa, M., Tsangaris, C., Alomar, C., Claro, F., Ioakeimidis, C., Galgani, F., Hema, T., Deudero, S., Romeo, T., Battaglia, P., Andaloro, F., Caliani, I., Casini, S., Panti, C., Baini, M., Cristina, M., Ped, C., Alomar, C., Claro, F., Ioakeimidis, C., Galgani, F., Hema, T., Deudero, S., Romeo, T., Battaglia, P., Andaloro, F., Caliani, I., Casini, S., Panti, C., Baini, M., 2018. Bioindicators for monitoring marine litter ingestion and its impacts on Mediterranean biodiversity. Environ. Pollut. 237, 1023–1040. https://doi.org/10.1016/j.envpol.2017.11.019.

Franceschini, S., Mattei, F., D'Andrea, L., Di Nardi, A., Fiorentino, F., Garofalo, G., Scardi, M., Cataudella, S., Russo, T., 2019. Rummaging through the bin: modelling marine litter distribution using Artificial Neural Networks. Mar. Pollut. Bull. 149, 110580 https://doi.org/10.1016/j.marpolbul.2019.110580.

Galgani, F., Brien, A.S., Weis, J., Ioakeimidis, C., Schuyler, Q., Makarenko, I., Griffiths, H., Bondareff, J., Vethaak, D., Deidun, A., Sobral, P., Topouzelis, K., Vlahos, P., Lana, F., Hassellov, M., Gerigny, O., Arsonina, B., Ambulkar, A., Azzaro, M., Bebianno, M.J., 2021. Are litter, plastic and microplastic quantities increasing in the ocean? Microplastics and Nanoplastics 1, 8–11. https://doi.org/10.1186/s43591-020-00002-8.

Galgani, F., Leaute, J.P., Moguedet, P., Souplet, A., Verin, Y., Carpentier, A., Goraguer, H., Latrouite, D., Andral, B., Cadiou, Y., Mahe, J.C., Poulard, J.C., Nerisson, P., 2000. Litter on the sea floor along European coasts. Mar. Pollut. Bull. 40, 516–527. https://doi.org/10.1016/S0025-326X(99)00234-9.

García-Hermosa, M.I., Woodall, L.C., 2023. Marine plastic: the solution is bigger than removal. Front. Sustain. 4 https://doi.org/10.3389/frsus.2023.1023480.

Garofalo, G., Quattrocchi, F., Bono, G., Di Lorenzo, M., Di Maio, F., Falsone, F., Gancitano, V., Geraci, M.L., Lauria, V., Massi, D., Scannella, D., Titone, A., Fiorentino, F., 2020. What is in our seas? Assessing anthropogenic litter on the seafloor of the central Mediterranean Sea. Environ. Pollut. 266, 115213 https://doi.org/10.1016/j.envpol.2020.115213.

Gerigny, O., Brun, M., Fabri, M.C., Tomasino, C., Le Moigne, M., Jadaud, A., Galgani, F., 2019. Seafloor litter from the continental shelf and canyons in French Mediterranean Water: distribution, typologies and trends. Mar. Pollut. Bull. 146, 653–666. https://doi.org/10.1016/j.marpolbul.2019.07.030.

Gislason, P.O., Benediktsson, J.A., Sveinsson, J.R., 2006. Random Forests for land cover classification. Pattern Recogn. Lett. 27 (4), 294–300. https://doi.org/10.1016/J.PATREC.2005.08.011.

Gorule, P. A., Šmejkal, M., Tapkir, S., Stepanyshyna, Y., Stejskal, V., Follesa, M. C., & Cau, A.(in press). Long-term sublethal exposure to polyethylene and tire wear particles: Effects on risk-taking behaviour in invasive and native fish. Science of The Total Environment, 168233. https://doi.org/10.1016/J.SCITOTENV.2023.168233.

Haarr, M.L., Falk-Andersson, J., Fabres, J., 2022. Global marine litter research 2015–2020: geographical and methodological trends. Sci. Total Environ. 820, 153162 https://doi.org/10.1016/j.scitotenv.2022.153162.

Halpern, B.S., Walbridge, S., Selkoe, K.A., Kappel, C.V., Micheli, F., D'Agrosa, C., Bruno, J.F., Casey, K.S., Ebert, C., Fox, H.E., Fujita, R., Heinemann, D., Lenihan, H.S., Madin, E.M.P., Perry, M.T., Selig, E.R., Spalding, M., Steneck, R., Watson, R., 2008. A global map of human impact on marine ecosystems. Science 1979 (319), 948–952. https://doi.org/10.1126/SCIENCE.1149345/SUPPL_FILE/HALPERN_SOM.PDF.

Halsband, C., Sørensen, L., Booth, A.M., Herzke, D., 2020. Car tire Crumb rubber: does Leaching produce a toxic chemical Cocktail in coastal marine systems? Front. Environ. Sci. 8, 557495 https://doi.org/10.3389/FENVS.2020.00125/BIBTEX.

Hastie, T., Tibshirani, R., 1986. Generalized Additive Models. https://doi.org/10.1214/SS/1177013604.

