

Article

Deciphering Soil Hydro-Physical Controls on Microplastic Fate Using Explainable Machine Learning

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Abstract

Understanding the environmental fate of microplastics (MPs) in agricultural soils remains a major challenge, particularly under field conditions where soil structure and hydraulic processes jointly regulate particle transport and retention. This study investigated whether hydro-physical soil functioning can explain the distribution and accumulation of MPs in pistachio orchard soils from a semi-arid region of southeastern Türkiye. A total of 42 soil samples were analyzed for MP abundance, size distribution, and morphology, together with key hydro-physical properties including texture, porosity, bulk density, aggregate stability, organic matter content, and soil water retention characteristics. To identify the dominant controls on MP occurrence, explainable machine learning approaches combining Random Forest (RF), Gradient Boosting Decision Trees (GBDT), and SHAP (SHapley Additive exPlanations) analysis were employed. Microplastic abundance differed among management systems. Former landfill or construction sites represented the largest proportion of the total recorded microplastic abundance (40.9%), followed by conventionally managed (25.2%), manure-amended (24.5%), and sewage-sludge-amended orchards (9.4%). Median microplastic abundances were 1433, 667, 4633, and 633 particles kg⁻¹ soil, respectively. Fine-sized MPs constituted the dominant particle fraction and exhibited strong associations with pore-system characteristics, indicating that pore-size compatibility governs their retention and mobility within the soil matrix. Morphology-specific analyses further revealed contrasting relationships between soil hydro-physical properties and individual MP forms, suggesting distinct retention pathways for granules, films, fragments, and fibers. Explainable AI analysis identified organic matter, silt content, bulk density, and water retention characteristics as the most influential predictors of MP occurrence. Among the tested models, RF demonstrated superior predictive robustness and generalization capacity. The findings demonstrate that hydro-physical soil functioning plays a central role in determining microplastic fate in agricultural soils and highlight the value of interpretable machine learning frameworks for uncovering the mechanisms underlying contaminant retention and redistribution. Integrating soil structural indicators with explainable artificial intelligence offers a promising pathway for improving microplastic risk assessment in agroecosystems.

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1. Introduction

Plastic contamination has emerged as one of the most pervasive environmental challenges of the twenty-first century. Although scientific attention initially focused on marine and freshwater ecosystems, growing evidence indicates that soils represent an equally important, and potentially larger, environmental sink for plastic-derived particles [1,2]. Due to repeated anthropogenic inputs and the limited mobility of contaminants in terrestrial systems, agricultural soils can accumulate substantial quantities of microplastics (MPs), thereby creating long-term reservoirs of plastic pollution. Beyond their persistence, MPs have attracted increasing concern because of their potential to influence soil functions that are fundamental for sustainable land management, including water regulation, nutrient cycling, carbon sequestration, and aggregate formation [3–6].

Agricultural environments are exposed to MPs through a variety of pathways. Organic amendments such as compost, livestock manure, and sewage sludge may introduce considerable numbers of plastic particles into cultivated soils [7–10]. In addition, the extensive use of plastic mulches, irrigation materials, greenhouse coverings, and other agricultural plastics contributes to the generation of secondary MPs through weathering and fragmentation processes. Atmospheric deposition has also been identified as a significant source, transporting MPs across considerable distances and delivering them even to remote agricultural landscapes. Consequently, MP contamination is no longer considered a localized phenomenon but rather a widespread component of modern agroecosystems [11,12].

Despite increasing documentation of MP occurrence in soils, the mechanisms governing their retention, redistribution, and long-term accumulation remain insufficiently understood. The environmental behavior of MPs is controlled not only by their intrinsic properties, such as size, shape, density, and surface characteristics, but also by the structural and hydraulic properties of the surrounding soil matrix [13–15]. Soil texture, pore-size distribution, pore connectivity, bulk density, and aggregate stability can directly influence particle transport pathways and retention processes. Previous studies have shown that fine particles may be retained through straining and filtration mechanisms, whereas larger particles are often restricted by physical barriers within the pore network. However, most available evidence has been derived from laboratory-scale column experiments or controlled incubation studies, which may not adequately represent the complexity and heterogeneity of field conditions [16].

In natural agricultural systems, hydro-physical soil functioning results from the interaction of soil structure, water retention characteristics, and pore-network architecture. These properties collectively regulate water movement, aeration, and particle transport within the soil profile [5,6,17]. Therefore, understanding MP behavior requires an integrated evaluation of soil hydro-physical characteristics rather than focusing on individual soil properties in isolation. Field-based studies investigating these interactions remain scarce, particularly in semi-arid environments where repeated wetting–drying cycles and strong seasonal fluctuations may substantially affect MP mobility and retention [15,16].

The inherently complex nature of soil systems presents additional challenges for identifying the dominant controls on MP distribution. Relationships between MPs and soil properties are often nonlinear, interactive, and scale-dependent, limiting the explanatory power of conventional statistical approaches [18,19]. In recent years, machine learning techniques have become increasingly valuable for analyzing complex environmental datasets because they can capture nonlinear relationships and interactions among

predictors. Nevertheless, predictive accuracy alone is insufficient when the objective is to understand the environmental processes underlying model outputs. Explainable artificial intelligence approaches, particularly SHAP (SHapley Additive exPlanations), provide an opportunity to interpret machine learning predictions and quantify the contribution of individual variables, thereby offering mechanistic insights alongside predictive capability [20,21]. Machine learning approaches, including tree-based ensembles and deep-learning models, have recently been applied to predict and interpret microplastic occurrence in soils and related environmental media, underscoring their growing role in this field [22–24].

Pistachio orchards constitute one of the most important agricultural systems in southeastern Türkiye and are increasingly exposed to diverse sources of plastic contamination associated with modern agricultural practices and organic amendments [9–12]. However, information on how hydro-physical soil functioning regulates the occurrence, retention, and redistribution of microplastics under field conditions remains limited, particularly in perennial orchard systems such as pistachio orchards. Although several studies have documented the occurrence of microplastics in agricultural soils, few have explicitly linked microplastic accumulation patterns to pore-system characteristics, water retention behavior, and soil structural functioning using field observations [13–16]. Moreover, explainable artificial intelligence has rarely been applied to identify and interpret the relative importance of these hydro-physical controls. Addressing these knowledge gaps is essential for improving mechanistic understanding of microplastic behavior and supporting sustainable soil management in semi-arid agroecosystems.

