RANDOM FOREST–BASED MAPPING OF RIVERINE PLASTIC POLLUTION FROM SENTINEL-2 IN GOOGLE EARTH ENGINE: LULC AND RAINFALL CONTROLS IN KENDAL REGENCY, INDONESIA

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ABSTRACT

Plastic pollution is a major environmental issue, especially in riverine and urban systems. Understanding its spatial distribution relative to land use/land cover (LULC) and precipitation is crucial. This study examined plastic waste distribution in Kendal Regency using a Plastic Index (PI) derived from remote sensing, Sentinel-2-based LULC classification, and precipitation data. Statistical analyses included boxplots, swarmplots, and correlation tests. PI values differed across LULC types, with higher values in settlements and industrial areas, and lower or negative values in forests and plantations. Irrigated paddies and water bodies showed high variability. In contrast, precipitation showed weak, inconsistent, and non-significant correlations with PI. Plastic accumulation is strongly linked to anthropogenic land cover rather than rainfall. The results highlight urbanization as a key driver of plastic pollution and provide insights for sustainable waste management strategies.

Keywords: *Plastic Index (PI); Land Use/Land Cover (LULC); Precipitation; Urbanization; Remote Sensing.*

1. INTRODUCTION

Plastic waste is a global environmental issue that is becoming increasingly urgent to address. Global plastic production exceeds 400 million tons per year, with a significant portion ending up on land, in rivers, and in the oceans. The accumulation of non-biodegradable plastic waste threatens the sustainability of ecosystems as well as human health (World Bank, 2021). Indonesia ranks among the largest contributors of plastic waste in the world, with an estimated 7.8 million tons of mismanaged plastic waste per year, much of which leaks into coastal and marine ecosystems (World Bank, 2021). This situation poses a serious threat to biodiversity and community well-being, thereby requiring comprehensive monitoring and mitigation strategies (Zahrah et al., 2024). Kendal Regency, located on the northern coast of Central Java, faces a similar problem. The presence of major watershed (DAS in Bahasa Indonesia) such as the Bodri and Blorong Rivers makes the area a natural transport route for plastic waste from upstream to the coast. Research by Hanif et al., (2021) found microplastic contamination at the mouth of the Kendal River, while Laksono et al., (2021) detected microplastics in coastal sediments in Kendal waters. These findings indicate that plastic accumulation in Kendal is a real issue with the potential to damage coastal and marine ecosystems. In addition, the growth of settlements, industrial activity, and agricultural intensification further increase the potential for plastic waste generation, particularly from single-use plastics and agricultural plastics.

Most previous studies have focused on ecological, socio-economic, or community-based waste management aspects. For example, Zahrah et al., (2024) highlighted the limitations of urban waste management systems in Indonesia, while local initiatives in Kendal such as the KerDUS Community focus on community-based zero-waste movements (Hidayati et al., 2025). However, studies specifically linking the spatial distribution of plastic waste with Land Use Land Cover (LULC)

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dynamics remain limited. In fact, remote sensing-based LULC mapping can illustrate land-use patterns closely associated with plastic waste generation potential (Rußwurm et al., 2023).

In recent years, machine learning approaches have developed rapidly in environmental research, including LULC classification, plastic waste detection, and modeling relationships among environmental factors (Aji et al., 2024). Algorithms such as Random Forest, Support Vector Machines, and Gradient Boosting have demonstrated high accuracy in land-cover classification and pollutant-distribution prediction due to their ability to handle nonlinear relationships and complex variables (Belgiu & Drăguţ, 2016). In the context of plastic waste management, machine learning models have been used to map potential plastic accumulation, identify pollution sources, and analyze interactions between biophysical characteristics and waste generation.

Furthermore, field surveys remain a crucial component in plastic waste distribution studies, as they validate satellite-derived observations and machine learning model outputs. Survey methods such as transect sampling, surface debris density measurements, and laboratory microplastic analyses provide the empirical data needed to ensure accuracy and enhance model reliability. Integrating field surveys with remote sensing–based LULC data and machine learning has been widely recommended as the most effective approach for comprehensively understanding the spatial dynamics of plastic waste. Therefore, a research framework is needed that integrates satellite imagery–based LULC classification, Plastic Index data from field surveys, hydrometeorological variables such as precipitation, and machine learning modeling particularly Random Forest to evaluate the spatial determinants of plastic waste distribution. This study aims to fill this gap through an integrative approach capable of revealing the relationships between land-use types (settlements, industry, agriculture, forests, water bodies, and coastal areas) and levels of plastic waste accumulation. The findings of this research are expected to not only contribute scientifically to environmental geospatial studies but also serve as a foundation for formulating policies on plastic waste management and sustainable spatial planning in Kendal Regency.

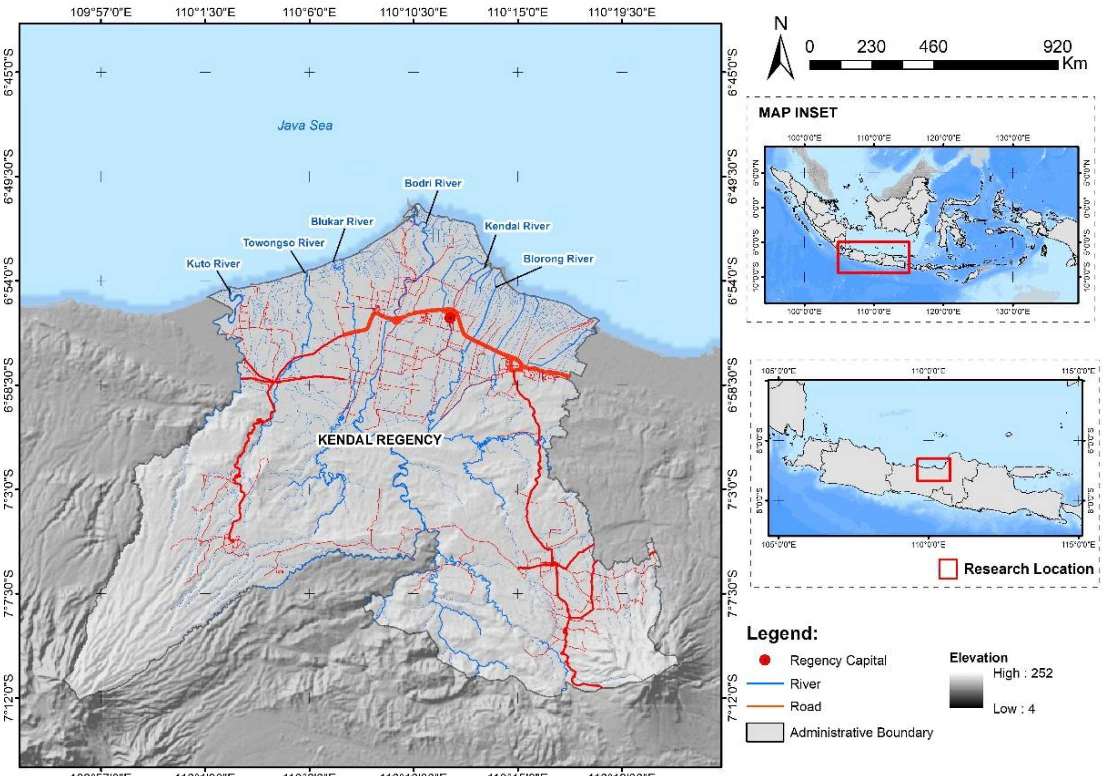


Fig. 1. Location of Kendal Regency.