Hernandez, I., Davies, J.S., Huvenne, V.A.I., Dissanayake, A., 2022. Marine litter in submarine canyons: a systematic review and critical synthesis. Front. Mar. Sci. 9, 965612 https://doi.org/10.3389/FMARS.2022.965612/BIBTEX.

Hijmans, R., Karney, C., Williams, E., Vennes, C., 2021. Package "Geosphere" Spherical Trigonometry.

Jambeck, J.R., Geyer, R., Wilcox, C., Siegler, T.R., Perryman, M., Andrady, A., Narayan, R., Law, K.L., 2015. Plastic waste inputs from land into the ocean. Science 347, 768–771. https://doi.org/10.1126/science.1260352, 1979.

Kole, P., Löhr, A.J., Van Belleghem, F.G.A.J., Ragas, A.M.J., 2017. Wear and tear of Tyres: a stealthy source of microplastics in the environment. Int. J. Environ. Res. Publ. Health 14 (1265 14), 1265. https://doi.org/10.3390/IJERPH14101265, 2017.

Lau, W.W.Y., Shiran, Y., Bailey, R.M., Cook, E., Stuchtey, M.R., Koskella, J., Velis, C.A., Godfrey, L., Boucher, J., Murphy, M.B., Thompson, R.C., Jankowska, E., Castillo Castillo, A., Pilditch, T.D., Dixon, B., Koerselman, L., Kosior, E., Favoino, E., Gutberlet, J., Baulch, S., Atreya, M.E., Fischer, D., He, K.K., Petit, M.M., Sumaila, U. R., Neil, E., Bernhofen, M.V., Lawrence, K., Palardy, J.E., 2020. Evaluating scenarios toward zero plastic pollution. Science 1461, eaba9475. https://doi.org/10.1126/science.aba9475, 80.

Laverre, M., Kerhervé, P., Constant, M., Weiss, L., Charrière, B., Stetzler, M., González-Fernández, D., Ludwig, W., 2023. Heavy rains control the floating macroplastic inputs into the sea from coastal Mediterranean rivers: a case study on the Tet River (NW Mediterranean Sea). Sci. Total Environ. 877, 162733 https://doi.org/10.1016/j.scitotenv.2023.162733.

Liaw, A., Wiener, M., 2002. Classification and Regression by randomForest 2 (3). http://www.stat.berkeley.edu/.

Madricardo, F., Ghezzo, M., Nesto, N., Mc Kiver, W.J., Faussone, G.C., Fiorin, R., Riccato, F., Mackelworth, P.C., Basta, J., De Pascalis, F., Kruss, A., Petrizzo, A., Moschino, V., 2020. How to deal with seafloor marine litter: an overview of the state-of-the-art and future perspectives. Front. Mar. Sci. 7, 1–16. https://doi.org/10.3389/fmars.2020.505134.

MEDITS working group, 2012. MEDITS. International Bottom Trawl Survey in the Mediterranean. Instruction Manual. Version 6. MEDITS-Handbook. Revision n.6. MEDITS Working group. April 2012. https://archimer.ifremer.fr/doc/00117/22783.

Melli, V., Angiolillo, M., Ronchi, F., Canese, S., Giovanardi, O., Querin, S., Fortibuoni, T., 2016. The first assessment of marine debris in a site of Community importance in the north-western adriatic sea (Mediterranean Sea). Mar. Pollut. Bull. https://doi.org/10.1016/j.marpolbul.2016.11.012.

Mifsud, R., Dimech, M., Schembri, P.J., 2013. Marine litter from circalittoral and deeper bottoms off the Maltese islands (Central Mediterranean). Mediterr. Mar. Sci. 14, 298. https://doi.org/10.12681/mms.413.

Millot, C., 1999. Circulation in the western Mediterranean Sea. J. Mar. Syst. 20, 423–442. https://doi.org/10.1016/S0924-7963(98)00078-5.

Pante, E., Simon-Bouhet, B., 2013. Marmap: a package for importing, plotting and analyzing bathymetric and Topographic data in R. PLoS One 8, e73051. https://doi.org/10.1371/journal.pone.0073051.

Parga Martínez, K.B., Tekman, M.B., Bergmann, M., 2020. Temporal trends in marine litter at three stations of the HAUSGARTEN observatory in the arctic deep sea. Front. Mar. Sci. 7, 1–16. https://doi.org/10.3389/fmars.2020.00321.

Pedrotti, M.L., Petit, S., Elineau, A., Bruzaud, S., Crebassa, J.-C., Dumontet, B., Martí, E., Gorsky, G., Cózar, A., 2016. Changes in the floating plastic pollution of the Mediterranean Sea in relation to the distance to land. PLoS One 11, e0161581. https://doi.org/10.1371/journal.pone.0161581.

Pierdomenico, M., Casalbore, D., Chiocci, F.L., 2019. Massive benthic litter funnelled to deep sea by flash-flood generated hyperpycnal flows. Sci. Rep. 1–10. https://doi.org/10.1038/s41598-019-41816-8.