Therefore, the objectives of this study were to (i) quantify MP abundance, size distribution, and morphological composition in pistachio orchard soils subjected to different management histories, (ii) evaluate the relationships between MPs and key hydro-physical soil properties, and (iii) identify the most influential predictors controlling MP accumulation using explainable machine learning approaches. We hypothesized that soil hydro-physical functioning, represented by pore-size distribution, water retention behavior, and structural stability, exerts stronger control over MP retention and partitioning than texture or organic matter content alone. By integrating field observations with interpretable machine learning models, this study provides new insights into the mechanisms governing MP fate in agricultural soils and contributes to the development of more robust frameworks for assessing microplastic contamination in land-based ecosystems.

2. Materials and Methods

2.1. Study Area

The study was conducted in commercial pistachio orchards located in Siirt Province, southeastern Türkiye (Figure 1). The region represents one of the major production areas for Siirt pistachio and is characterized by a continental climate with hot, dry summers and cool, wet winters. Long-term climatic records indicate a mean annual temperature of 16.3 °C and an average annual precipitation of approximately 716 mm. Historical temperature records range from −19.3 °C to 46.0 °C [25]. In addition to conventional orchard management, some fields in the study area have received sewage sludge originating from the Siirt Municipal Wastewater Treatment Plant as a soil amendment. This practice provided an opportunity to investigate microplastic occurrence under contrasting management histories and potential contamination sources. The study area encompasses a heterogeneous soil landscape developed under semi-arid climatic conditions and diverse parent materials. Accordingly, the investigated orchards do not represent a single Reference Soil Group according to the World Reference Base for Soil Resources. Instead, the dominant soils occurring across the study area are mainly represented by Calcisols, Cambisols, Leptosols, Fluvisols, and locally Vertisols, reflecting variations in geomorphology, parent material, and landscape position.

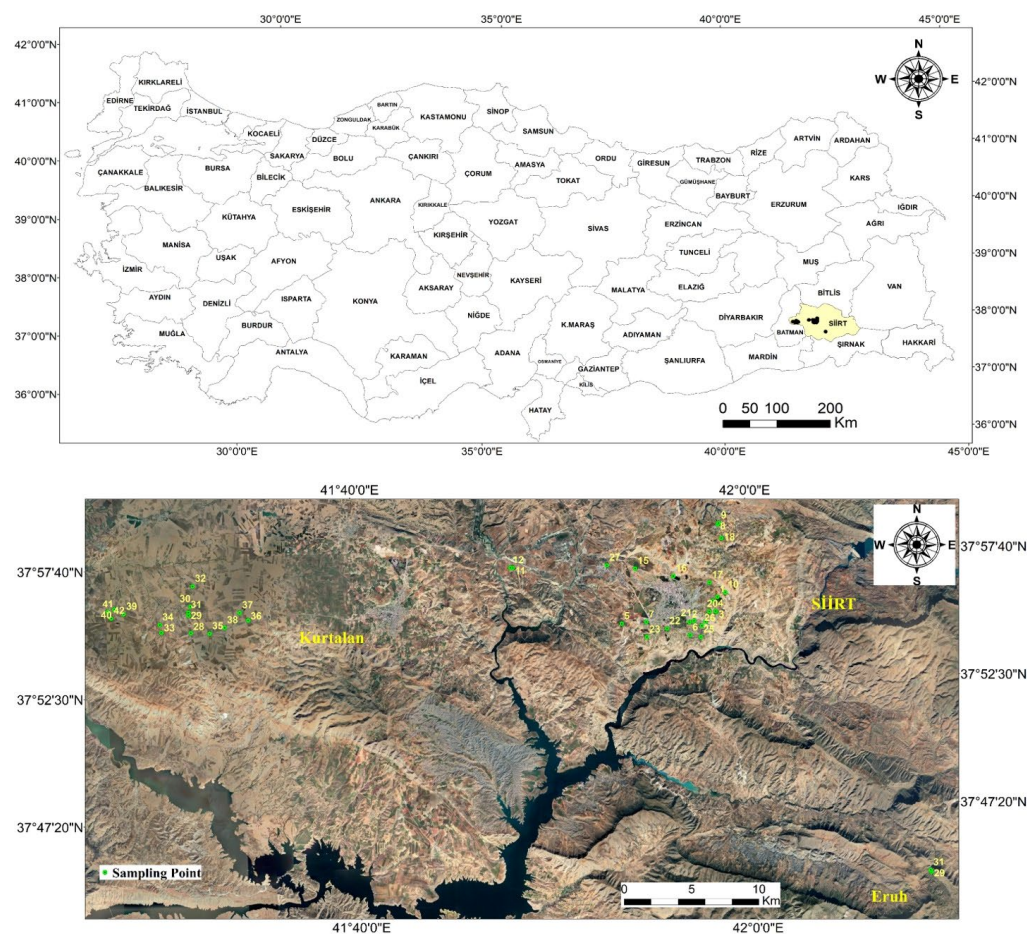


Figure 1. Location of the study area and soil sampling sites in Siirt Province, southeastern Türkiye.

2.2. Soil Sampling and Laboratory Analyses

A total of 42 surface soil samples were collected in December 2024 from pistachio orchards distributed across Siirt Province, Türkiye, representing different management conditions, including sewage-sludge-amended, manure-amended, and conventionally managed sites. The sampling strategy was designed to capture the principal potential sources of microplastic contamination in the region. Accordingly, orchards receiving sewage sludge or animal manure applications, orchards located near a former municipal solid waste disposal site, the city center, and major transportation routes, as well as orchards where pistachio seedlings had previously been cultivated in plastic nursery tubes, were included in the sampling scheme. Sampling locations were distributed throughout the study area, with distances between orchards ranging from approximately 0.2 to 20 km to ensure broad spatial representativeness.

Sampling was performed at a depth of 0–15 cm, corresponding to the topsoil layer most directly influenced by agricultural management practices and potential microplastic inputs. This depth was selected because pistachio orchards in the study area generally have relatively shallow soils, and sewage sludge, manure, and other surface amendments are typically incorporated into the upper soil layer through routine tillage. Moreover, the majority of active roots are concentrated within this surface horizon, making the 0–15 cm layer the most relevant zone for assessing microplastic accumulation under local management conditions. Similar sampling depths have also been adopted in previous agricultural soil microplastic studies [26–28]. At each orchard, three subsamples were randomly collected, homogenized, and combined into a single composite sample representative of the orchard before transportation to the laboratory. Orchard classification was based on

historical management records, including sewage sludge application, manure application, and previous nursery practices involving plastic seedling tubes.

