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Research paper

Microplastic distribution and risk assessment in soil environment across Asian regions

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ABSTRACT

Plastic pollution has emerged as a growing global environmental problem in recent years. As a major region for plastic production and consumption, Asia is at the forefront of this challenge. Although multiple studies have focused on microplastic (MP) pollution in aquatic systems in the region, understanding of their distribution characteristics and ecological impacts in terrestrial ecosystems remains limited, particularly at an intercontinental scale. In addition, standardized ecological risk assessment methods and predictive frameworks for soil microplastics (MPs) remain lacking. This study investigated the spatiotemporal distribution of MP pollution in Asian countries, focusing on the differences between various regions in terms of quantity density, morphological characteristics (shape, size, and color), and land-use types. By integrating data from 128 studies published between 2018 and 2025, totaling 3370 sampling points, a comprehensive database was constructed to reveal the MP distribution patterns and potential risks. The analysis found significant spatial heterogeneity in Asian regions, with higher concentrations found in South Eastern Asia (8227.55 items/kg), Eastern Asia (3122.73 items/kg), and Southern Asia (2407.07 items/kg). The highest quantity densities of MPs were found in industrial and urban soils (4995.2 and 4359.6 items/kg), followed by agricultural soils (2812.8 items/kg), shedding light on the influence of intensive human activities and plastic inputs. In terms of morphological characteristics, fragments, fibers, and films shaped MPs predominated in most soils, with white, transparent, and black particles being the most common. Moreover, the analysis suggested possible vertical migration and gradual accumulation of MPs within soil profiles. Based on spatial distribution and morphological characteristics, this study evaluated the ecological risk using pollution load index and potential ecological risk index suggesting that certain regions may exhibit comparatively higher reported risk levels under the present assessment framework, particularly in Viet Nam, Indonesia, India, Iran, Bangladesh, and China, based on the currently available dataset. Lastly, machine learning models were applied for preliminary classification of soil MP ecological risk levels, with the random forest model showing the highest accuracy (99.5%), followed by GBDT (98.6%) and KNN (88.4%). This study provides spatial evidence for risk-oriented and predictive assessment of soil MP pollution across Asia and offers data support for future management and policy interventions.

1. Introduction

Plastics are extensively utilized in contemporary society due to their low production cost, high resistance to chemical reactions, and robust mechanical properties (PlasticsEurope, 2022). Global plastic production continues to increase, reaching an estimated 414 million tonnes in 2023 (PlasticsEurope, 2024), while the latest PlasticsEurope report indicates a further 4.1% increase in 2024, corresponding to approximately 430.8

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million tonnes (PlasticsEurope, 2025). This upward trend is closely linked to continuing industrialization and urbanization (Rehman et al., 2026; Wu et al., 2022). Of this, only ~21% of plastics are recycled or incinerated globally, the remaining 79% persist as environmental waste storing in landfill sites or natural surroundings (Brown, 2019; Salahuddin et al., 2023). Improper dumping and poor recycling of plastics facilitate the formation of tiny particles known as microplastics (MPs), <5 mm in diameter (Thompson et al., 2004, 2024), undergoes further physical, biological, and photo degradation to form primary and secondary MPs (Song et al., 2024; Geyer et al., 2017; Andrady, 2017). These "pollutants" can enter into the atmosphere, rivers, lakes, coastal regions and soil environment (Fan et al., 2025) such as urban soils (Chen et al., 2022), agricultural lands (Islam et al., 2024), and industrial soils (Guo et al., 2025) through different sources including fishing, transportation, plastic mulching, industrial discharge and inadequate waste management (Wang et al., 2021; Li et al., 2023). Although initial microplastic (MP) research focused primarily on marine systems (Cole et al., 2011), nevertheless growing evidence indicates that the presence of MPs in soil can disrupt ecosystems and pose long-term risks to agricultural productivity and food security (Wang et al., 2023). Therefore, a thorough investigation into the MP distribution in terrestrial ecosystems is essential to develop systematic ecological management policies and implementation of effective risk improvement approaches (Zhao et al., 2024).

Asia is the largest continent in the world covering 44.6 million square kilometers, which is around 30% of the entire land area of the Earth (Penagos Gaviria et al., 2022), around 4.7×10^9 inhabitants, nearly 59% of the global population (Estes, 2007). This continent is the largest producer and consumer of plastic in the world (Oktavilia et al., 2020), however the management and disposal of plastic pose significant challenges to the region. In 2019, Asia accounted for approximately 51% of global plastic production, with China contributing 31%, Japan 3%, and other Asian countries collectively 17% contribution (Statista, 2021). In this region, soil MP pollution is particularly pronounced in the areas with high levels of plastic-covered agriculture, urbanization, and industrial activities (Collard et al., 2024).

During the last decade, research on MP pollution has increased significantly across Asian countries. However, the current evidence base remains fragmented because of uneven geographic coverage, differences in local economic and environmental conditions, and substantial methodological heterogeneity among studies (Haque and Fan, 2023; Ali et al., 2024). Existing research has examined MP sources, transformation pathways, and environmental risks in different contexts (Behera et al., 2023; Yu et al., 2025; Liu et al., 2023), but much of this work has focused primarily on aquatic or coastal environments, while soil ecosystems have received comparatively less large-scale attention. In addition, broader syntheses have often been limited by geographic scope, environmental focus, or analytical integration. For example, regional reviews in Southeast Asia have summarized MP occurrence across water and sediment environments while highlighting uneven national coverage and poor methodological harmonization (Ali et al., 2024). National-scale studies in China have compiled extensive datasets and explored distribution patterns and ecological risks, but have remained restricted to a single country and often combined terrestrial and aquatic matrices (Duan et al., 2024). Likewise, some framework-based meta-analyses have incorporated ecological risk indices, yet have mainly focused on coastal or aquatic environments rather than soil systems (Liu et al., 2023; Ranjani et al., 2021). Moreover, differences in land-use classification, abundance metrics, and methodological design continue to limit direct comparison of MP contamination across regions and soil types. Consequently, an Asia-wide, soil-focused synthesis that standardizes published data and integrates spatial distribution, land-use comparison, ecological risk assessment, driver analysis, and predictive modeling has remained lacking. The present study was designed to address these gaps by compiling soil MP data across Asian regions into a unified analytical framework and by providing a broader and more integrated assessment than previous country-specific, matrix-mixed, or purely descriptive investigations.

This analysis collected the published data on MP pollution in Asian countries from 2018 to 2025 to investigate MP distribution in soil environment and potential environmental risks. The key objectives of this study were to; a) evaluate the spatiotemporal distribution of MPs including mass load, chemical composition, morphological characteristics, b) estimate the potential risks associated with MP pollution, and c) develop and apply machine learning (ML) models for preliminary classification of MP ecological risk levels and to explore the predictive potential of the compiled dataset, thereby supporting decision makers in designing policies to minimize long-term soil pollution.

2. Methodology

2.1. Bibliographic data

A comprehensive bibliographic search was conducted using Web of Science (WOS), ScienceDirect, and Google Scholar, and the detailed search strategy is provided in Text S1. In total, 3630 papers related to MP pollution were initially retrieved and compiled into a structured database. After removing duplicates and excluding studies that did not meet the objectives of this study or for which the full text was not accessible, 128 papers were retained for further analysis (see Fig. S1 for the data screening process). These studies covered 17 countries across Asia, including Eastern Asia (China, Japan, and Korea), Southern Asia (India, Pakistan, Bangladesh, Sri Lanka, Iran, and Maldives), South Eastern Asia (Indonesia, Malaysia, Philippines, Thailand, and Viet Nam), Central Asia (Kazakhstan), and Western Asia (Turkey and the United Arab Emirates).