2. STUDY AREA

Kendal Regency is one of the regions in Central Java Province, located on the northern coast of Java Island with an area of approximately 1,002.23 km². Geographically, Kendal Regency lies between 6°50′–7°24′ S and 109°40′–110°18′ E, bordered by the Java Sea to the north, Semarang Regency to the east, Temanggung Regency to the south, and Batang Regency to the west (BPS Kendal, 2023). This geographical setting gives Kendal diverse landscape characteristics, ranging from coastal lowlands to hilly and mountainous areas in the southern part. The research location map is shown in (**Fig. 1**).

Hydrologically, Kendal Regency is traversed by several important watersheds (DAS). The Bodri River is the main and largest river, while other significant rivers include the Blorong, Kendal, Towongso, Kuto, and Blukar Rivers, all of which flow directly into the Java Sea. These rivers serve vital functions, not only as sources of irrigation and domestic water but also as natural transport routes for materials from upstream to downstream. This condition makes Kendal's coastal areas highly vulnerable to pollution, including the accumulation of plastic waste carried by river flows. In terms of land use and land cover (LULC), Kendal Regency is dominated by agricultural land (rice fields and dry fields), settlements, industry, protected forests, and coastal zones. Industrial areas have rapidly expanded in the lowland and coastal regions, particularly in the subdistricts of Kaliwungu, Brangsong, and Kendal City, supported by the presence of the Kendal Industrial Estate (KIK) as one of the national strategic zones. The rapid growth of industry and urbanization has implications for increasing plastic waste generation, especially in areas adjacent to rivers and coastal zones (Cordova et al., 2018).

In addition to its physical characteristics, several socio-economic and waste management indicators further highlight Kendal's vulnerability to plastic pollution. Kendal Regency has a population of approximately 1.05 million inhabitants with an average density of around 1,050 persons per km^2, concentrated mainly in the northern lowlands. Urban settlements account for roughly half of the population, reflecting ongoing urban expansion along the coastal industrial corridor. The regency also hosts a substantial number of industrial facilities particularly manufacturing, food processing, and textile industries clustered around the Kendal Industrial Estate and other industrial clusters. Solid waste generation is estimated at 800-900 tons per day, yet formal waste management infrastructure, including temporary disposal sites (TPS), community-based waste processing (TPS 3R), and the regional landfill, remains limited in coverage and operational capacity. These conditions contribute to the leakage of mismanaged plastic waste into drainage networks and river systems.

This study focuses on six major rivers in Kendal Regency, namely the Kuto, Towongso, Blukar, Bodri, Kendal, and Blorong Rivers. The selection of these rivers is based on several academic considerations. In terms of environmental significance, these rivers serve as the primary transport pathways for plastic waste from upstream areas toward vulnerable coastal zones. From the perspective of socio-economic drivers, all six rivers flow through areas with intensive economic activities—including industrial zones, densely populated settlements, and commercial centers—that have a high potential for plastic leakage. Based on their hydrological characteristics, these rivers exhibit substantial discharge and watershed sizes and function as the main regional drainage channels that carry various anthropogenic materials to the sea. The final consideration is data availability, as these rivers have existing documentation and field survey records, enabling the verification of remote sensing analysis. This study utilizes Sentinel-2 imagery acquired between 30 May and 11 June, selected to coincide with the timing of field surveys conducted along the six rivers. This temporal alignment ensures consistency between the spatial conditions observed during fieldwork and the remote sensing data used in the analysis.

3. DATA AND METHODS

3.1. Sentinel-2 Satellite Imagery

This study utilizes Sentinel-2 Level-2A imagery, which provides orthorectified and atmospherically corrected surface reflectance processed using the Sen2Cor algorithm, ensuring more accurate reflectance values for spectral analysis (Louis et al., 2016). Sentinel-2, an Earth observation mission operated by the European Space Agency (ESA), is equipped with the MultiSpectral Instrument (MSI) comprising 13 spectral bands with spatial resolutions of 10 m (Blue, Green, Red, NIR), 20 m (Red Edge, SWIR), and 60 m (Coastal aerosol, Water vapor, Cirrus), a 290 km swath width, and a combined revisit time of 5 days for Sentinel-2A and Sentinel-2B (Drusch et al., 2012; Delwart, 2015). Image selection was conducted using several criteria, including a maximum cloud coverage threshold of ≤10%, availability of Level-2A surface reflectance products on Google Earth Engine (GEE), stable radiometric conditions, and acquisition dates representative of normal dry-season hydrological conditions.

The selection procedure involved filtering the *COPERNICUS/S2_SR* collection based on the study area, date range (30 May–11 June, aligned with the field survey period), and cloud percentage, followed by identifying the scene with the lowest cloud contamination. Although the images were already atmospherically corrected via Sen2Cor, additional preprocessing involved masking cloud and shadow pixels using the Sentinel-2 Scene Classification Layer (SCL), specifically removing cloud shadow, medium-probability cloud, high-probability cloud, thin cirrus, and snow/ice classes to retain only valid surface reflectance. The preprocessed imagery was then used to extract spectral information through several indices, including the Plastic Index (PI) for detecting plastic waste (Biermann et al., 2020), NDVI for vegetation assessment, NDBI for identifying built-up areas, NDWI for delineating water bodies, and the Turbidity Index (TI) for evaluating water turbidity. Together, these indices provide a comprehensive analytical framework for identifying the spatial distribution of plastic waste while accounting for the surrounding environmental conditions.

3.2. Rainfall Data from CHIRPS

This study also utilizes CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data) as a source of rainfall information. CHIRPS is a quasi-global rainfall dataset developed by the Climate Hazards Group (University of California, Santa Barbara) in collaboration with the U.S. Geological Survey (USGS), covering latitudes from 50°N to 50°S. The dataset offers a spatial resolution of 0.05° (~5 km) with daily, dekadal, and monthly temporal resolutions from 1981 to the present (Funk et al., 2015). CHIRPS integrates satellite-based infrared precipitation estimates from geostationary platforms with in-situ rain gauge observations from thousands of stations worldwide, producing long-term, consistent, and improved rainfall records compared to using satellite or gauge data alone. In this study, CHIRPS is used to analyse rainfall variability across the study area, which is essential for understanding river hydrological dynamics and their relationship to plastic waste distribution in aquatic systems.