To minimize contamination during field sampling and laboratory processing, all equipment were thoroughly cleaned before use, and samples were transported in aluminum-foil-lined containers. Soil designated for microplastic analysis was sieved to <5 mm and stored in glass containers. Additional subsamples intended for soil characterization were passed through a 2 mm sieve. Undisturbed soil cores (100 cm³ steel cylinders; two replicates per site) were collected for the determination of bulk density and water retention properties. Following air drying, visible plant residues and coarse organic materials were manually removed prior to analysis. The physical and hydro-physical properties evaluated in this study, together with the analytical methods employed, are summarized in Table 1.

Table 1. Soil hydro-physical properties measured, and analytical methods employed for their determination.

Property	Method	Reference
Texture	Bouyoucos hydrometer method	[29]
Bulk density	Core method	[30]
Field Capacity (FC), Permanent Wilting Point (PWP)	Pressure plate apparatus	[31]
Water =Filled Pore Space (WPFS)	Calculated from total porosity and volumetric water content	[32]
Aggregate stability	Wet sieving method	[33]
Organic Matter	Modified Walkley-Black method	[34]

2.3. Microplastic Extraction and Characterization

Microplastics were isolated using a density separation procedure adapted from Liu et al. [35]. Soil samples previously sieved to <5 mm were dried at 60 °C for 24 h. Subsequently, 30 g subsamples were subjected to three consecutive density separations using a NaCl solution with a density of 1.2 g cm⁻³. The supernatant obtained after each separation step was passed through a 33 µm mesh, and residual organic matter was removed using 30% H₂O₂ at 60 °C for 72 h. Following digestion, the suspension was vacuum-filtered onto Whatman GF/C glass-fiber filters (Cytiva, Little Chalfont, UK).

Potential microplastic particles were visually identified using a Zeiss stereomicroscope (Stemi Series; Carl Zeiss Microscopy GmbH, Jena, Germany) operated at magnifications ranging from 1× to 50×, and image acquisition was performed using Labscope software (v4.4.0; Carl Zeiss Microscopy GmbH, Jena, Germany).. Digital images were analyzed using ImageJ software (version 1.54, National Institutes of Health, Bethesda, MD, USA) to determine particle dimensions. Identified particles were classified according to morphology (fiber, fragment, film, and granule) and assigned to predefined size classes ranging from <200 µm to >5 mm.

2.4. Feature Selection and Predictor Screening

Prior to model development, predictor variables were evaluated to reduce redundancy and minimize multicollinearity. Spearman rank correlation analysis was used to identify highly correlated variables, and variance inflation factor (VIF) analysis was applied as an additional screening criterion (Table 2).

Clay content was excluded from the final predictor set because of its strong association with both microporosity and wilting point. To retain mechanistically meaningful information while avoiding redundancy, microporosity was retained as a direct indicator of soil pore structure and wilting point as an indicator of water retention behavior. The final predictor set consisted of organic matter content, silt content, bulk density, available water content, wilting point, sand content, aggregate stability, and macroporosity. All retained predictors exhibited variance inflation factors below the conventional threshold of 10 (wilting point = 8.3, sand = 7.5, bulk density = 4.7, macroporosity = 3.6, available water

content = 2.2, silt = 2.2, organic matter = 1.7, aggregate stability = 1.6); the complete VIF screening of all candidate variables and the final predictor set is provided in Supplementary Table S1.

Table 2. Spearman correlation coefficients among soil physical and hydraulic properties.

	Clay	Silt	Sand	AS	OM	FC	WP	AW	TP	MicP	MacP	BD	WFPS
Clay	1	−0.15	−0.90 **	0.35 *	−0.27	0.87 **	0.28	0.45 **	0.44 **	0.88 **	−0.06	−0.43 **	0.56 **
Silt		1	−0.29	−0.42 **	0.21	0.02	−0.42	−0.04	0.22	−0.03	0.13	−0.26	−0.09
Sand			1	−0.15	0.17	−0.85 **	−0.45 **	−0.41 **	−0.52 **	−0.86 **	0.06	0.53 **	−0.50 **
AS				1	−0.07	0.37 *	0.17	0.39 *	0.11	0.37 *	−0.07	0.02	0.22
OM					1	−0.13	0.02	−0.39	−0.31	−0.14	0.38	0.05	0.08
FC						1	−0.32	0.06 **	0.41	0.98	0.05	−0.35 *	0.72 **
WP							1	0.14	−0.21	−0.32	−0.07	0.28	−0.22
AW								1	0.36	0.62 **	−0.04	0.09	0.41 **
TP									1	0.46	−0.04	−0.72 **	−0.29
MicP										1	0.05	−0.39 **	0.68 **
MacP											1	0.05	0.07
BD												1	0.21
WFPS													1

AS: aggregate stability; OM: organic matter; FC: field capacity; WP: wilting point; TP: total porosity; AW: available water content; MicP: microporosity; MacP: macroporosity; BD: bulk density; WFPS: water-filled pore space; significance levels are indicated by * $p < 0.05$, ** $p < 0.01$

2.5. Machine Learning Modeling and Interpretation

Microplastic abundance (particles kg^{-1} soil) was modeled using Random Forest (RF) and Gradient Boosting Decision Tree (GBDT) algorithms. Tree-based models were selected because of their ability to capture nonlinear relationships and interactions among environmental variables without required standardization. Because microplastic abundance was strongly right-skewed (skewness = 1.6), the target was log-transformed as modeling+ 1) prior to modelling, and all error metrics were back-transformed to the original scale (particles kg^{-1}) to preserve physical interpretability.

Given the small sample size ($N = 42$) relative to the number of predictors ($P = 8$), a single train–test partition yields unstable and optimistically biased performance estimates; nested cross-validation was therefore adopted to obtain an unbiased evaluation [36,37]. An outer leave-one-out cross-validation (LOOCV) loop was used for performance estimation, while an inner three-fold GridSearchCV loop performed hyperparameter tuning, so that model selection and error estimation were kept strictly separate and selection-induced optimism was avoided [38].

Hyperparameters were formally optimized rather than fixed a priori. The search space deliberately constrained model complexity to limit overfitting: for RF, the number of trees, maximum tree depth ($\in \{3, \text{unrestricted}\}$), minimum samples per leaf, and the fraction of features per split; for GBDT, the learning rate ($\in \{0.03, 0.05\}$), maximum tree depth ($\in \{2, 3\}$), and subsampling fraction. The selected hyperparameter combinations are reported in Supplementary Table S2. Because each outer LOOCV fold contains a single test observation, a per-fold coefficient of determination is undefined; R^2 was therefore computed on the pooled out-of-fold predictions and is reported as Q^2_{LOO} [36].