The data extracted from these studies comprised 3370 sampling locations. However, the final dataset showed substantial regional imbalance in sampling effort, with 2842 sampling points from Eastern Asia, 347 from Southern Asia, 99 from South Eastern Asia, 80 from Western Asia, and only 2 from Central Asia. This uneven distribution reflects differences in research intensity, site accessibility, and reporting availability across regions and should be taken into account when interpreting cross-regional comparisons. The extracted information included geographical coordinates (longitude and latitude), soil type, sampling depth, MP abundance, polymer type, particle size, shape, and color.

2.2. Eligibility criteria

The evaluation of collected studies was done following the screening standards as: 1) study area should be soils in the Asian continent, 2) collected data should contain unique and detailed field data related to MPs, 3) sample, pre-treatment and methodical protocols must follow quality control principles, 4) only studies providing precise data on MP abundance, polymer type, shape, color, size, geographical coordinates and sampling depth are included, 5) studies that reported MP abundance in items/kg or g of dry weight (dw) are included for analysis, 6) only studies with MP data that could be extracted directly or indirectly and reported in consistent or convertible units were included in the analysis.

2.3. Data extraction and standardization

The data were extracted from the included studies following the methods of Shi et al. (2023) and Duan et al. (2016). MP spatial distribution, polymer composition, size, shape, color and other information were extracted using GetData Digitizing tools, Plot digitizer and Origin software. These Digitizer tools were used to extract coordinates and morphological features of each data point from the figures. After that the collected data was standardized to maintain the comparability of all sampling sites. Geographical coordinates were standardized to the World Geodetic System 1984 (WGS-84), and MP abundance values were unified as items/kg dry weight (dw). Most of the included studies already reported abundance in items/kg dw. For the small number of studies reporting abundance in units such as items/g, values were directly converted to items/kg (dw) by proportional scaling. For example, values reported as items/g were multiplied by 1000. MP morphological features (shape, color, and size) and polymer types were consistently computed as percentages. Finally, all the information was compiled containing geographical coordinates, sampling depth, abundance, morphological characteristics of MPs for each sampling location.

2.4. Sample collection, pre-treatment and quantification

Selected studies sampled the soil from 14 different depths (0–2 cm, 0–3 cm, 0–5 cm, 5–10 cm, 0–10 cm, 10–15 cm, 0–15 cm, 0–18 cm, 15–20 cm, 10–20 cm, 0–20 cm, 0–30 cm, 20–50 cm, 0–200 cm) in the field from different land-use types (e.g., urban lands, agricultural soils, industrial areas, riparian and coastal soils, transportation soils). The purpose of compiling depth information from these studies was to explore broad depth-related variation in MP abundance across the pooled Asia-wide dataset. Because the included studies covered different regions, land-use types, and site conditions, the depth grouping was used as a comparative framework to identify general tendencies rather than to assume full equivalence among all samples.

In the analyzed studies, sampling was made random or in grid. Samples were then dried and sieved. MPs were extracted by density separation methods using saturated solutions of zinc chloride ($ZnCl_2$), sodium chloride (NaCl) and calcium chloride ($CaCl_2$). Quantification and characterization was mostly through optical microscopy. In some cases, advanced methods that combine spectroscopy with chromatography such pyrolysis-gas chromatography–mass spectrometry (Py-GC–MS) and thermal extraction-desorption GC–MS were also used for both qualitative and quantitative polymer composition. Otherwise, Raman and Fourier-transform infrared (FTIR) spectroscopy were used for MP identification. A detailed study-by-study summary of the sample pre-treatment procedures and identification/quantification methods used in the included studies is provided in Table S1.

2.5. Risk assessment

In this study, we used the pollution load index (PLI) and potential ecological risk index (PERI) (Li et al., 2021) for assessing the hazard associated with soil MPs. These indices provide a comparative framework for evaluating how the measured MP concentrations and polymer-related hazard characteristics vary relative to the selected reference value and risk-classification scheme. This indicator based risk assessment involves the analysis of MP abundance, polymer composition and hazard quantification.

2.5.1. Pollution load index (PLI)

PLI was calculated using the methods of Tomlinson et al. (1980) and Hakanson (1980) to evaluate the MP contamination in soil samples. PLI associated to each sampling site is related to MP concentration factors (CF_i), as given below:

$$CF_i = C_i/_{C_0} \tag{1}$$

$$PLI_i = \sqrt{CF_i} \tag{2}$$

$$PLI_{zone} = \sqrt[n]{PLI_1 \times PLI_2 \times \ldots PLI_n} \tag{3}$$

where CF is the MP pollution coefficient, C_i is MP concentration at sampling site i, C_0 is the background abundance value generalized from the available studies. Because a true baseline of zero would make the contamination factor and pollution load index calculations mathematically undefined (i.e., $CF = C_i/C_0$ when $C_0 = 0$), a non-zero reference value is required. In the absence of an internationally accepted background concentration for soil MPs, this study set C_0 to 0.41 items/kg, corresponding to the minimum abundance reported in the compiled dataset. This approach follows the practice adopted in several large-scale synthesis studies when standardized baseline values are unavailable, where the minimum observed concentration is used as an operational reference for comparative risk assessment (Duan et al., 2024; Liu et al., 2023). However, this value should not be interpreted as a pristine natural background for soil MPs, but rather as a pragmatic reference point for relative comparison within the current dataset. PLI_i represents PLI of MPs at site i, and PLI_{zone} denotes PLI in specific study zone designed as the n-th root of the product of PLI values from n sampling sites within that study region.

2.5.2. Potential ecological risk index (PERI)

To calculate the degree of MP pollution in Asian soils, PERI was also calculated (Peng et al., 2018).

$$T_{ri} = \sum_{n=1}^{n} P_n/_{C_i} \times S_n \tag{4}$$

$$PERI_i = T_{ri} \times CF_i \tag{5}$$

where T_{ri} is toxicity coefficient representing the toxicity level and biological sensitivity at sampling site i. P_n is the polymer (e.g., polyethylene (PE), polypropylene (PP), polystyrene (PS), etc.) percentage at each sampling site, S_n symbolizes the hazard score of polymers (listed in Table S2). This study set the hazard score 1 for rayon and unclassified (other) polymers as previously reported by Wei et al. (2025). The resulting CF, PLI, Tri and PERI of the sampling points and their particular study zones using overhead stated equations provided in Table S3. Grading standards from PLI and PERI classes showed in Table 1.

3. Results and discussion

3.1. MP distribution on spatial scales across Asian regions

MP research in Asia from 2018 to 2025 showed annual trend of sampling sites (Fig. 1A). Site distribution in Eastern, Southern, Western, South Eastern, and Central Asian regions showed that the most of sampling sites were distributed in agricultural soils (cropland and vegetable plots), urban soils (parks, residential areas, and commercial zones), industrial soils (landfills and wastelands), transportation areas, riparian and coastal soils (comprising riverbanks, lakes, mangroves, and wetlands etc.), and some other soils including drylands, beach soils, forests, grasslands and sandy soils (Fig. 1B).

MP distribution in soil environment varied significantly across Asian regions represented in the compiled literature. Based on the currently available published dataset, the highest mean abundance (8227.55 items/kg) was observed in South Eastern Asia, particularly in Viet Nam, Indonesia and Thailand, followed by Eastern Asia (3122.73 items/kg, especially in China), and Southern Asia (2407.07 items/kg) (Fig. 2A). However, these regional comparisons should be interpreted with caution because sampling effort was highly uneven among regions. Eastern Asia contributed the vast majority of sampling points, whereas Southern Asia, South Eastern Asia, Western Asia, and particularly Central Asia were represented by much smaller datasets. Such imbalance may strongly influence regional mean values and variability, since

Table 1
Grading standards of assessment indicators (Ranjani et al., 2021; Lithner et al., 2011).