To enhance the reliability of rainfall inputs, CHIRPS has been extensively validated and applied across a wide range of hydrological and climate-related studies. Previous research has demonstrated its robustness for monitoring rainfall patterns (Paredes-Trejo et al., 2021), flood modelling in data-scarce regions (Rayamajhi et al., 2025), drought assessment (Tikuye et al., 2025), and improving runoff estimation in ungauged basins. Its strong performance in tropical humid environments has also been confirmed in Southeast Asia, further reinforcing its suitability for the present study, particularly in characterising rainfall variability and assessing its influence on riverine plastic waste dynamics in Kendal Regency.

3.3. River Data

The river data used in this study were obtained from the Environmental Agency of Kendal Regency in vector format. This dataset serves as a reference for delineating the research area, particularly in the analysis of plastic waste distribution along river channels. The rivers selected for this study are the major rivers located within Kendal Regency, as they play a significant role in transporting materials, including plastic waste, from upstream areas to downstream and eventually to the sea. By utilizing river vector data, the mapping of waste distribution can be conducted more accurately, while also enabling integration with other spatial datasets, such as land use/land cover (LULC) and plastic waste sampling points obtained from field surveys.

3.4. Land Use Land Cover (LULC) Data

Land Use/Land Cover (LULC) data in this study were obtained through the extraction of Sentinel-2 satellite imagery for the year 2024. The extraction process utilized relevant band composites to distinguish the spectral characteristics of each land cover type, allowing the identification of land use patterns along the riverbanks. The classification results were used to determine land use categories, including Dry Forest, Mixed Crops, Settlements, Industrial Buildings, Irrigated Rice Fields, Agricultural Land, Mixed Plantations, Water Bodies, Shrubs, and Plantations, which serve as important factors in understanding environmental dynamics (Aji et al., 2024).

The presence of plastic waste accumulated in river channels is often associated with the surrounding land use types. For instance, densely populated settlement areas tend to contribute more significantly to waste accumulation compared to natural vegetation areas. Sentinel-2–based LULC not only provides a spatial representation of land cover conditions but also serves as a foundation for examining the relationship between plastic waste distribution and land use characteristics along the riverbanks.

3.5. Integrated Geospatial and Machine Learning Methodology

This study employed an integrated geospatial and machine learning framework to analyse riverine plastic waste distribution, Land Use/Land Cover (LULC) patterns, and their relationship with precipitation in Kendal Regency. All spatial analyses were implemented using Google Earth Engine (GEE), enabling efficient processing of multi-source remote sensing and environmental datasets. The overall methodological workflow is illustrated in (**Fig. 2**).

3.5.1. Overall Analytical Workflow

The methodological framework consisted of four main stages: (1) extraction and preprocessing of satellite-based spectral data and rainfall information; (2) derivation of spectral indices related to vegetation, built-up areas, water bodies, turbidity, and plastic waste; (3) application of Random Forest (RF) models for both plastic index prediction and LULC classification; and (4) integration of plastic waste distribution, LULC patterns, and precipitation data to examine their spatial interrelationships along major river corridors. This integrated approach was designed to capture both anthropogenic and environmental drivers of plastic accumulation at the landscape scale.

3.5.2. Overall Analytical Workflow

Plastic waste detection was based on multispectral information derived from Sentinel-2 Level-2A imagery acquired between 30 May and 11 June 2025 and temporally aligned with field surveys. Several spectral indices were calculated to enhance the discrimination of plastic materials from other surface features.

Vegetation conditions were characterized using the Normalized Difference Vegetation Index (NDVI), defined as NDVI = (NIR−Red)/(NIR+Red), while built-up areas were highlighted using the Normalized Difference Built-up Index (NDBI), calculated as NDBI = (SWIR−NIR)/(SWIR+NIR). Water-related features were enhanced using the Normalized Difference Water Index (NDWI), expressed as NDWI = (Green−NIR)/(Green+NIR).

Turbidity conditions were represented by the Turbidity Index (TI), computed as TI = (RedEdge−Red)/(RedEdge+Red). Plastic waste distribution was quantified using the Plastic Index (PI), defined as PI = NIR/(NIR+Red), derived from spectral band ratios and index-based corrections sensitive to synthetic materials in aquatic environments. In this formulation, *Green*, *Red*, *RedEdge*, *NIR*, and *SWIR* represent the green, red, red-edge, near-infrared, and shortwave infrared bands of Sentinel-2 imagery, respectively.

All indices were spatially constrained to the study area and masked using cloud and shadow information from the Sentinel-2 Scene Classification Layer to ensure that only valid surface reflectance pixels were retained. The resulting multi-index dataset constituted the feature space for subsequent Random Forest modeling.