Three complementary robustness analyses were added. First, a repeated five-fold cross-validation (three repeats) with a 95% percentile interval was used to characterize the variance of the performance estimate (Molinario et al., 2005) [39]. Second, a mean-predictor null model and a label permutation test (60 permutations of the target) were used to assess whether the observed performance exceeded that expected by chance [40]. Third, because

the 42 sampling points are distributed across orchards and may exhibit spatial autocorrelation, a spatial block cross-validation was performed using Group KFold on 15 orchard blocks delineated by geographic proximity, thereby preventing spatial proximate samples from occurring simultaneously in the training and test folds [41].

As a sensitivity analysis addressing whether site management history improves prediction beyond hydro-physical functioning, management categories (conventional, manure-amended, sewage-sludge-amended, and former landfill/construction) were additionally one-hot encoded and appended to the predictor set, and the LOOCV performance was re-estimated. All machine learning analyses were implemented in Python 3.10 using scikit-learn, with a fixed random seed (`random_state = 42`) to ensure reproducibility.

To improve model interpretability, variable importance was assessed using permutation importance for RF and gain-based importance metrics for GBDT. In addition, SHAP (SHapley Additive exPlanations) analysis was employed to quantify the contribution of individual predictors to model outputs [20,21]. Global variable importance was evaluated using mean absolute SHAP values, while SHAP summary plots were used to visualize the direction and magnitude of predictor effects on microplastic abundance.

2.6. Statistical Analysis

Descriptive statistics and correlation analyses were performed using XLSTAT software (version 2023.3.1; Addinsoft, Paris, France). Because microplastic abundance data exhibited non-normal distributions and substantial variability among sampling sites, median values and interquartile ranges were used to describe central tendency and dispersion.

Relationships between soil hydro-physical properties and microplastic characteristics were evaluated using Spearman rank correlation analysis. All machine learning analyses, including model training, nested cross-validation, and SHAP interpretation, were conducted in Python 3.10 using the scikit-learn framework [42]. Model performance was assessed using the coefficient of determination computed on pooled out-of-fold predictions (Q^2_{LOO}), root mean square error (RMSE), and mean absolute error (MAE), all reported on the original measurement scale.

3. Results

3.1. Variability of Soil Hydro-Physical Properties

Substantial spatial variability was observed among the investigated pistachio orchard soils (Table 3). Texture ranged from sandy to clay-rich conditions, reflecting the heterogeneous nature of the study area. Clay content exhibited considerable variation, whereas silt content showed a narrower distribution. Aggregate stability values were generally high, indicating relatively stable soil structural conditions across most sites.

Organic matter content displayed the greatest variability among the measured soil properties, suggesting strong differences in management history and organic inputs among orchards. Water retention characteristics also varied substantially, with field capacity and wilting point spanning wide ranges. Similarly, total porosity and pore-size distribution exhibited marked differences among sampling locations. Macroporosity showed the highest coefficient of variation among pore-related parameters, indicating considerable heterogeneity in preferential flow pathways and soil structural organization. Bulk density was comparatively stable across the study area, whereas water-filled pore space exhibited moderate variability.

Table 3. Descriptive statistics of soil physical, hydraulic, and microplastic-related properties across the study sites.

Variables	Unit	Min	Max	Mean	SD	CV (%)	Skewness	Kurtosis
Clay	%	10.0	60.9	38.5	14.1	37	−0.27	−0.95
Silt		10.0	36.6	21.9	6.4	29	0.09	−0.83
Sand		18.6	77.7	39.6	14.6	37	0.86	0.05
Aggregate Stability		32.2	79.1	60.7	13.8	23	−0.45	−1.05
Organic Matter		0.74	11.36	2.92	1.84	63	2.39	8.21
Field Capacity		14.1	42.9	32.4	6.9	21	−0.73	−0.21
Wilting Point		6.8	28.0	18.4	5.4	29	−0.13	−0.67
Available Water		6.0	21.4	14.0	3.6	26	−0.26	−0.49
Total Porosity	cm ³ cm ^{−3}	0.35	0.76	0.50	0.10	19	0.91	0.42
Micro Porosity		0.14	0.42	0.32	0.07	21	−0.74	−0.21
Macro Porosity		0.06	0.43	0.18	0.09	48	1.01	0.42
Bulk Density	g cm ^{−3}	1.04	1.72	1.42	0.15	11	−0.32	−0.16
WFPS	%	34.2	87.8	65.6	13.3	20	−0.58	−0.47

WFPS: water-filled pore space; SD: standard deviation; CV: coefficient of variation.

3.2. Microplastic Abundance Under Different Management Histories

Microplastic abundance differed markedly among sampling locations and management categories (Table 4). Across all sites, MP concentrations exhibited a highly skewed distribution, with a limited number of locations accounting for disproportionately high particle counts. Consequently, median values were considered more representative than arithmetic means.

Microplastic abundance differed among land-use and management types (Table 4). Descriptive statistics showed that manure-amended orchards exhibited the highest median microplastic abundance (4633 particles kg^{−1} soil), followed by former landfill or construction sites (1433 particles kg^{−1} soil), conventionally managed orchards (667 particles kg^{−1} soil), and sewage-sludge-amended orchards (633 particles kg^{−1} soil). Although these descriptive statistics indicated numerical differences among management groups, the Kruskal–Wallis test showed that the differences were not statistically significant ($H = 3.43$, $p = 0.330$), reflecting considerable within-group variability.

Table 4. Descriptive statistics of soil microplastic abundance (particles kg^{−1} soil) by management history and legacy site conditions in pistachio orchards.

Microplastic Source	Min	Max	Q1	Median	Q3	Mean	CV (%)	Skewness	Kurtosis
Total number of plastics	100	8533	317	1083	2425	1973	121	1.59	1.35
Former Landfill or Construction site	133	8533	392	1433	2425	2424	114	1.23	−0.07
Manure Applied	200	7733	867	4633	6867	4060	75	−0.13	−1.70
Conventional Farming	233	5967	400	667	2867	1605	103	1.36	1.01
Sewage Sludge Applied	100	1833	317	633	1142	780	74	0.52	−1.08

CV: coefficient of variation; Q1: first quartile; Q3: third quartile. Although median values differed among management groups, the Kruskal–Wallis test indicated that these differences were not statistically significant ($H = 3.43$, $p = 0.330$).