PLI class	Hazard category	PERI	Risk class
<10	I	<150	Minor
10–20	II	150–300	Medium
20–30	III	300–600	High
30–40	IV	600–1200	Dangerous
>40	V	>1200	Very dangerous

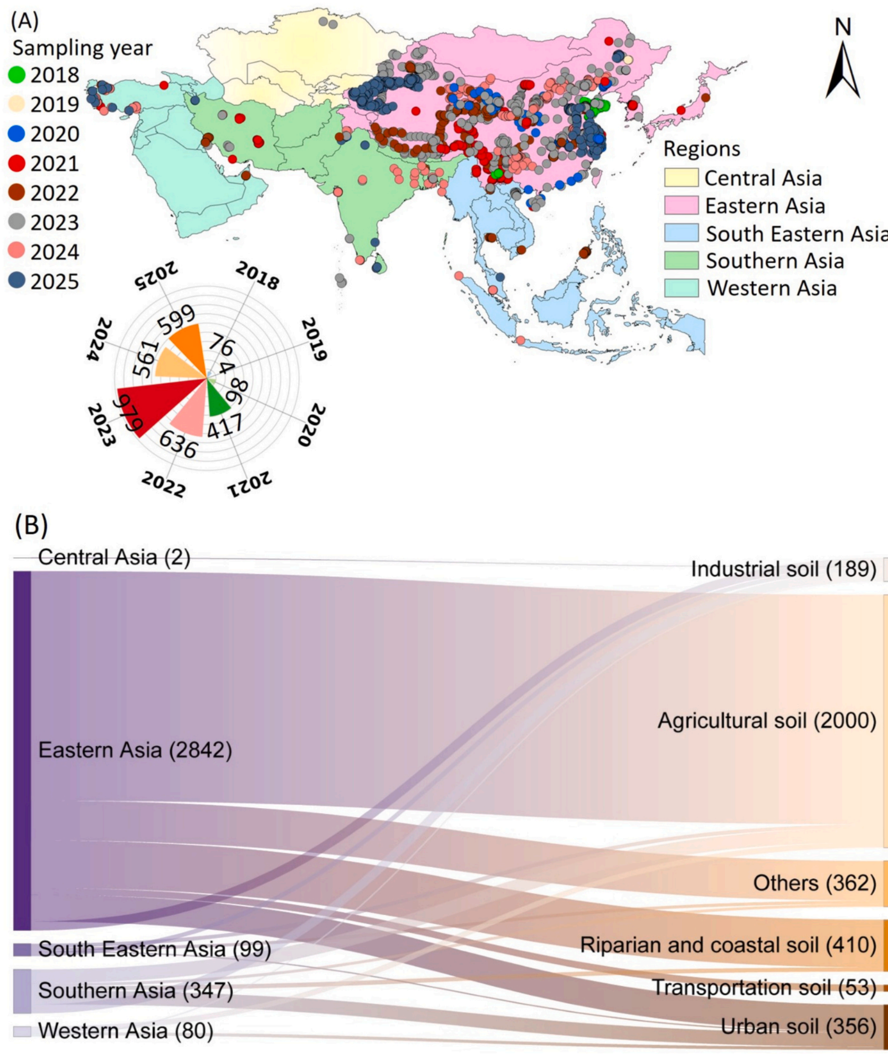

Fig. 1. Geographical distribution of soil sampling sites used to investigate MP pollution across Asia from 2018 to 2025. Spatial distribution of sampling sites, with colored dots indicating different sampling years; the rose plot shows the annual sampling trend (A), distribution of sampling points across diverse land-use types and Asian regions, represented by a Sankey plot (B). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

larger datasets are more likely to capture a broader range of contamination conditions, while smaller datasets may be disproportionately shaped by hotspot-oriented sampling or a limited number of study locations. In particular, the results from under-sampled regions, especially Central Asia, should be regarded as preliminary and not statistically representative of broader regional conditions. Remarkably, South Eastern Asia showed the widest range of MP abundance with concentrations ranging from low as 0.41 to 88,000 items/kg, reflecting the pronounced heterogeneity in sources and environmental conditions. Eastern Asia, particularly China also revealed a broad variability (3–137,600 items/kg), highlighting localized hotspots of severe contamination. Southern Asia and Western Asia presented intermediate ranges, while Central Asia recorded the lowest variation (19.25–22.25 items/kg), although this likely reflects the extremely limited number of available sampling points rather than a robust indication of lower regional MP inputs.

Although South Eastern Asia showed a higher mean MP abundance than Eastern Asia, this contrast should be interpreted cautiously because the two regional datasets differed substantially in sample size and representativeness. The Eastern Asian dataset included a much larger number of sampling points and covered a broader range of land-use types and pollution settings, including both relatively contaminated and less contaminated sites. In contrast, the South Eastern Asian dataset was comparatively limited and disproportionately represented by highly contaminated hotspot environments, such as agricultural soils in Viet Nam (Doan et al., 2023) and landfill soils in Indonesia (Pratiwi et al., 2024). Under such conditions, regional mean values may be strongly influenced by targeted hotspot sampling, while larger and more heterogeneous datasets are more likely to approximate broader regional conditions. Therefore, the observed difference between South Eastern Asia and Eastern Asia is more directly explained by sampling structure and representativeness than by regional environmental governance alone. In addition, differences in land-use structure, intensity of agricultural plastic use, industrial activities, landfill leakage, urban inputs, and local environmental conditions may also contribute to the observed regional variation in MP abundance. Differences in waste-management practices, recycling capacity, and plastic-control policies may still contribute to regional variation (Vuk et al., 2025), but the present dataset does not allow these factors to be isolated as primary causal drivers. Accordingly, the regional comparison presented here should be regarded as an overview of currently reported observations rather than a fully balanced estimate of true region-wide background contamination levels.