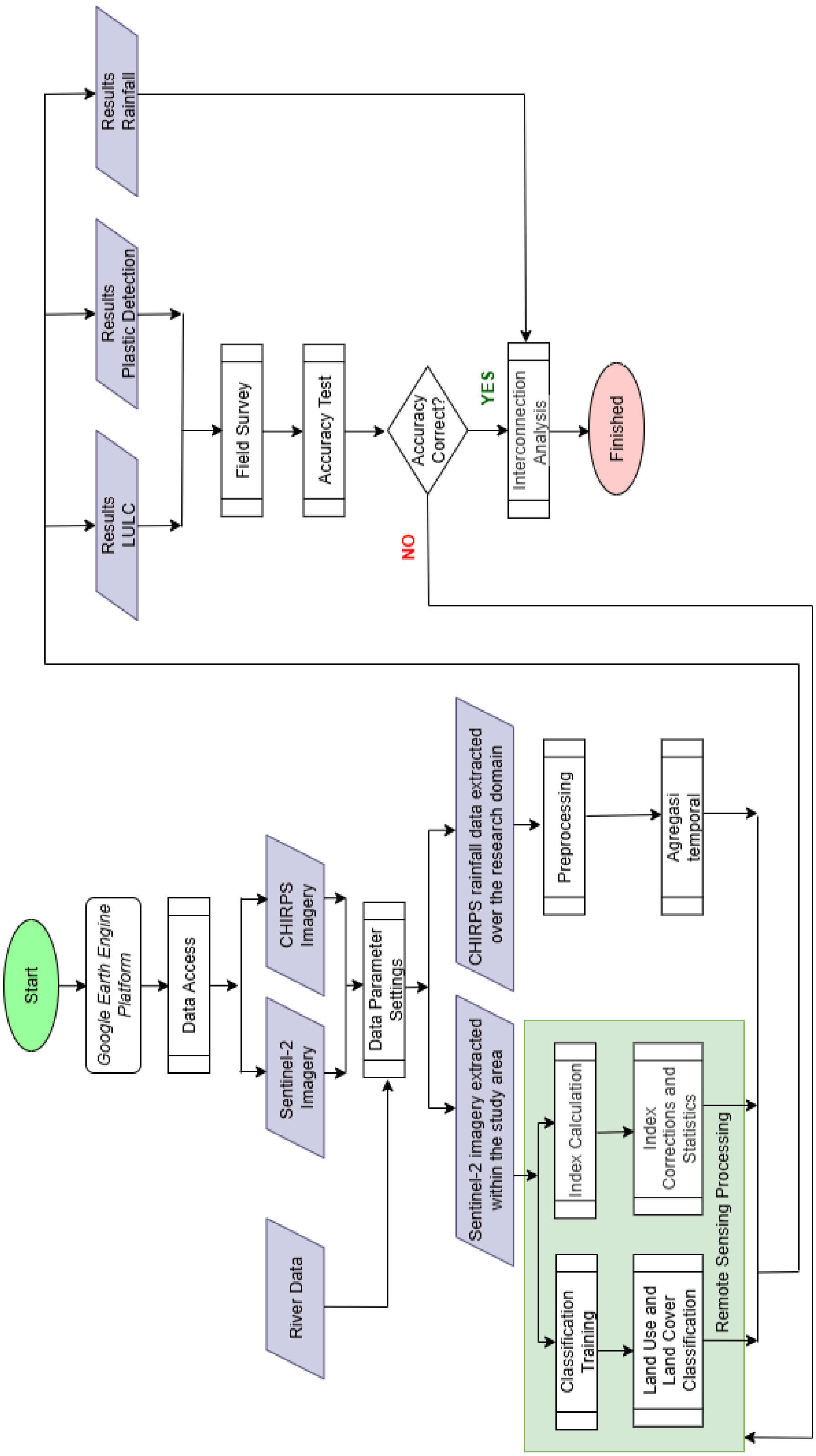


Fig. 2. Research flow.

3.5.3. Random Forest Modeling Framework

Random Forest (RF) regression was employed to model the spatial distribution of plastic waste by predicting Plastic Index (PI) values from multispectral indices. RF was selected due to its robustness in handling non-linear relationships, high-dimensional feature spaces, and multicollinearity, which are common in remote sensing data. The RF model was trained using a set of predictor variables derived from spectral indices (NDVI, NDWI, NDBI, TI) and spectral bands, with PI as the response variable. To evaluate model sensitivity to parameterization, RF models were trained using different numbers of decision trees (50, 100, and 150). Training and validation datasets were constructed using field-validated sample points collected along six major rivers. This design ensured that the model learned relationships representative of diverse hydrological and land-use contexts within the study area.

3.5.4. Model Performance Evaluation and Optimization

Model performance was assessed using three standard regression metrics: the coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). MAE quantifies the average absolute difference between observed and predicted PI values, while RMSE emphasizes larger prediction errors and reflects overall model accuracy. R^2 measures the proportion of variance in observed PI values explained by the model. To improve robustness and reduce overfitting, a k-fold cross-validation approach was applied. Performance metrics were evaluated across different tree numbers to identify the optimal RF configuration. The final model selection was based on the combination of highest R^2 and lowest MAE and RMSE values, ensuring stable and reliable prediction of plastic waste distribution.

3.5.5. Model Performance Evaluation and Optimization

Land Use/Land Cover classification was conducted using Sentinel-2 imagery for the year 2024, applying a Random Forest classifier consistent with the Indonesian National Standard for land cover classification (SNI 7645:2010). Ten LULC classes were identified, including Dryland Forest, Agricultural Land, Mixed Crops, Plantations, Mixed Plantations, Shrubs, Settlements, Industrial Buildings, Irrigated Rice Fields, and Water Bodies. To ensure relevance to riverine plastic dynamics, LULC analysis was focused on a 500-m buffer surrounding major rivers. This buffer-based approach captures land-use characteristics most likely to influence plastic input, transport, and accumulation within river systems. Classification accuracy was evaluated using standard accuracy assessment metrics, including overall accuracy and the kappa coefficient.

3.5.6. Integration of Plastic Index, LULC, and Rainfall

Following validation of both plastic detection and LULC classification results, spatial integration analysis was performed to examine relationships among PI values, LULC classes, and precipitation patterns. Daily rainfall data derived from CHIRPS were temporally aggregated to match the plastic detection period and spatially aligned with river corridors. The integrated dataset enabled statistical and spatial analyses of plastic waste distribution across different land-use types and rainfall regimes. This final stage provided the basis for identifying dominant spatial drivers of plastic accumulation and for interpreting the relative influence of anthropogenic land use versus hydrometeorological variability.

4. RESULTS AND DISCUSSIONS

4.1. Map of Plastic Waste Detection Results

The results of waste detection in Kendal Regency are shown in **(Fig.3)**. The figure above presents a map of plastic waste detection in Kendal Regency. The results indicate that plastic waste is distributed across the six major rivers in the region. The detection outcomes reveal a gradient ranging from low to high concentrations, represented by a color scheme from green to red. Several sample pixels are highlighted on the map, demonstrating that different river segments exhibit varying levels of plastic waste concentration (low, medium, and high).

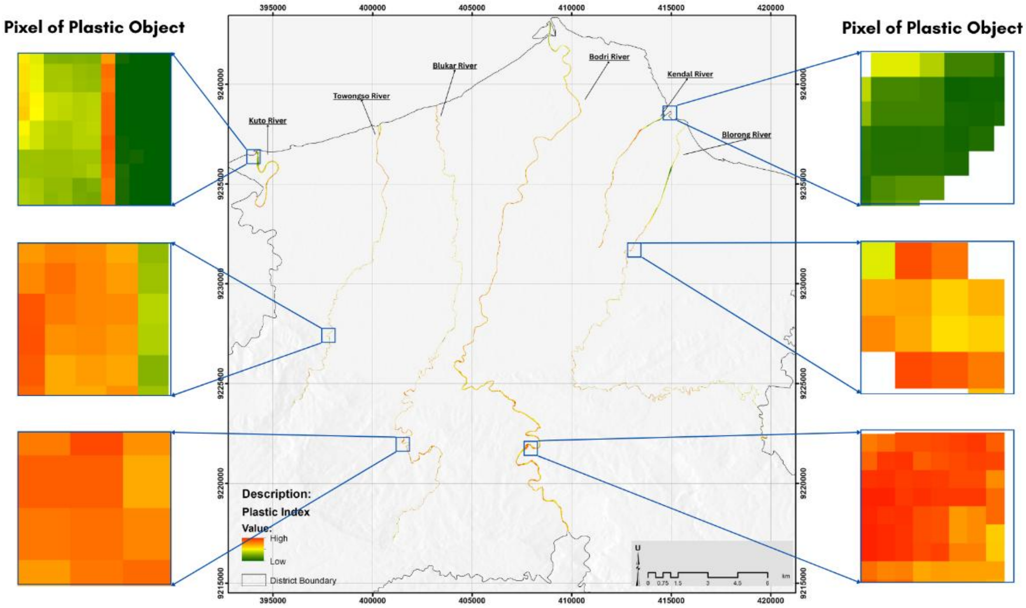


Fig. 3. Map of plastic waste distribution in six rivers in Kendal.