3.3. Microplastic Morphology and Size Distribution

Microplastic particles displayed pronounced differences in both morphology and size distribution (Table 5, Figure 2). Granules represented the dominant particle type across the study area, whereas fibers constituted the second most abundant morphology.

In contrast, fragments and films occurred less frequently and were characterized by highly heterogeneous spatial distributions.

Size distribution analysis revealed a strong dominance of the smallest particle fraction ($<200\ \mu\text{m}$), with abundance declining progressively as particle size increased. Larger size classes occurred less frequently and contributed only a minor proportion of the total MP pool. The predominance of fine particles suggests extensive fragmentation and weathering processes within the soil environment. The large coefficients of variation observed for several morphological and size categories indicate substantial spatial heterogeneity, reflecting differences in contamination sources, management practices, and local soil conditions.

Table 5. Descriptive statistics of microplastics (particles kg^{-1} soil) by shape and size class in soil samples.

Statistic	Min	Max	Q1	Median	Q3	Mean	CV %	Skewness	Kurtosis
Fiber	33	533	133	200	300	228	58	0.84	−0.26
Fragment	0	233	0	0	67	33	157	1.97	4.18
Film	0	100	0	0	0	6	348	3.68	12.44
Granule	0	8200	167	733	2217	1707	133	1.56	1.14
0–200 μm	0	8300	167	750	2217	1732	133	1.57	1.20
200–500 μm	0	233	0	33	92	52	117	1.15	0.49
500 μm –1 mm	0	167	33	33	67	51	80	1.20	1.17
1–2 mm	0	300	33	67	67	66	93	1.79	3.97
2–5 mm	0	267	33	50	100	73	92	1.08	0.55

CV: Coefficient of variation; Q1: first quartile; Q3: third quartile.



Figure 2. Microplastic particles of diverse morphology and size in sewage sludge-amended pistachio orchard soils.

Spearman rank correlation analysis revealed distinct relationships between MP size fractions and soil properties (Table 6). The finest fraction (0–200 μm) showed a significant positive correlation with aggregate stability ($r = 0.31$, $p < 0.05$) but strong negative correlations with macroporosity ($r = -0.49$, $p < 0.01$), total porosity ($r = -0.41$, $p < 0.01$), and field capacity ($r = -0.41$, $p < 0.01$). The 200–500 μm fraction was negatively correlated only with macroporosity ($r = -0.48$, $p < 0.01$). Intermediate-sized MPs (500 μm –1 mm) were positively correlated with microporosity ($r = 0.49$, $p < 0.01$), clay content ($r = 0.39$, $p < 0.05$), and water-filled pore space ($r = 0.41$, $p < 0.01$), while showing a negative association with wilting

point ($r = -0.33$, $p < 0.05$). The largest particles (2–5 mm) were positively associated with organic matter content ($r = 0.36$, $p < 0.05$) and bulk density ($r = 0.36$, $p < 0.05$).

Table 6. Spearman correlation coefficients between selected soil properties and the abundance of microplastic size categories.

Soil Property	0–200 μm	200–500 μm	500 μm –1 mm	1–2 mm	2–5 mm
Clay	−0.30	−0.08	0.39 *	0.03	0.17
Silt	0.20	0.04	−0.30	0.10	−0.11
Sand	0.22	0.03	−0.23	−0.06	−0.17
Organic Matter	−0.11	−0.16	0.09	0.20	0.36 *
Aggregate Stability	0.31 *	0.15	0.17	−0.10	−0.13
Total Porosity	−0.41 **	−0.11	0.36 *	0.06	0.06
Micro Porosity	−0.14	0.20	0.49 **	0.03	−0.04
Macro Porosity	−0.49 **	−0.48 **	0.02	0.08	0.18
Bulk Density	−0.28	−0.28	0.08	0.21	0.36 *
Field Capacity	−0.41 **	−0.12	0.36 *	0.06	0.06
Wilting Point	−0.08	−0.29	−0.33 *	0.09	0.27
Available Water	−0.03	−0.13	−0.17	−0.11	−0.05
Water-Filled Pore Space	−0.12	0.17	0.41 **	−0.01	−0.23

Statistically significant correlation coefficients are shown in bold; significance levels are indicated by * $p < 0.05$, ** $p < 0.01$.

Shape-specific correlations also showed clear patterns (Table 7). Total MP abundance was significantly negatively correlated with available water content ($r = -0.46$, $p < 0.01$) and microporosity ($r = -0.33$, $p < 0.05$). Granules exhibited strong negative correlations with available water content ($r = -0.49$, $p < 0.01$), microporosity ($r = -0.41$, $p < 0.01$), and clay content ($r = -0.31$, $p < 0.05$), but a positive correlation with organic matter ($r = 0.31$, $p < 0.05$). Films were positively correlated with both organic matter ($r = 0.41$, $p < 0.01$) and silt content ($r = 0.32$, $p < 0.05$). Fragments showed a significant positive association only with aggregate stability ($r = 0.32$, $p < 0.05$). Fibers, present in all samples, displayed no statistically significant correlations with any measured soil parameter.

Table 7. Spearman correlation coefficients between selected soil properties and the relative abundance of microplastic shape categories.

Soil Property	Total MP	Fiber	Fragment	Film	Granule
Clay	−0.22	0.15	0.21	−0.06	−0.31 *
Silt	0.18	−0.03	−0.07	0.32 *	0.20
Sand	0.15	−0.15	−0.16	−0.06	0.22
Organic Matter	0.27	−0.02	0.25	0.41 **	0.31 *
Aggregate Stability	−0.06	0.10	0.32 *	0.03	−0.10
Total Porosity	−0.21	0.08	0.17	0.04	−0.28
Microporosity	−0.33 *	0.03	0.18	0.07	−0.41 **
Macroporosity	−0.09	−0.06	−0.05	−0.08	−0.08
Bulk Density	−0.06	−0.11	−0.30	−0.14	−0.02
Field Capacity	−0.33 *	0.04	0.17	0.06	−0.41 **
Wilting Point	−0.06	0.23	0.25	0.15	−0.14
Available Water	−0.46 **	−0.22	−0.02	−0.12	−0.49 **
Water- Filled Pore Space	−0.08	0.03	0.07	0.07	−0.12

Statistically significant correlation coefficients are shown in bold; significance levels are indicated by * $p < 0.05$, ** $p < 0.01$.