Pierdomenico, M., Bernhardt, A., Eggenhuisen, J.T., Clare, M.A., Lo Iacono, C., Casalbore, D., Davies, J.S., Kane, I., Huvenne, V.A.I., Harris, P.T., 2023. Transport and accumulation of litter in submarine canyons: a geoscience perspective. Front. Mar. Sci. 10, 1224859 https://doi.org/10.3389/FMARS.2023.1224859/BIBTEX.

Pusceddu, A., Bianchelli, S., Martin, J., Puig, P., Palanques, A., Masque, P., Danovaro, R., 2014. Chronic and intensive bottom trawling impairs deep-sea biodiversity and ecosystem functioning. Proc. Natl. Acad. Sci. USA 111, 8861–8866. https://doi.org/10.1073/pnas.1405454111.

R Core Team, 2023. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria (R-proje ct.org/).

Rochman, C.M., 2016. Strategies for reducing ocean plastic debris should be diverse and guided by science. Environ. Res. Lett. 11, 41001 https://doi.org/10.1088/1748-9326/11/4/041001.

Rochman, C.M., Browne, M.A., Halpern, B.S., Hentschel, B.T., Hoh, E., Karapanagioti, H. K., Rios-Mendoza, L.M., Takada, H., Teh, S., Thompson, R.C., 2013. Policy: Classify plastic waste as hazardous. Nature 494, 169–171. https://doi.org/10.1038/494169a.

Ronchi, F., Galgani, F., Binda, F., Mandić, M., Peterlin, M., Tutman, P., Anastasopoulou, A., Fortibuoni, T., 2019. Fishing for litter in the adriatic-Ionian macroregion (Mediterranean Sea): strengths, weaknesses, opportunities and threats. Mar. Pol. 100, 226–237. https://doi.org/10.1016/j.marpol.2018.11.041.

Russo, T., D'Andrea, L., Parisi, A., Martinelli, M., Belardinelli, A., Boccoli, F., Cignini, I., Tordoni, M., Cataudella, S., 2016. Assessing the fishing footprint using data integrated from different tracking devices: Issues and opportunities. Ecol. Indicat. 69, 818–827. https://doi.org/10.1016/j.ecolind.2016.04.043.

Russo, T., D'Andrea, L., Parisi, A., Cataudella, S., 2014. VMSbase: an R-package for VMS and Logbook data management and analysis in fisheries ecology. PLoS One 9, e100195. https://doi.org/10.1371/journal.pone.0100195.

Scornet, E., 2017. Tuning parameters in random forests. ESAIM: Proceedings and Surveys 60, 144–162. https://doi.org/10.1051/PROC/201760144.

Smith, L., Turrell, W.R., 2021. Monitoring plastic Beach litter by number or by weight: the Implications of fragmentation. Front. Mar. Sci. 8, 702570 https://doi.org/10.3389/FMARS.2021.702570/BIBTEX.

Spedicato, M.T., Zupa, W., Carbonara, P., Fiorentino, F., Follesa, M.C., Galgani, F., García-ruiz, C., Jadaud, A., Ioakeimidis, C., Lazarakis, G., Lembo, G., Mandic, M., Maiorano, P., Sartini, M., Serena, F., Cau, A., Esteban, A., Isajlovic, I., Micallef, R., Thasitis, I., 2019. Spatial distribution of marine macro-litter on the seafloor in the northern Mediterranean Sea : the MEDITS initiative. Sci. Mar. 1, 1–14.

Strafella, P., Fabi, G., Spagnolo, a., Grati, F., Polidori, P., Punzo, E., Fortibuoni, T., Marceta, B., Raicevich, S., Cvitkovic, I., Despalatovic, M., Scarcella, G., 2015. Spatial pattern and weight of seabed marine litter in the northern and central Adriatic Sea. Mar. Pollut. Bull. 91, 120–127. https://doi.org/10.1016/j.marpolbul.2014.12.018.

Tubau, X., Canals, M., Lastras, G., Rayo, X., Rivera, J., Amblas, D., 2015. Marine litter on the floor of deep submarine canyons of the Northwestern Mediterranean Sea: the role of hydrodynamic processes. Prog. Oceanogr. 134, 379–403. https://doi.org/10.1016/j.pocean.2015.03.013.

Viejo, J., Cózar, A., Quintana, R., Martí, E., Markelain, G., Cabrera-Castro, R., Arroyo, G. M., Montero, E., Morales-Caselles, C., 2023. Artisanal trawl fisheries as a sentinel of marine litter pollution. Mar. Pollut. Bull. 191, 114882 https://doi.org/10.1016/j.marpolbul.2023.114882.

Wood, Simon, 2023. Mixed GAM Computation Vehicle with Automatic Smoothness Estimation. CRAN Repository. https://doi.org/10.1201/9781315370279.

Woodall, L.C., Sanchez-Vidal, A., Canals, M., Paterson, G.L.J., Coppock, R., Sleight, V., Calafat, A., Rogers, A.D., Narayanaswamy, B.E., Thompson, R.C., 2014. The deep sea is a major sink for microplastic debris. R. Soc. Open Sci. 1 https://doi.org/10.1098/RSOS.140317.

Wright, D., 2011. GIS for the Oceans.