The visualization of plastic-related pixels indicates substantial spatial heterogeneity across river locations. The applied classification system, which employs a color gradient, provides a clear representation of the distribution patterns. Similar approaches have been widely used in remote sensing-based plastic detection research, where multispectral or satellite imagery was classified to map riverine and coastal plastic pollution (Cortesi et al., 2021; Nivedita et al., 2024). Sample pixels on different river sections show distinct spectral characteristics, emphasizing the variability of plastic pollution intensity.

The findings further suggest that plastic waste is not evenly distributed across the region. The highest concentrations (red–orange pixels) are clustered in specific areas, likely associated with anthropogenic activities such as dense settlements, industrial zones, and disposal points. In contrast, areas dominated by green pixels indicate relatively lower levels of plastic pollution, reflecting better environmental conditions. These results align with previous studies that demonstrate the strong linkage between land use, especially settlements and industrial areas, and plastic accumulation in rivers (Cerra et al., 2025; Cortesi et al., 2022). Such heterogeneity underscores the importance of targeted mitigation strategies in high-risk zones where anthropogenic pressure is most pronounced.

To validate the detection model, 147 field samples were collected along major rivers **(Fig.4)**. The field survey involved validating the detected pixels with actual plastic waste conditions, particularly waste deposited in river bends, sandbars, or other accumulation points. Accuracy assessment was conducted using three statistical metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2). The regression analysis yielded highly satisfactory results.

The MAE value of 0.0536 indicates an average prediction error of only ~0.054 units, reflecting high model accuracy. Similarly, the RMSE of 0.0728 demonstrates relatively low prediction error, consistent with the MAE value. The R^2 value of 0.8892 shows that approximately 88.92% of the variance in the observed data is explained by the model, confirming its strong predictive capability. The scatter plot **(Fig.5)** further illustrates the alignment between predicted and observed values, with most data points clustering around the 1:1 reference line, indicative of high model reliability.

Model performance was further assessed through cross-validation and hyperparameter tuning to ensure robustness. A 3-fold cross-validation approach was employed to reduce bias from single data partitioning. Performance was consistently evaluated using MAE, RMSE, and R^2 metrics, and averaged across folds as the final performance indicators.

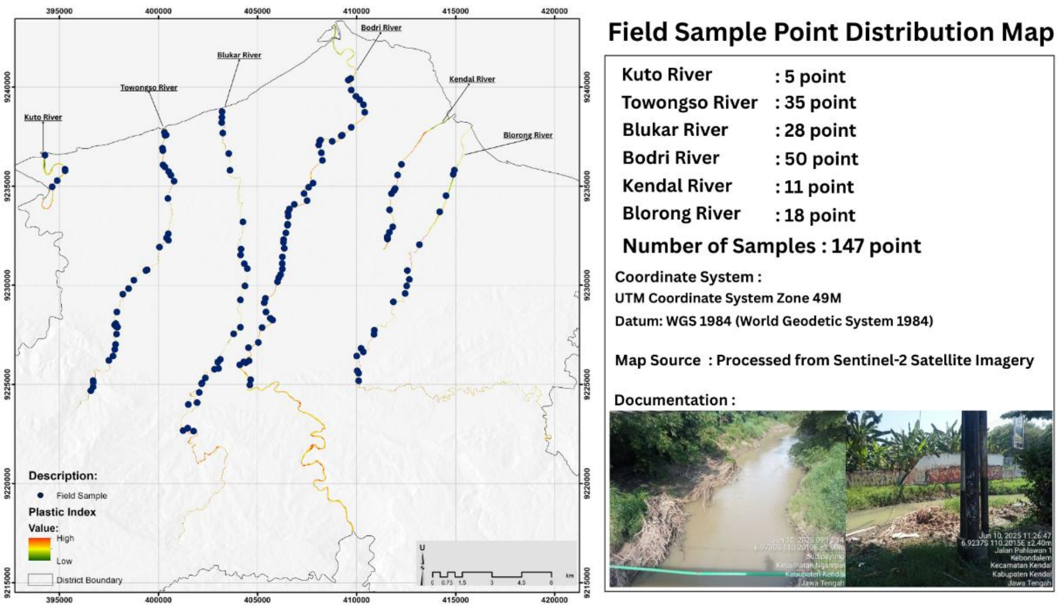


Fig. 4. Field Sample Point Distribution Map.

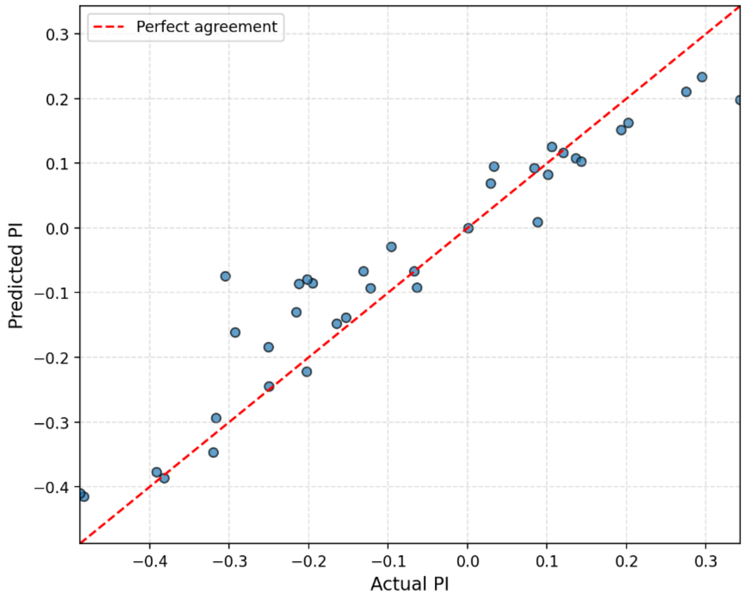


Fig. 5. Graph of Predicted vs. Actual Model Values.

The evaluation of the Random Forest model with varying numbers of trees is shown in **(Fig.6-8)**. The results demonstrate a clear improvement in predictive performance with increasing tree counts. As shown in **(Fig.6)**, the mean R^2 value improved from 0.883 (50 trees) to 0.888 (100 trees), and further to 0.890 (150 trees). Similarly, the average MAE exhibited a declining trend **(Fig.7)**, decreasing from 0.0586 (50 trees) to 0.0576 (100 trees), and finally to 0.0574 (150 trees). The RMSE values followed a comparable pattern **(Fig.8)**, with values decreasing from 0.0725 (50 trees) to 0.0715 (100 trees), and further to 0.0710 (150 trees). These results highlight that increasing the number of trees in the Random Forest algorithm contributes to more stable and accurate predictions of the Plastic Index (PI), which is consistent with findings in other machine learning-based remote sensing studies (Cortesi et al., 2021, 2022).