3.4. Predictor Importance and Model Interpretation

Explainable machine learning analysis revealed that a limited subset of soil properties accounted for most of the variation in MP abundance (Figure 3). Among the evaluated predictors, organic matter content and silt content emerged as the dominant variables influencing model predictions. Bulk density and available water content also contributed substantially, whereas aggregate stability, sand content, and macroporosity exerted comparatively smaller effects.

The SHAP summary analysis provided additional insight into the direction of predictor effects. Higher organic matter and silt contents were generally associated with increased predicted MP abundance, indicating enhanced particle retention under conditions favoring organo-mineral interactions and fine-textured soil environments. In contrast, higher bulk density and greater available water content tended to reduce predicted MP abundance, suggesting lower accumulation potential under denser soil conditions or where particle redistribution may be facilitated.

Although several hydro-physical variables contributed simultaneously to model predictions, their relative influence differed considerably, highlighting the complex and non-linear nature of MP–soil interactions. These results demonstrate that MP occurrence cannot be explained by a single soil property but instead reflects the combined influence of structural, textural, and water retention characteristics.

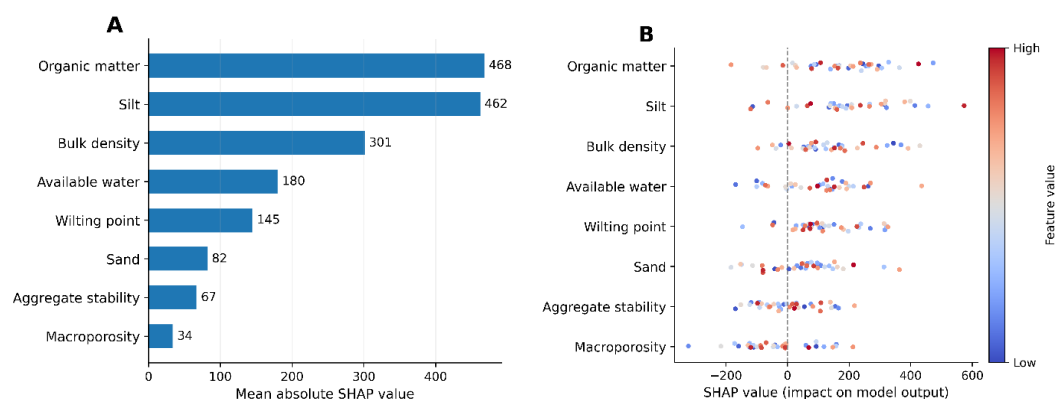


Figure 3. SHAP-based interpretation of predictor importance and effects on microplastic abundance. (A) Mean absolute SHAP values showing the overall importance of the selected soil hydro-physical predictors. (B) SHAP summary plot illustrating the magnitude and direction of each predictor's contribution to model predictions. Each point represents an individual observation, and color indicates the corresponding feature value (red = high, blue = low). The vertical dashed line represents a SHAP value of zero (no impact on model output).

3.5. Model Performance

The two algorithms were re-evaluated under the nested leave-one-out cross-validation framework, and the results differ markedly from the optimistic estimates obtained from a single train–test split (revised Table 8). Under a single 70/30 split the models appeared skillful (GBDT training $R^2 = 1.00$; RF training $R^2 = 0.87$), but their performance on the held-out fold collapsed (GBDT test $R^2 = -0.27$; RF test $R^2 = 0.15$), confirming the overfitting anticipated for $N = 42$ with eight predictors. Under nested LOOCV, RF yielded $Q^2_{LOO} = 0.04$ and GBDT yielded $Q^2_{LOO} = -0.30$, the latter being poorer than a mean-predictor null model ($Q^2 = -0.05$). Repeated five-fold cross-validation gave RF $R^2 = 0.11$ (95% CI 0.07–0.14) and a negative mean for GBDT, while spatial block cross-validation reduced both estimates further (RF = -0.06 ; GBDT = -0.43). A label permutation test indicated that the RF performance was not statistically distinguishable from chance ($p = 0.11$), and one-hot

encoding of management history did not improve prediction ($Q^2_{LOO} = 0.05$ versus 0.04). Taken together, these results indicate that RF is the more stable of the two algorithms but that hydro-physical predictors alone do not provide a generalizable quantitative predictor of absolute microplastic abundance in this small, heterogeneous field dataset; the models are therefore interpreted as descriptive tools for identifying influential variables rather than as predictive instruments.

Table 8. Model performance summary.

Model	Q^2_{LOO}	R^2 5-Fold CV (Mean $\pm$ SD)	95% CI	R^2 Spatial	CVRMSE (Particles kg^{-1})	MAE (Particles kg^{-1})
Random Forest	0.04	0.11 ± 0.03	0.07–0.14	−0.06	2447	1490
Gradient Boosting	−0.30	$−0.25 \pm 0.19$	−0.46 to −0.03	−0.43	2673	1778
Null model (mean)	−0.05	n/a	n/a	n/a	2583	1589

Q^2_{LOO} : leave-one-out cross-validated coefficient of determination; R^2 : coefficient of determination; CV: cross-validation; SD: standard deviation; CI: confidence interval; RMSE: Root Mean Square Error; MAE: Mean Absolute Error.

4. Discussion

4.1. Legacy Land Use and Management Effects on Microplastic Accumulation

The marked differences in MP abundance among the investigated orchards indicate that historical land use and management practices remain important determinants of MP accumulation in pistachio-growing soils. The highest MP concentrations were observed in sites located on or near former landfill and construction areas, where median abundances exceeded those recorded under conventional agricultural management by several fold. These findings suggest that legacy contamination sources continue to influence soil MP inventories long after the original waste inputs have ceased, highlighting the long-term persistence of plastic particles in terrestrial environments.

Orchards receiving sewage sludge amendments contained greater MP abundances than conventionally managed sites, supporting previous evidence that wastewater-derived materials represent an important pathway for MP introduction into agricultural soils [43,44]. However, MP concentrations in the present study were considerably lower than those reported from long-term sludge-application experiments. Such differences may reflect variation in sludge characteristics, treatment efficiency, application frequency, and environmental conditions. In addition, the semi-arid climate of the study area may facilitate the redistribution of smaller particles through preferential flow pathways during episodic wetting events, thereby reducing surface accumulation [16].