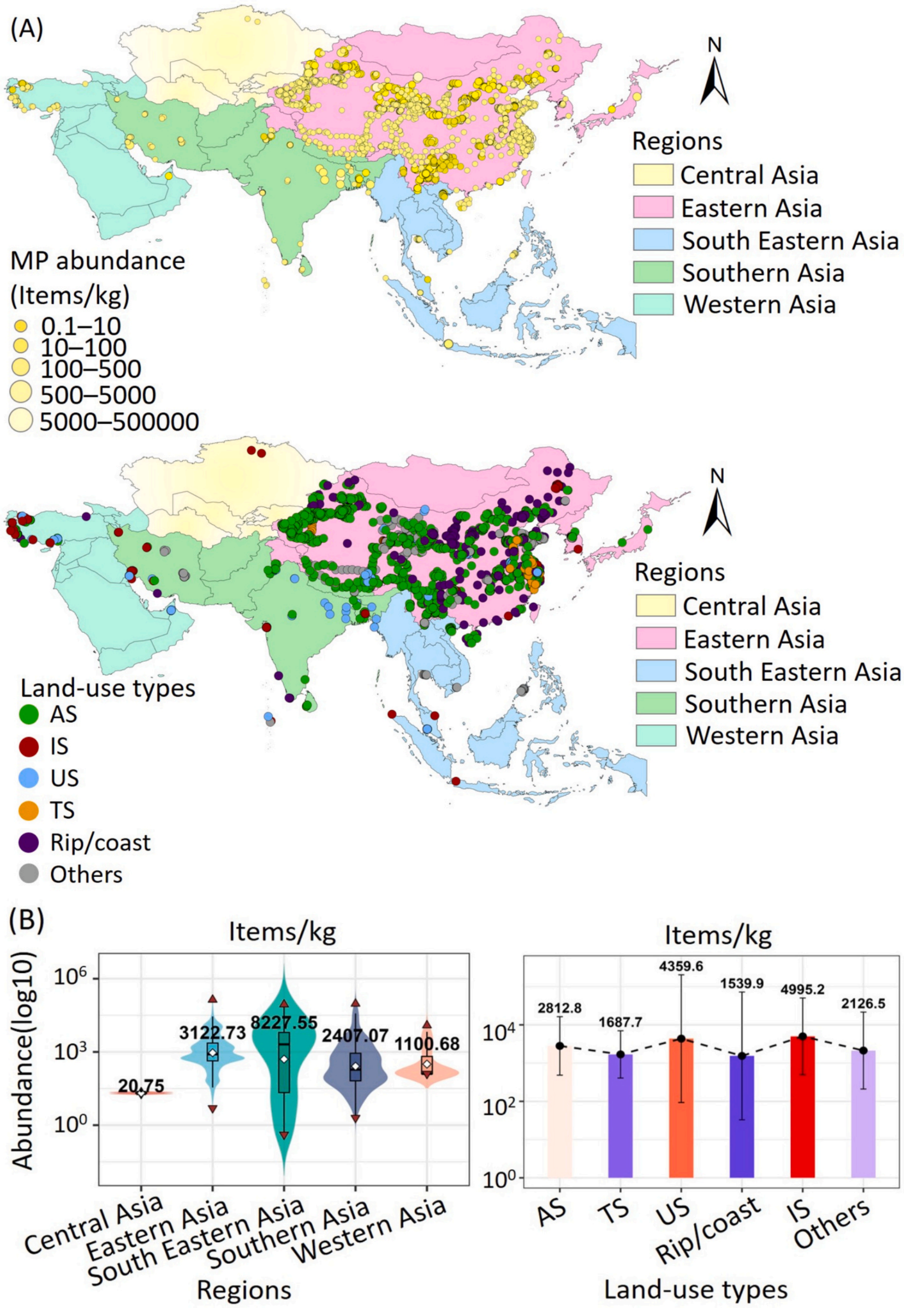

Fig. 2. Spatial distribution of MPs across Asian regions and land-use types (A), violin plot shows MP abundance (items/kg) across the regions, and bar plot represents MP abundance (items/kg) among different land-use types (B).
Note: AS: agricultural soil. IS: industrial soil. US: urban soil. TS: transportation soil. Rip/Coast: riverbanks, lakes, mangroves, and wetlands. Other: drylands, beach soils, forests, grasslands and sandy soils.

3.2. MP occurrence across land-use types

MP distribution varied markedly across different land-use types (Fig. 2B). The highest mean abundance (4995.2 items/kg) was recorded in industrial soils. This pattern is likely associated with direct plastic handling, industrial emissions, improper disposal of plastic-containing materials, and landfill leakage, all of which can generate concentrated local inputs of MPs. Urban soils also showed relatively high levels (4359.6 items/kg), which may reflect dense human activity together with multiple diffuse sources, including packaging waste, municipal refuse, construction-related disturbance, road dust, atmospheric deposition, and traffic-associated plastic debris. Agricultural soils exhibited moderate but still substantial MP abundance (2812.8 items/kg), likely due to the widespread use of plastic mulch, greenhouse films, irrigation inputs, and the application of sewage sludge or biosolids, as well as the gradual fragmentation of residual agricultural plastics in soil. Transportation soils and riparian/coastal soils showed comparatively lower mean values (1687.7 items/kg, and 1539.9 items/kg, respectively), although both categories displayed considerable variability. In transportation soils, MP inputs may arise from road runoff, vehicle-related plastic wear, roadside litter, and atmospheric deposition. In riparian and coastal soils, MP abundance is likely influenced by runoff, sediment deposition, hydrological connectivity, and the redistribution of particles from adjacent urban, agricultural, or industrial sources. Other soils (2127 items/kg), particularly beach soils, may also receive substantial MP inputs from tourist activities, recreational littering, and localized waste accumulation. Overall, the observed differences among land-use types likely reflect variation in dominant source pathways, input intensity, environmental transport, and local management conditions, rather than a single controlling factor.

In addition to spatial differences, MP abundance also varied over time across different land-use types and Asian regions. Industrial and urban soils, particularly around 2024, as well as Eastern and South Eastern Asia, especially after 2022, showed noticeable inter-annual variation, with higher reported MP abundance in recent years (2018–2025). The corresponding temporal trends are presented in Fig. 3A–B.

3.3. Variation in MP abundance according to soil depth

Different soil depths were reported in the selected studies (as described in Section 2.4). To facilitate comparison, these depths were grouped into three categories: shallow (0–15 cm), mid (15–30 cm), and deep (>30 cm). Specifically, the shallow group included 0–2, 0–3, 0–5, 5–10, 0–10, 10–15, and 0–15 cm; the mid group included 15–20, 0–18, 0–20, and 0–30 cm; and the deep group included 20–50 and 0–200 cm. Based on this classification, the compiled dataset contained 2295 sampling points in the shallow layer, 1038 in the mid layer, and only 37 in the deep layer.

The results showed a significant difference in MP abundance among the three depth groups. Kruskal-Wallis analysis (Kruskal and Wallis, 1952) indicated significant depth-related heterogeneity in MP abundance ($\chi^2 = 18.69$, df = 2, $p < 0.001$). Subsequent pairwise Wilcoxon comparisons (Wilcoxon, 1945) also showed significant differences between shallow and mid layers ($p < 0.001$), as well as between the deep layer and the other two groups ($p < 0.05$). The mean MP abundance was highest in the deep layer (5387 items/kg), followed by the mid layer (3248 items/kg) and shallow layer (3069 items/kg) (Fig. 4). However, this pattern should be interpreted with caution. The deep-soil category was represented by a much smaller number of sampling points than the shallow and mid-depth groups, which increases the likelihood that its mean value was influenced by a limited number of highly contaminated sites or point-source-affected environments. Therefore, the relatively high MP abundance observed in the deep layer should not be interpreted as definitive evidence that deeper soils generally contain higher MP concentrations than surface soils across all natural settings. Rather, the current results indicate that MPs can occur beyond the soil surface and may, in some cases, accumulate in deeper layers.

Taken together, the available evidence suggests that MPs are not restricted to the soil surface and may migrate vertically within soil profiles (Fan et al., 2025). Vertical migration of MPs within soil profiles may be influenced by several processes, including downward transport with percolating water, root penetration, soil-fauna activity, anthropogenic disturbance, and repeated wet–dry cycles, while smaller particles are generally more likely to infiltrate deeper soil horizons or even groundwater (Kerimov et al., 2018; Zhang et al., 2022; Lwanga et al., 2022; Luo et al., 2024; Rillig et al., 2017). Nevertheless, more balanced depth-stratified sampling across diverse land-use types and contamination settings is needed to determine whether the observed depth-related pattern is broadly representative.

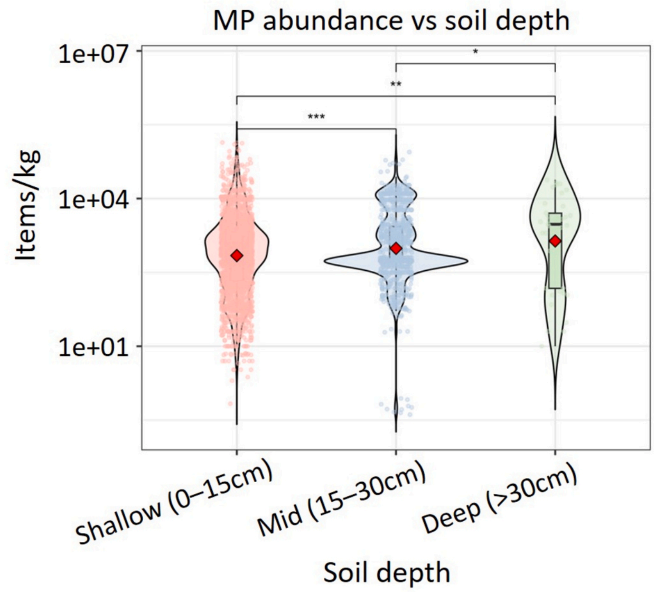

Fig. 4. Distribution of MP abundance across different soil depths. Violin plots show the variability and distribution within each depth group, while the individual scatter points indicate sampling observation, and red diamonds indicate the mean values. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.4. Morphological characteristics of MPs

Chemical composition and physical characteristics of MPs are strongly affected by their source or origin, migration, transformation and hazard impacts (Liu and Zheng, 2025; He et al., 2023). These tiny particles can certainly enter food web posing ecological and health risks. MP shape, color, size, and polymer composition are summarized in Fig. 5, while comparative investigations across land-use types and regions based on selected studies over time are further demonstrated in Fig. 6(A–D).