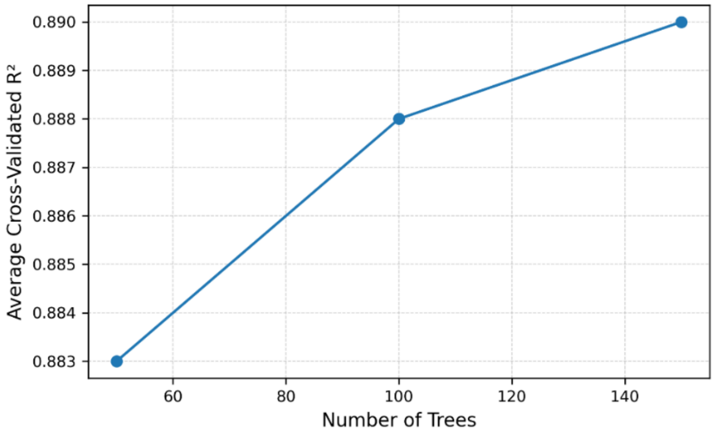


Fig. 6. Cross-Validation Graph.

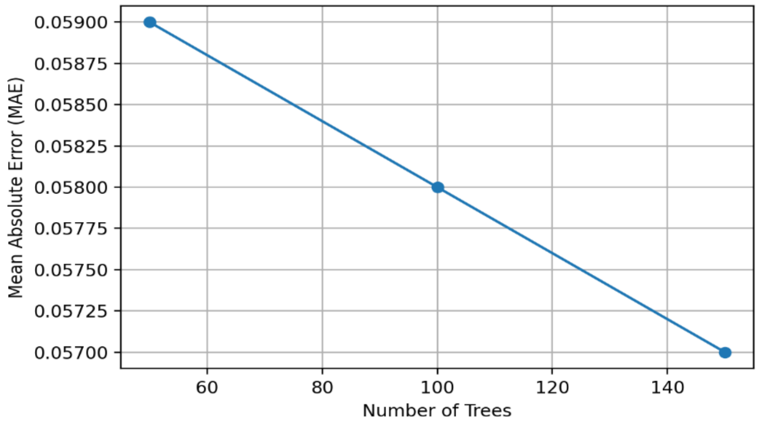


Fig. 7. Graph of the Relationship between Mean Absolute Error and Number of Trees.

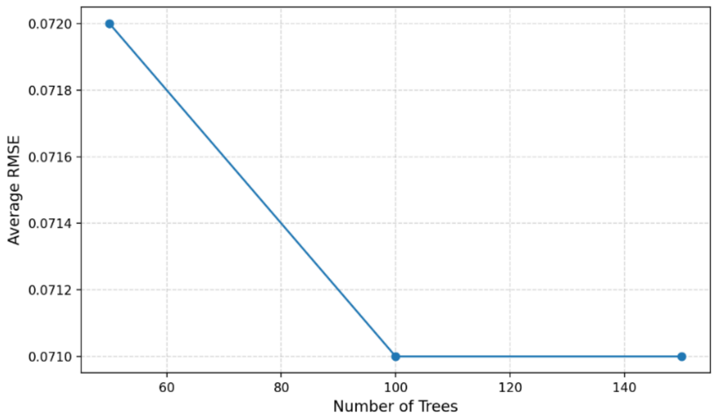


Fig. 8. Graph of the Relationship between Root Mean Square Error and Number of Trees.

Overall, the model evaluation confirms that the adopted Random Forest approach is both robust and reliable in detecting plastic waste distribution from satellite imagery. The strong predictive performance, validated through statistical metrics and cross-validation, demonstrates the potential of machine learning-based remote sensing techniques in supporting sustainable riverine waste management (Nivedita et al., 2024).

4.2. Land Use Land Cover (LULC) Mapping

The LULC classification for 2024 was conducted using Sentinel-2 imagery, referring to the Indonesian National Standard (SNI) 7645 of 2010 on Land Cover Classification. The standard was applied at a scale of 1:25,000 with ten land cover classes, namely: Dry Forest, Agricultural Land, Mixed Crops, Plantations, Mixed Plantations, Shrubs, Settlements, Industrial Buildings, Irrigated Rice Fields, and Water Bodies. The accuracy assessment results showed an overall accuracy of 98% and a kappa coefficient of 97%. These values are higher compared to the previous classification, which had an accuracy of 89% and a kappa of 85%. This improvement indicates that Sentinel-2-based classification methods provide more reliable results for LULC mapping (Belgiu & Drăguț, 2016; Phiri et al., 2020). Based on the Land Use/Land Cover (LULC) map of Kendal Regency in 2024 **(Fig. 9)**, the spatial distribution of land cover exhibits considerable complexity. In the northern coastal areas, Water Bodies (blue) and Irrigated Rice Fields (light green) dominate, reflecting intensive rice cultivation activities and the presence of coastal water bodies. Meanwhile, the central to southern parts of the region are dominated by Agricultural Land, Mixed Crops, and Plantations, consistent with Kendal Regency's characteristics as an agriculture- and plantation-based area (SNI, 2010).