Compared with sewage sludge, manure applications appeared to contribute less substantially to MP enrichment. Although livestock manure has been recognized as a potential carrier of MPs originating from feed additives, packaging materials, and agricultural plastics, its influence in the studied orchards was relatively limited [8,10]. The contrasting MP abundances observed among management types can be explained by differences in both the quantity and persistence of plastic inputs and the subsequent interactions between particles and the soil environment. Sewage sludge constitutes a direct pathway for introducing large numbers of secondary microplastics originating from household wastewater, synthetic textile fibers, personal care products, and fragmented urban plastic debris that are not completely removed during wastewater treatment [9,45]. Once introduced into agricultural soils, these particles may become physically retained within stable soil aggregates and fine pore domains through filtration, mechanical straining, pore throat restriction, and organo-mineral interactions, thereby promoting their long-term persistence under field conditions. In contrast, conventionally

managed orchards receive comparatively fewer direct plastic inputs, whereas manure-amended soils generally contain lower microplastic loads because most plastic contamination originates indirectly from livestock feed, bedding materials, or agricultural packaging rather than from concentrated urban waste streams. Consequently, differences among management systems reflect not only variation in the amount of plastic introduced but also differences in the capacity of soils to retain and preserve these particles over time.

Overall, the results indicate that legacy contamination and wastewater-derived amendments exert stronger controls on MP accumulation than routine agricultural management practices. This interpretation is further supported by recent regional studies identifying former waste disposal sites as persistent hotspots of soil MP contamination [46,47].

4.2. Hydro-Physical Regulation of Microplastic Size Distribution

The observed relationships between MP size classes and soil hydro-physical properties indicate that particle retention is closely linked to the architecture of the soil pore system. Among all size fractions, the smallest MPs exhibited the strongest associations with pore-related variables, suggesting that pore-size distribution plays a central role in determining their mobility and accumulation.

Fine MPs (<200 μm) were negatively associated with macroporosity, total porosity, and field capacity, implying greater retention in soils characterized by restricted pore connectivity. This pattern is consistent with physical filtration and size-exclusion mechanisms, where the likelihood of particle retention increases as pore-throat dimensions approach particle size [1,48]. Conversely, soils containing well-developed macropore networks may facilitate preferential transport and downward movement of fine particles, particularly under repeated wetting–drying cycles typical of semi-arid environments [15,16].

Intermediate-sized MPs displayed positive relationships with microporosity and clay content, suggesting selective accumulation within finer pore domains. Such environments provide a larger number of retention sites and reduce particle mobility through increased physical impedance [14]. In contrast, larger particles exhibited comparatively weak relationships with most pore-system variables but showed positive associations with organic matter content and bulk density, indicating reduced transport potential and enhanced surface retention.

Although organic matter is frequently considered an important factor governing MP persistence in soils, significant linear relationships between organic matter and MP size fractions were not detected in the present study. This discrepancy may reflect the inherently nonlinear nature of MP–soil interactions under field conditions, where multiple physical and hydraulic processes operate simultaneously [18,19].

Our findings are also consistent with recent field investigations conducted in other agricultural systems. For example, field studies have shown that microplastic accumulation and redistribution in agricultural soils are jointly controlled by soil physical characteristics and management-related inputs, including mulching practices, irrigation, and organic amendments [49]. Likewise, recent experimental evidence has demonstrated that soil texture and pore architecture strongly influence particle retention and connectivity, thereby affecting microplastic transport within the soil profile [5]. Although the relative contribution of individual factors varies among agricultural systems, these studies collectively support our conclusion that hydro-physical soil properties play a central role in regulating the environmental fate and retention of microplastics under field conditions.

4.3. Morphology-Dependent Retention Mechanisms

In addition to particle size, MP morphology appeared to influence retention patterns within the studied soils. The contrasting relationships observed among fibers, granules, films, and fragments suggest that different particle shapes interact with soil structural features through distinct transport and retention mechanisms.

Fibers were detected in all samples but exhibited no statistically significant relationships with any measured hydro-physical property. This lack of association suggests that fiber distribution is largely controlled by external loading processes rather than by intrinsic soil characteristics. Atmospheric deposition, irrigation water, and amendment-derived inputs may therefore play a more important role in determining fiber abundance than soil retention processes themselves [1,14].

Granules displayed the strongest associations with soil properties, exhibiting negative relationships with clay content, microporosity, and available water content, while showing a positive association with organic matter. The relatively smooth and rounded geometry of granules may reduce physical entrapment within fine pore networks, allowing them to respond differently to soil structural conditions than more irregular particle forms. Their positive relationship with organic matter may further indicate preferential accumulation in biologically active surface horizons where organic residues and particulate contaminants tend to co-occur.

Fragments exhibited a unique positive relationship with aggregate stability. This observation suggests that stable aggregates may physically encapsulate irregularly shaped particles, thereby limiting their redistribution within the soil matrix [1,4]. Similar mechanisms have been proposed for the protection of particulate organic matter within aggregate structures, where physical isolation reduces mobility and promotes long-term persistence.

Film-shaped MPs showed positive associations with both silt and organic matter contents. Owing to their flexible geometry and relatively large surface area, films may be more susceptible to adhesion processes and organo-mineral interactions than other particle types [14,18]. Collectively, these findings demonstrate that particle morphology represents an important determinant of MP fate in soils and emphasize the need for morphology-specific assessments when evaluating environmental risks associated with plastic contamination.

4.4. Interactions Between Microplastics and Soil Hydro-Physical Functioning

The relationships identified in this study indicate that MP distribution is closely linked to the hydro-physical functioning of the soil system. In particular, the negative association between fine MPs and macroporosity highlights the importance of preferential flow pathways in regulating particle transport under field conditions. Soils characterized by well-developed macropore networks may facilitate the downward movement of small particles, thereby reducing their accumulation within surface horizons [50,51]. Similarly, the negative correlations between total MP abundance and both available water content and microporosity suggest that retention processes are influenced by the interaction between pore architecture and water dynamics. These findings support the concept that MP transport cannot be interpreted solely as a function of particle characteristics but must also be considered within the broader context of soil hydraulic behavior.

Previous laboratory and mesocosm studies have shown that MPs may themselves modify soil physical properties, affecting aggregate formation, pore continuity, water retention, and bulk density [5,52–54]. However, evidence for such feedback mechanisms was limited in the present field investigation. For example, fiber abundance showed no significant relationships with aggregate stability or pore-related variables despite their frequently reported influence on soil structure. This discrepancy likely reflects the complexity of field environments, where natural variability, management history, and environmental conditions simultaneously influence both soil properties and MP occurrence.