Based on the dimensions, MPs were divided into large and small sizes. Results showed that small particles (<0.5 mm) were prominent accounting for 38.6%. This supremacy of small-sized particles was consistent across diverse land-use types and regions over time, signifying fragmentation of larger plastic debris and detection of fine particles in recent studies. Larger MPs (>5 mm) were recorded in agricultural and riparian/coastal soils (Fig. 6D), reflecting direct plastic inputs and

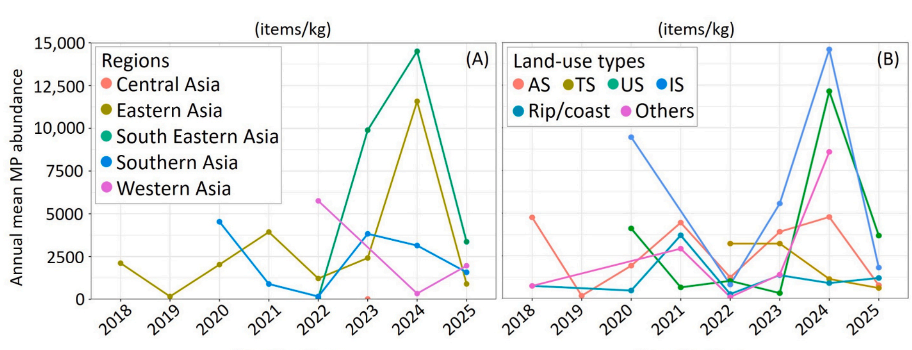

Fig. 3. Annual mean MP abundance (items/kg) with respect to temporal variation across Asian regions and diverse land-use types (A–B).

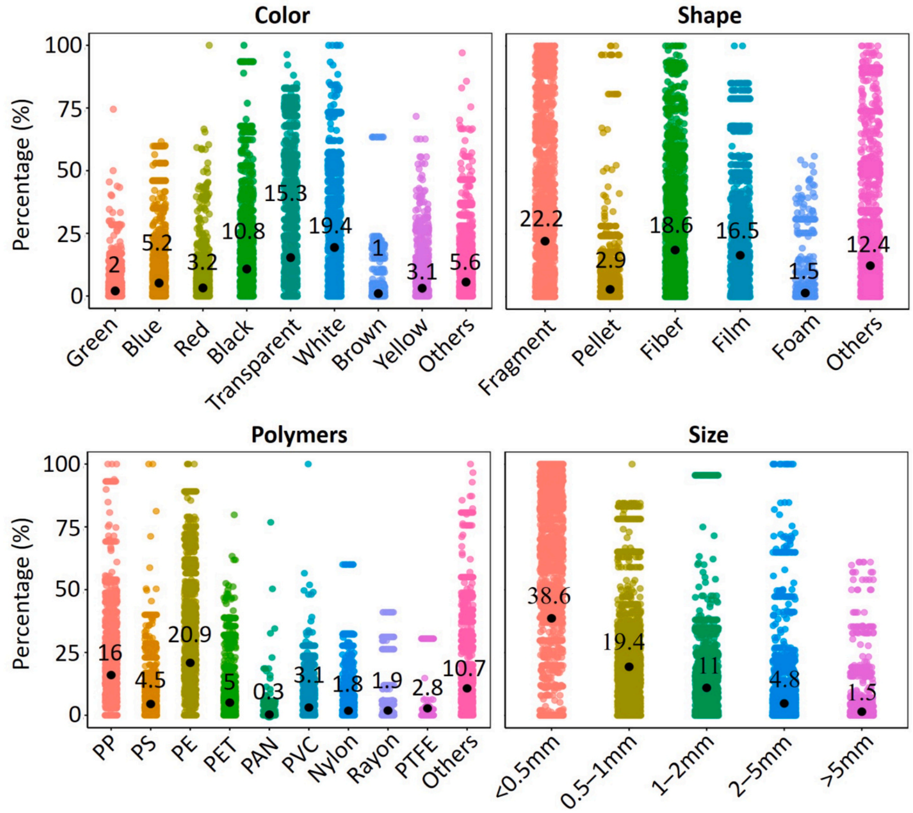

Fig. 5. Characteristics of MPs in soils systems across Asia. The four panels show the percentage distribution of MP color, shape, polymer type, and size, respectively. The black dots within the plots represent the mean percentage values for each category. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

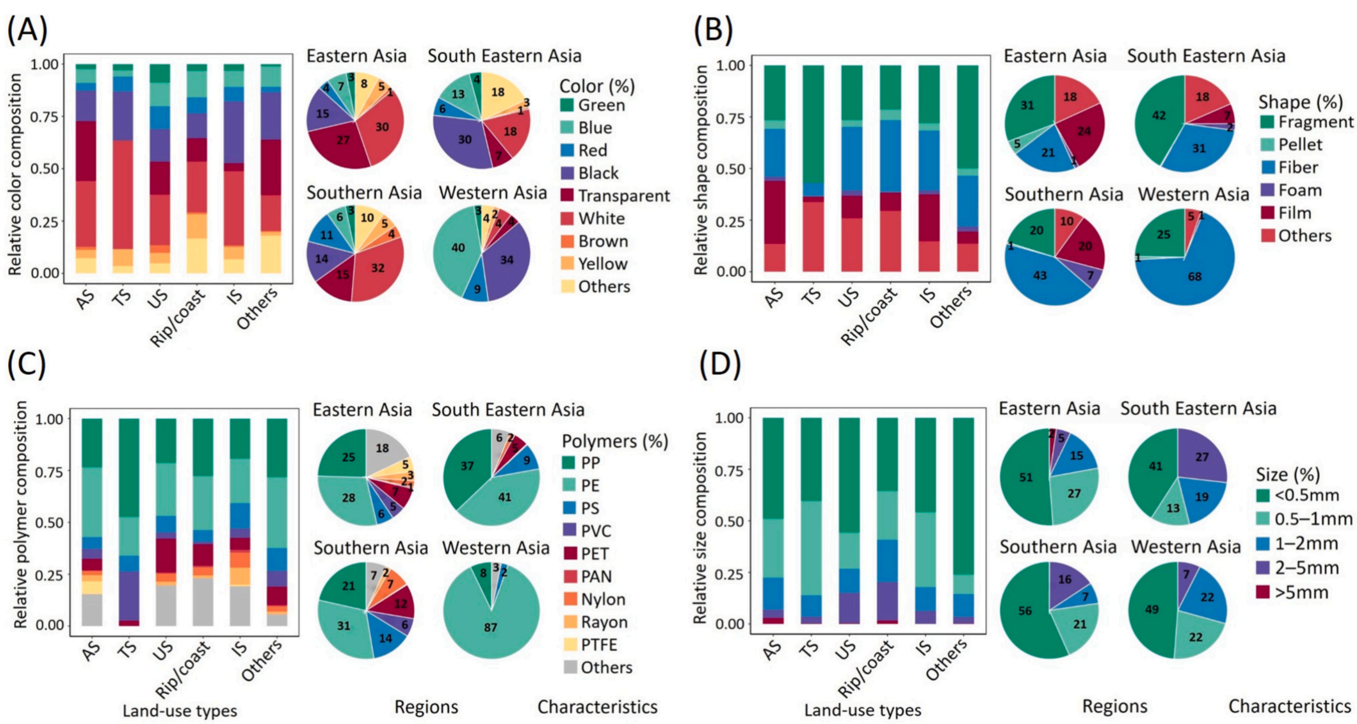

Fig. 6. Comparative analysis of MP morphological characteristics across land-use types and Asian regions. Color composition (A), shape composition (B), polymer composition (C), and size composition (D). Stacked bar plots show the relative composition of MP characteristics across different land-use types, while pie charts show their proportional distribution across Asian regions. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

degradation of macroplastics.