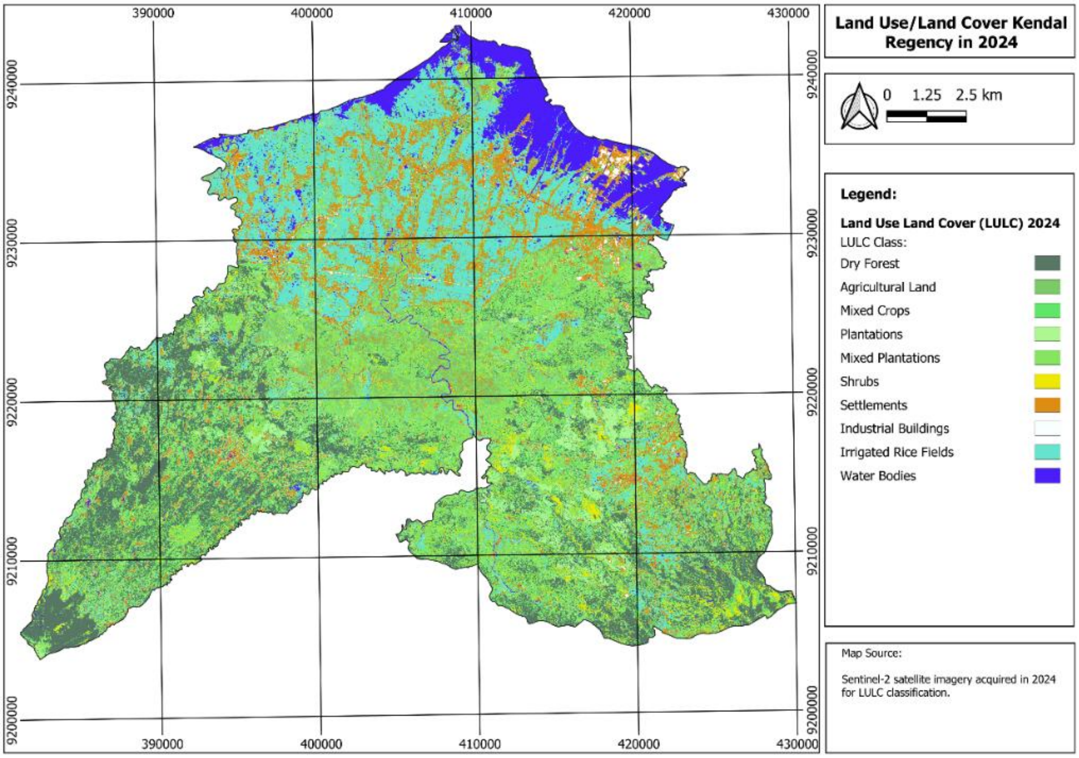
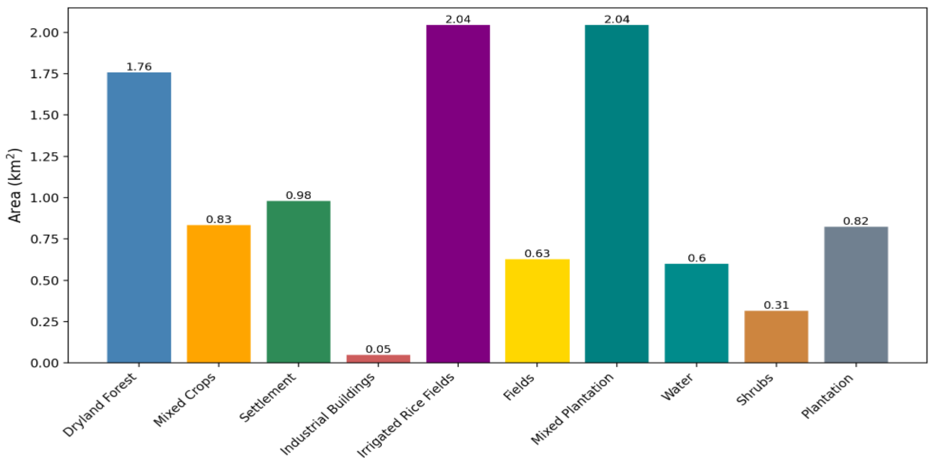
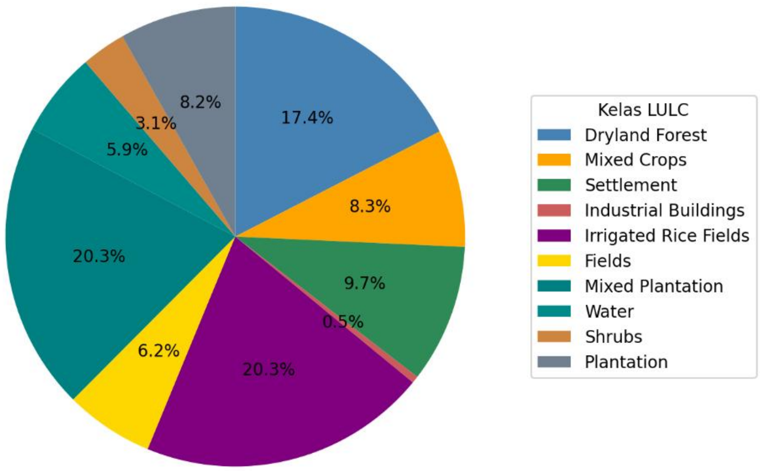


Fig. 9. LULC Map of Kendal Regency in 2024.

The Settlements and Industrial Buildings classes appear concentrated along major transportation corridors and urban centers, indicating increased urbanization activities. This distribution also highlights development pressures on ecological balance, particularly around major rivers (Chen et al., 2024). In contrast, Shrubs and Mixed Plantations appear sporadically, signaling land degradation or transitional land use. Furthermore, the area-based analysis of each land cover class reveals clear quantitative differences that reflect the region's landscape structure **(Fig. 10)**. The largest land cover categories are Mixed Plantation and Irrigated Rice Fields, each covering approximately 204 km² (20.3%), highlighting the dominance of plantation systems and irrigated agriculture across Kendal Regency. Dryland Forest accounts for around 176 km² (17.4%), indicating the presence of significant forested areas, particularly in the upland southern regions that contribute to ecological stability.



a)



b)

Fig. 10. Distribution of land use and land cover (LULC) classes in the study area: (a) total area (ha) and (b) relative proportion (%).

The Settlement class occupies about 97 km² (9.7%), while Mixed Crops covers roughly 82 km² (8.3%), reflecting the distribution of residential and diversified agricultural zones in the mid-regency areas. Plantation areas comprise around 81 km² (8.2%), further emphasizing the importance of estate-crop cultivation in the local economy. Meanwhile, Fields extend over approximately 62 km² (6.2%), representing areas dominated by seasonal cropping systems. Water Bodies, primarily found in the northern coastal zone, cover around 59 km² (5.9%), consistent with the presence of coastal waters and aquaculture ponds. Shrubs, representing transitional or degraded land, occupy the smallest area of roughly 30 km², appearing in scattered patches across the region. Industrial Buildings cover a minimal area of about 3 km², but are spatially clustered along major corridors, consistent with the concentration of manufacturing zones. The Area of Interest (AOI) of the study was focused on areas surrounding major rivers in Kendal Regency **(Fig. 11)**. To obtain a land cover distribution representation relevant to river dynamics, LULC analysis was conducted within a 500-meter buffer from each major river. This approach was chosen to ensure that the mapping results align with the study's objective, namely to examine the relationship between land cover distribution and aquatic environmental conditions, particularly concerning the potential distribution of plastic waste in the study area.