Consequently, the observed patterns suggest that hydro-physical soil characteristics currently exert stronger control over MP retention than reciprocal MP-induced alterations of soil structure. Nevertheless, long-term feedback processes cannot be excluded, particularly in systems subjected to repeated organic amendments or increasing climatic variability associated with more frequent wetting–drying cycles [6,17].

In addition to hydro-physical processes, biological activity may also contribute to the redistribution of microplastics in agricultural soils. Soil fauna, particularly earthworms and dung beetles, can alter soil structure through bioturbation, promoting the vertical transport and burial of particles within the soil profile. Such processes may be especially relevant in manure-amended orchards, where the activity of these organisms is often enhanced by increased organic matter inputs. Although soil fauna were not evaluated in the present study, bioturbation may have contributed to the observed microplastic retention patterns and should be considered in future investigations integrating soil biological and hydro-physical processes [55,56].

4.5. Insights from Explainable Machine Learning

A central outcome of the machine learning analysis is that predictive generalization was limited: under nested LOOCV the best model (RF) attained only $Q^2_{\text{LOO}} \approx 0.04$, an estimate not statistically distinguishable from chance (permutation $p = 0.11$), and GBDT did not outperform a mean-predictor baseline. This limitation is stated explicitly at the outset because it conditions the interpretation of all subsequent results. The moderate-to-low performance is attributable to several convergent factors: the small sample size relative to the number of predictors, the strongly skewed and outlier-influenced target distribution, and, most importantly, the fact that absolute microplastic abundance is governed largely by drivers that were not measured, including the quantity and timing of organic and sludge inputs, the mass of legacy contamination, polymer type, microbial activity, and irrigation or rainfall intensity. The pronounced site heterogeneity and spatial dispersion of the sampling points further constrain transferability.

Within these constraints, the explainable-AI analysis remains informative as a descriptive rather than predictive tool. The SHAP framework characterizes the structure that the fitted RF model exploits: organic matter and silt content contributed positively to predicted microplastic abundance, whereas bulk density and available water content contributed negatively. Critically, these directions are corroborated by the independent Spearman correlation analysis (e.g., positive associations of films with organic matter and silt, and negative associations of total abundance with available water content and microporosity), which lends mechanistic credibility to the SHAP rankings even though the model's out-of-sample predictive skill is low. The positive influence of organic matter and silt is mechanistically consistent with enhanced retention through organo-mineral associations, greater specific surface area, and abundant fine-pore retention sites, whereas the negative influence of bulk density and available water content is consistent with reduced pore space for particle immobilization and greater potential for redistribution during wetting events. SHAP values derived from a weakly predictive model must nonetheless be interpreted with caution, as they describe within-sample associations rather than validated causal effects.

The practical implication is that hydro-physical properties primarily regulate the retention and redistribution of microplastics, whereas the absolute abundance is dominated by management history and external contamination sources. Future modeling efforts should therefore incorporate quantitative amendment records, legacy-contamination inventories, polymer-specific data, and high-resolution pore-network characterization, and should be trained on substantially larger and spatially replicated datasets before predictive, as opposed

to explanatory, use can be justified; recent generative and physics-informed machine learning models of microplastic accumulation illustrate this direction [23,24,57].

4.6. Study Limitations and Future Recommendations

Several limitations should be considered when interpreting these findings. First, the sample size ($N = 42$) is small relative to the eight predictors, which limits statistical power and the transferability of the machine learning models; the rigorous nested-LOOCV and permutation analyses reported here are intended to prevent the overstatement of predictive skill that a single train–test split would have produced. Second, the dataset represents a single sampling campaign, so temporal dynamics of microplastic accumulation and redistribution could not be assessed. Third, microplastics were identified visually following density separation with saturated NaCl solution (1.2 g cm^{-3}). Although NaCl is one of the most widely used density separation media because of its simplicity and low toxicity, its relatively low density limits the recovery of high-density polymers such as polyvinyl chloride (PVC) and polyethylene terephthalate (PET) [58,59]. Consequently, these polymers may not have been fully recovered in the present study, and polymer identity was not confirmed by FTIR or Raman spectroscopy. Therefore, the reported microplastic abundances should be interpreted as visually identified microplastics rather than polymer-confirmed measurements. Fourth, the exact volumes, frequencies, and dates of sewage-sludge and manure applications were not available and could not be included as quantitative predictors.

Future work should address these limitations by (i) enlarging and spatially replicating the sampling design to support robust predictive modeling, (ii) incorporating high-density separation solutions (e.g., ZnCl_2 or NaI) together with polymer-specific identification using FTIR or Raman spectroscopy and quantitative management records into the feature set, (iii) adding process-relevant covariates such as microbial activity and irrigation intensity, and (iv) extending the design to multiple sampling periods to capture temporal dynamics. Until such data are available, hydro-physical predictors are best used to explain the mechanisms of microplastic retention rather than to predict absolute abundance.

5. Conclusions

This study suggests that hydro-physical soil functioning plays an important role in regulating microplastic occurrence, retention, and distribution in pistachio orchard soils under semi-arid conditions. While management history was associated with overall microplastic abundance, particularly in orchards affected by legacy waste disposal activities and sewage-sludge applications, the spatial distribution of microplastics within soils appeared to be primarily influenced by hydro-physical properties associated with pore-system architecture and water retention behavior. However, because these findings are based on a single sampling campaign, they should be interpreted with appropriate caution. Long-term monitoring across multiple sampling periods is needed to confirm the temporal stability of these relationships and to better distinguish hydro-physical controls from management-induced feedback.

The observed relationships between microplastic size fractions and soil structural characteristics indicate that pore-size distribution and pore connectivity are key determinants of particle retention and mobility. Morphology-specific analyses further revealed that different microplastic forms interact with soil structural domains through distinct mechanisms, emphasizing that assessments based solely on total microplastic abundance may overlook important ecological and transport-related processes.

The explainable machine learning framework successfully identified organic matter, silt content, bulk density, and water-related properties as the principal predictors of microplastic occurrence. More importantly, the integration of SHAP analysis with field

observations provided mechanistic insights into how hydro-physical soil characteristics influence contaminant behavior under realistic agricultural conditions. Overall, the findings highlight the need to incorporate soil hydro-physical indicators into microplastic monitoring and risk-assessment frameworks. Future studies should combine detailed pore-network characterization, polymer-specific analyses, and long-term management records to improve our understanding of microplastic dynamics and support the development of sustainable mitigation strategies for agricultural soils.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/land15081399/s1>, Table S1: VIF of the final predictor set; Table S2. Selected hyperparameters (modal across LOOCV folds).

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