The study also revealed that white (19.4%), transparent (15.3%) and black (10.8%) were the most common attributes in the soil media across Asia, however that red, green, blue, brown, yellow and other colors (such as pink, orange) were also present. Comparative analyses showed that the relative distribution of MP colors persisted stable across land-use types and regions, with lighter-colored MPs continuing over time, possibly due to weathering and photo-degradation practices.

Additionally, fragment, fiber and film shaped MPs were the most common shapes in the collected literature accounting for the greatest proportion of 22.2%, 18.6% and 16.5%, respectively. Weathering and fragmentation of large plastic items introduce MP fragments while films are mainly come from plastic packaging and plastic cover. Fiber shaped MPs are mainly originate from synthetic fibers (Sheikhi et al., 2024) including polyester, polyamide (PA) and spandex in textiles and can be extensively distributed in soils and water environment (Periyasamy and Tehrani-Bagha, 2022). Relative investigation further disclosed that fragments and fibers dominated across land-use types and regions (Fig. 6B), highlighting constant degradation and non-stop inputs of plastic materials into terrestrial environments.

MPs with complex form and composition can enter into soil through a wide range of sources (Li et al., 2023). As shown in Fig. 5, PE and PP were the main polymer types found in various land-use types across Asia, accounting for more than 18%. Specifically, PE is generally used in films making, film repackaging, material insulation and foam production. PP is a worldwide thermoplastic material which is generally used in clothing manufacturing, vehicles parts, wire and cables, plastic woven bags and in formation of chemical containers. Moreover, comparative trend analyses across land-use types and regions proved the determined dominance of PE and PP (Fig. 6C), indicating continued plastic inputs rather than short-term contamination measures. Additionally, due to their low density PP and PE can transfer and renovate, highlighting greater detection proportions in different environments. Furthermore, particles like PS, polyacrylonitrile (PAN), polyvinyl chloride (PVC), polytetrafluoroethylene (PTFE), rayon, and nylon (PA) were also found at the sampling sites of selected studies. It should be noted that, despite available information on MP abundance in the Central Asia, there were neither systematic details concerning the morphological features of MPs covered in the literature collected, which enables information concerning the polymer types, shape, color, and size to be available for this region. The morphological study was restricted to regions where such information was recorded.

3.5. Risk assessment of MPs

To evaluate relative MP pollution pressure and ecological risk across Asian soils, this study applied the PLI and PERI frameworks. These indices integrate MP abundance with polymer-related hazard information and provide a comparative basis for screening spatial variation in reported pollution and risk levels across the compiled dataset (Peng et al., 2018; Qiu et al., 2023). On the basis of this framework, our study comparatively assessed the reported MP pollution load and potential ecological risk in soils across Asia using the currently available published data (Table S3). Geographical distribution and results of statistical analysis of pollution load and ecological risk classes in soils across Asian regions are illustrated in Fig. 7. The average value for PLI_{zone} was noted as 62.86 and corresponding percentage for class V was 51.70% (Fig. 7A) indicating very high pollution load across the Asia. Average highest pollution loads were observed in South Eastern Asia (95.25) such as Viet Nam, Thailand and Indonesia, followed by Eastern Asia (64.74) especially in China. Other Asian regions such as Southern Asia (particularly India, Iran and Bangladesh), Western Asia (Turkey) and Central Asia also showed pollution load accounting for 44.02, 39.02, and 7.10, respectively. Meanwhile, Central Asia showed minimum pollution load (class I) which reflects the limited number of studies from this region. Moreover, the ecological risk level was considerably higher, with 55.40% (Fig. 7B) of sites classified as very dangerous (PERI > 1200) across Asia, except in Central Asia, likely due to the limited number of studies conducted in soil environment. However, this classification should be interpreted as a relative hazard-ranking result under the present assessment framework rather than as direct evidence of confirmed ecological harm at those sites. In other words, the "very dangerous" category indicates comparatively higher potential ecological concern based on MP abundance and polymer-related hazard coefficients, but does not by itself demonstrate measured biological or ecosystem damage in the field. Generally, ecological risk assessment results constructed on PLI significantly depend on MP abundance but the assessment results could vary significantly with the selection of background abundance value. The selection of background values remains a critical challenge in the ecological risk assessment of MPs (Jiang et al., 2023). In the absence of standardized background concentrations for soil MPs, the minimum baseline concentration or lowest observed abundance within a compiled dataset has been used in some studies as an operational reference for risk assessment (Cole et al., 2011; Qi et al., 2020; Kabir et al., 2021). In the present study, 0.41 items/kg was selected as the reference value because a true baseline of zero would render the CF and PLI calculations mathematically invalid. This value corresponds to the minimum reported abundance among the included studies and was adopted solely as a pragmatic reference to enable comparative assessment within the compiled dataset, rather than to represent a pristine or undisturbed soil background. Accordingly, the resulting PLI and PERI classifications should be interpreted as relative indicators for comparing contamination severity across sites and regions under the current framework, rather than as absolute ecotoxicological thresholds or universally standardized benchmarks. Some studies have alternatively used non-effect concentrations (NECs) as reference values in PLI and PERI assessments (Qiu et al., 2023). However, the derivation of NECs for MPs remains complicated by substantial uncertainty in ecological and biological toxicity estimation, which can lead to inconsistent and non-comparable outcomes (Duan et al., 2024). These methodological differences highlight the current lack of integrated regulatory standards for MP risk assessment and emphasize the need for more harmonized approaches to characterize ecological and biological risks.

3.6. Potential drivers of MP pollution

Due to the diverse sources and distribution of MPs in various environments, establishing a complete "source-sink" migration pathway remains a significant challenge (Qiu et al., 2023). This study evaluated the relationship between MP abundance at various sampling sites and regional socioeconomic indicators as well as environmental variables. By utilizing datasets from the World Bank and the Food and Agriculture Organization (FAO), we explored potential drivers of MP pollution under different soil conditions. The socioeconomic and environmental variables were matched to the compiled MP dataset at the national level based on the location information available for each sampling record.

Correlation analysis showed that MP abundance was positively associated with several socioeconomic indicators (Fig. 8), particularly industrial gross domestic product (IGDP) ($p < 0.001$), per capita GDP ($p < 0.05$), and total GDP ($p < 0.001$), suggesting that broader patterns of economic development may be linked to increased plastic use, waste generation, industrial activity, and infrastructure expansion. However, these indicators should be interpreted cautiously as macro-level proxies rather than direct causal variables. Economic growth is not a single uniform driver of MP pollution; instead, it encompasses multiple sectors and activities that may contribute differently to MP inputs, including industrial production and discharge, agricultural plastic use, transportation-related emissions, packaging waste, and landfill leakage. Therefore, while the observed correlations suggest that more economically active regions may face greater pressure from MP pollution, the present dataset does not allow precise attribution to specific economic sectors or source pathways.

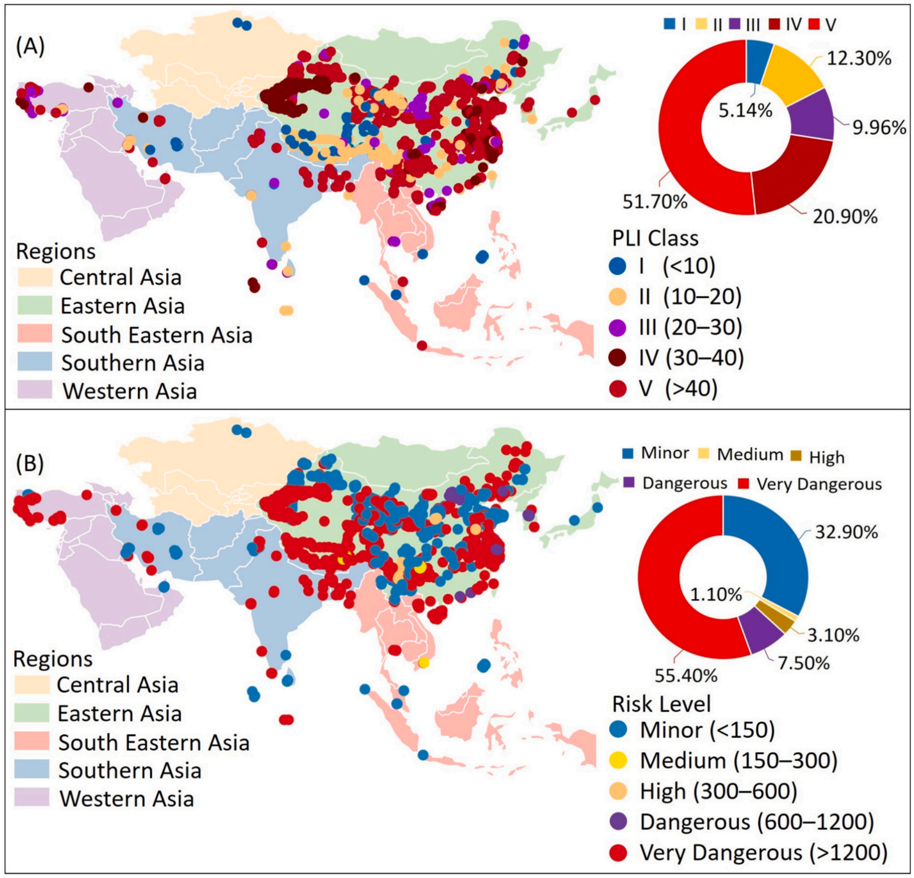

Fig. 7. Spatial distribution of MP pollution and ecological risk classes in soil systems across Asia. PLI classes and their percentage distribution (A), PERI classes and their percentage distribution (B).

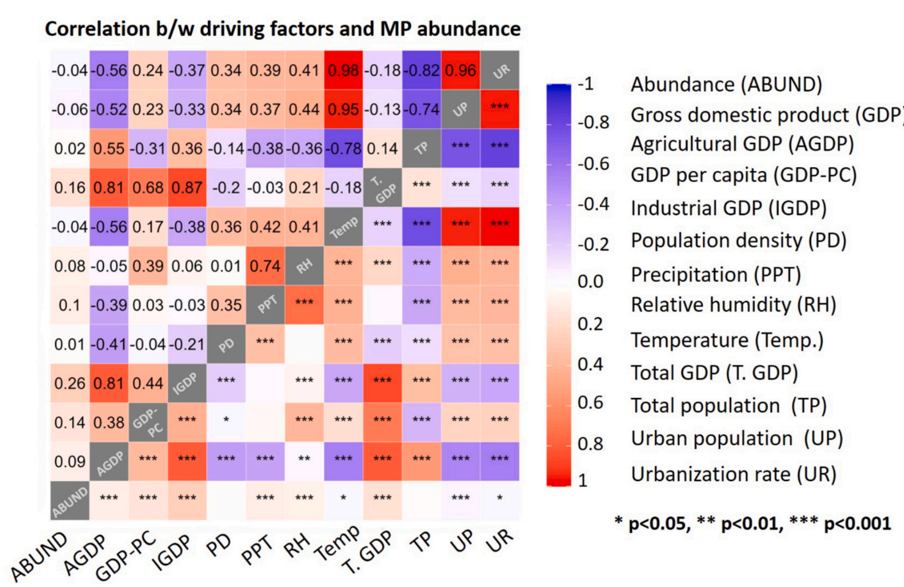

Fig. 8. Correlation analysis between driving factors and MP abundance in soil ecosystems across Asian regions.

The weak correlation between MP abundance and urbanization rate or urban population should also be interpreted carefully and does not necessarily contradict the higher MP abundance observed in urban soils. Urbanization rate and urban population are broad demographic indicators measured at regional or national scales, whereas MP contamination in urban soils is often determined by localized anthropogenic activities and site-specific conditions, such as traffic density, waste disposal practices, construction activities, industrial emissions, and land-use intensity. As a result, heavily contaminated urban sites may occur even when broader urbanization indicators do not show a strong linear relationship with MP abundance across the full dataset. This suggests that localized source intensity and land-use characteristics may be more influential than demographic indicators alone in explaining site-level MP contamination.

Environmental factors, including temperature, precipitation, and relative humidity, also exhibited strong inter-correlations, reflecting the close linkage among regional climatic conditions (e.g., temperature-humidity, $p < 0.001$). Nevertheless, their direct relationship with MP abundance was comparatively weak in the present analysis. This suggests that climatic variables may influence MP weathering, transport, redistribution, and retention in soils, but are less likely than anthropogenic inputs to explain the major spatial differences in reported MP abundance at the regional scale. Overall, the results suggest that socioeconomic conditions and localized land-use pressures may be more influential than broad demographic or climatic indicators in shaping reported soil MP contamination, although these interpretations remain subject to uncertainty due to the aggregated and heterogeneous nature of the compiled dataset. Future studies should incorporate more source-specific explanatory variables, such as plastic production intensity, agricultural film application, waste-management efficiency, landfill density, traffic activity, and industrial structure, to better resolve the mechanisms underlying MP distribution patterns. Because the present correlation analysis is exploratory, it does not account for non-independence among studies, uneven sampling intensity, or other forms of sampling bias.

3.7. Research limitations and future outlook

This study provides a synthesis of published data on the abundance, physicochemical characteristics, ecological risks, and potential drivers of MPs in soils across Asia. Nevertheless, the findings should be interpreted with appropriate caution due to substantial methodological heterogeneity among the included studies (Prata et al., 2019). Variations in sampling design, site representativeness, environmental matrices, sample pre-treatment, analytical identification methods, and reporting practices inevitably affect the comparability and robustness of the compiled dataset (Bryant and Ma, 2023). While methods such as microscopy, FTIR, and Raman spectroscopy are widely applied for MP detection and characterization, their performance is influenced by differences in sample preparation requirements, instrumental sensitivity, and operator expertise. In particular, differences in sampling tools, field sampling strategies, instrument types, and analytical sensitivity among studies may have influenced the detection efficiency and characterization of MPs, thereby contributing to uncertainty in cross-study comparison. Moreover, current ecological and health risk assessments rely primarily on abundance metrics, physicochemical characteristics, and polymer hazard data, but remain limited by the absence of standardized datasets, inconsistent quantitative frameworks, uncertain long-term toxicological evidence, and the lack of an agreed background reference value for soil MPs (Li et al., 2024). Consequently, the spatial patterns and risk levels reported here should not be interpreted as definitive or fully standardized benchmarks for all Asian soils, but rather as a comparative regional synthesis of the currently available evidence. Therefore, the observed regional differences may arise from both genuine environmental variation and methodological inconsistencies across studies. A further limitation of this study is the strong imbalance in regional sampling effort across Asia. The compiled dataset was heavily dominated by Eastern Asia, while Southern Asia, South Eastern Asia, Western Asia, and particularly Central Asia were represented by much smaller numbers of sampling points. Such disparity reduces the statistical comparability of regional means and increases the risk that apparent cross-regional patterns may reflect differences in research intensity, study accessibility, or hotspot-focused sampling rather than true large-scale environmental gradients. Therefore, the regional results reported here should be interpreted as broad tendencies based on available evidence, not as fully representative continental benchmarks. An additional source of uncertainty in the present study arises from the choice of background reference value itself. Although the minimum observed concentration was adopted following precedent in large-scale synthesis studies, it may still reflect residual anthropogenic influence rather than true background conditions. As a result, the absolute magnitude of PLI-based classifications should be interpreted with caution, and the present framework is more appropriately viewed as a comparative screening tool than as a basis for defining absolute contamination thresholds. Despite these constraints, this synthesis provides a useful basis for identifying broad contamination tendencies, potential hotspots, and key priorities for future investigations based on harmonized monitoring and risk-assessment approaches.

3.7.1. ML for MP risk classification

On the basis of the compiled dataset and the comparative ecological risk assessment described above, ML was further applied as a complementary analytical step to evaluate whether site-level MP characteristics could support classification of PERI-based risk categories. The purpose of including ML in this study was not to replace the descriptive and comparative framework, but to extend it toward a preliminary predictive perspective. In this way, the ML component builds directly on the preceding distribution, risk assessment, and driver-analysis results and provides an additional tool for future risk screening and data-driven environmental management.

Recent studies have increasingly applied artificial intelligence (AI) and ML approaches in MP research to improve particle identification, quantification, and predictive analysis (Lin et al., 2022). AI is also gradually becoming a new tool for predicting the toxicity of MPs by linking its chemical composition to biological reactions, thus providing a new direction for hazard assessment. It can also support remediation efforts by improving separation, degradation, and removal strategies, thereby simultaneously advancing both source prevention and end-of-pipe treatment. However, more research is needed to ensure the reliability and broad applicability of AI models under real-world conditions.

This study trained three supervised ML models, namely k-nearest neighbor (KNN), random forest (RF) and gradient boosting decision tree (GBDT). Descriptors such as polymer types and abundance were used to divide PERI of MP pollution into five categories ("minor," "medium," "high," "dangerous," "very dangerous"). The performance of the model on the test data was evaluated with a confusion matrix and summary metrics (Fig. S2). All three models correctly identified most "minor" and "very dangerous" sites, with only a small amount of confusion between adjacent categories. Among them, the RF model performed best, with an overall accuracy of 99.5% and a Cohen's Kappa of 0.99, indicating almost complete agreement with the actual risk category. GBDT performed slightly less well (accuracy 98.6%; $K = 0.98$), but still significantly superior to KNN (accuracy 88.4%; $K = 0.79$). These results indicate that tree-based ensemble approaches, especially RF are suitable for classifying the MP risk levels based on site characteristics. Recent studies have shown that machine learning is increasingly being applied in MP research to improve identification, quantification, and predictive analysis, particularly where conventional analytical workflows are time-consuming and subject to operator-dependent variability. Studies by Lin et al. (2022), Jin et al. (2024), and Hu et al. (2024) have highlighted that ML and AI techniques can strengthen MP classification by improving pattern recognition from microscopy, FTIR, Raman spectroscopy, and image-based datasets, while also supporting more automated and data-driven analysis. In the present study, the ML component was not intended to replace the descriptive and comparative framework, but to extend the ecological risk assessment toward a preliminary predictive perspective. The comparatively strong performance of RF and GBDT suggests that nonlinear relationships among polymer composition, abundance, and risk-category structure can be effectively captured by tree-based ensemble models, whereas KNN appears more sensitive to overlap between adjacent classes. At the same time, the current ML results should be interpreted cautiously, because model performance depends on the structure, size, and class balance of the compiled dataset, and does not yet represent a universally transferable prediction framework for all soil environments. Future work should incorporate more balanced datasets, external validation, and additional source and environment-related predictors to improve model generalizability and environmental interpretability (Su et al., 2023).

4. Conclusion

This study synthesized published evidence on soil MP pollution across Asian countries and, in doing so, helps address the previously identified lack of an Asia-wide, soil-focused comparative assessment. The analysis revealed broad differences in reported abundance, occurrence, physical characteristics, and ecological risk among regions and land-use types. Based on the currently available literature, South Eastern Asia showed the highest reported mean abundance, followed by Eastern Asia and Southern Asia; however, these regional differences should be interpreted cautiously because the compiled dataset was strongly imbalanced in sampling effort across regions. Across land-use types, industrial and urban soils, particularly those influenced by industrial emissions, landfill leachate, and intensive human activities generally exhibited higher reported MP levels than other soil categories. The available literature also showed that MPs in Asian soils display considerable diversity in morphology, particle size, color, and polymer composition, reflecting multiple sources, transformation processes, and environmental behaviors. Based on the currently available evidence, countries such as Viet Nam, Thailand, India, Turkey, and China appear to include some of the more highly contaminated reported sites, underscoring the need to identify dominant sources and develop targeted mitigation strategies.

However, these findings should be interpreted with appropriate caution. The reliability and comparability of the current evidence base are constrained by inconsistencies in sampling schemes, uneven regional representation, differences in environmental media, and variation in sample pre-treatment, detection, and characterization methods among studies. Likewise, the ecological risk assessment remains affected by uncertainty associated with non-standardized datasets, inconsistent quantitative approaches, and the absence of universally accepted background values and harmonized evaluation frameworks for soil MPs. Therefore, the patterns and risk levels reported in this study should not be regarded as definitive or fully standardized benchmarks for all Asian soils, but rather as a comparative regional synthesis of the presently available literature. Even with these limitations, this study provides useful quantitative evidence for policymakers, environmental managers, and researchers by identifying broad contamination tendencies, potential high-risk areas, and key priorities for future standardized monitoring and assessment. To improve the robustness and practical value of future research, there is an urgent need to establish harmonized lifecycle regulatory frameworks supported by data-driven risk assessment systems. In this context, the integration of "AI for Science" approaches, including ML and computer vision, holds considerable promise for improving MP characterization, simulating pollutant dynamics, and advancing prediction of the ecological toxicity of emerging pollutants.

4.1. Environmental implication

Microplastic (MP) pollution has emerged as a critical environmental concern due to its adverse effects on ecosystem and human health. Although Asia represents one of the world's largest hubs for plastic production and utilization, comprehensive assessments of MP pollution remain notably insufficient, particularly at an intercontinental scale. This study reveals that soils across Asia act as major sinks for MPs, with pronounced spatial heterogeneity driven by land-use and human activities. The identification of high-risk regions and dominant MP characteristics highlight potential long-term threats to soil health, ecosystem functioning, and food security. By integrating ecological risk indices with machine learning predictions, this work provides a data-driven framework to support early warning, targeted mitigation, and policy development for soil MP pollution management at regional and continental scales.

CRediT authorship contribution statement

Zia Ur Rehman: Writing – original draft, Visualization, Methodology, Investigation, Conceptualization. **Jing Song:** Writing – review & editing, Supervision, Funding acquisition, Formal analysis. **Chunhui Wang:** Writing – review & editing, Validation, Supervision, Project administration, Funding acquisition. **Luís Miguel Nunes:** Writing – review & editing, Validation. **Syed Shabi Ul Hassan Kazmi:** Writing – review & editing, Visualization. **Muhammad Azeem:** Writing – review & editing, Visualization. **Linxuan Fu:** Writing – review & editing, Visualization. **Yu Zhang:** Writing – review & editing, Visualization. **Gang Li:** Writing – review & editing, Validation, Supervision, Funding acquisition.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT-5 (OpenAI, San Francisco, CA, USA) in order to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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.

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Appendix A. Supplementary data

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Data availability

Data will be made available on request.

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