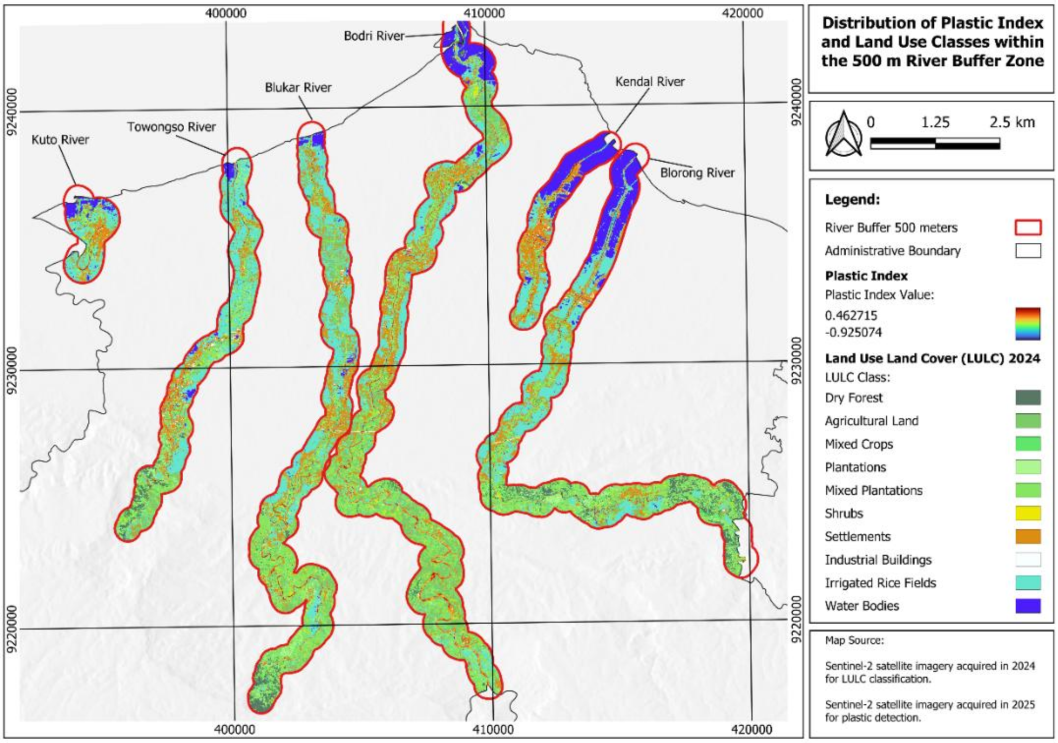


Fig. 11. Map of Plastic Waste Distribution and 500-Meter LULC Buffer.

4.3. The Relationship between Plastic Waste Detection Locations, LULC, and Rainfall

In this analysis, LULC classes include Dryland Forest, Mixed Crops, Settlements, Industrial Buildings, Irrigated Paddy Fields, Dry Fields, Mixed Plantations, Water Bodies, Scrub, and Plantations. However, the current dataset only contains observations for Dryland Forest, Settlements, Irrigated Paddy Fields, Mixed Plantations, Water Bodies, and Scrub. The statistical analysis of PI values across observed LULC classes highlights a strong anthropogenic influence on plastic accumulation patterns. Settlements exhibit the highest median PI values (approximately +0.10 to +0.15), which directly reflects household waste generation, commercial activities, and inadequate solid waste management systems. This class serves as the primary source zone for plastic pollution in the landscape **(Fig. 12)**.

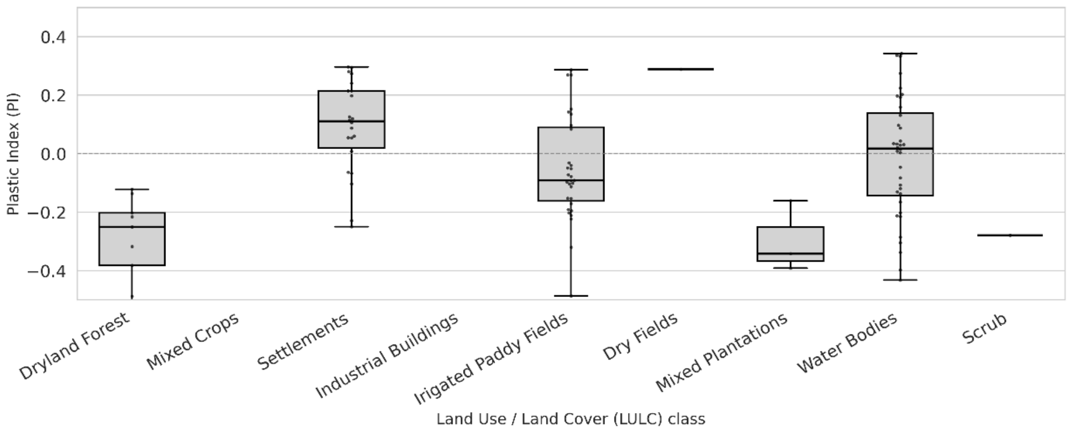


Fig. 12. Distribution of Plastic Index (PI) across LULC classes using Boxplot and Swarmplot.

Water Bodies display the greatest spatial variability in PI values, with observations ranging from approximately -0.45 to +0.35. While the median value remains close to zero (~+0.02), the presence of extreme positive outliers (up to +0.35) indicates that certain water bodies act as significant accumulation sinks, receiving plastics transported by surface runoff, drainage, and riverine flow. This heterogeneity suggests that water bodies with high hydrological connectivity to settlements or agricultural areas experience localized hotspots of plastic accumulation, whereas more isolated or upstream water bodies remain relatively unaffected. In contrast, negative PI values are consistently observed across vegetated and less-disturbed landscapes. Mixed Plantations show the lowest median PI (~-0.35), followed by Scrub (median ~-0.28) and Dryland Forest (median ~-0.25). These negative values reflect the buffering role of vegetated land covers, where vegetation acts as a physical barrier to plastic transport and accumulation. The lower levels of direct human activity in these areas also contribute to reduced plastic inputs.

Irrigated Paddy Fields demonstrate moderate negative median PI values (around -0.10) with relatively low variability. This pattern suggests that while irrigated agriculture is less contaminated than settlements, the irrigation infrastructure and water management practices may still introduce some plastic materials, particularly if irrigation water is sourced from potentially contaminated water bodies or located near waste-generating areas. Notably absent from the analysis are Mixed Crops, Industrial Buildings, Dry Fields, and Plantations. The lack of observations in these classes may indicate either their limited spatial extent in the study area or sampling gaps. Future research should prioritize targeted sampling in these land use types, particularly Mixed Crops and Industrial Buildings, which are expected to show elevated PI values based on their anthropogenic character.

Overall, the results demonstrate a clear land use gradient in plastic pollution: human-dominated landscapes (Settlements) function as primary sources with elevated PI values, Water Bodies serve as dynamic transport and variable accumulation zones, while vegetated and less-disturbed areas (Mixed Plantations, Scrub, Dryland Forest) consistently show negative PI values, acting as natural buffers. This spatial pattern underscores the critical importance of integrated land use planning, improved solid waste management in settlement areas, and the preservation of vegetated buffers to mitigate plastic pollution at the landscape scale.

The application of locally weighted scatterplot smoothing (LOWESS) regression to the relationship between plastic index (PI) and land use/land cover (LULC) classes reveals a distinct non-linear pattern that reflects the complex interplay between anthropogenic activities and plastic accumulation dynamics across the landscape **(Fig. 13)**. The smoothed trend line demonstrates substantial variability in PI values across the LULC gradient, with peaks corresponding to human-dominated land uses and troughs associated with vegetated or semi-natural landscapes.

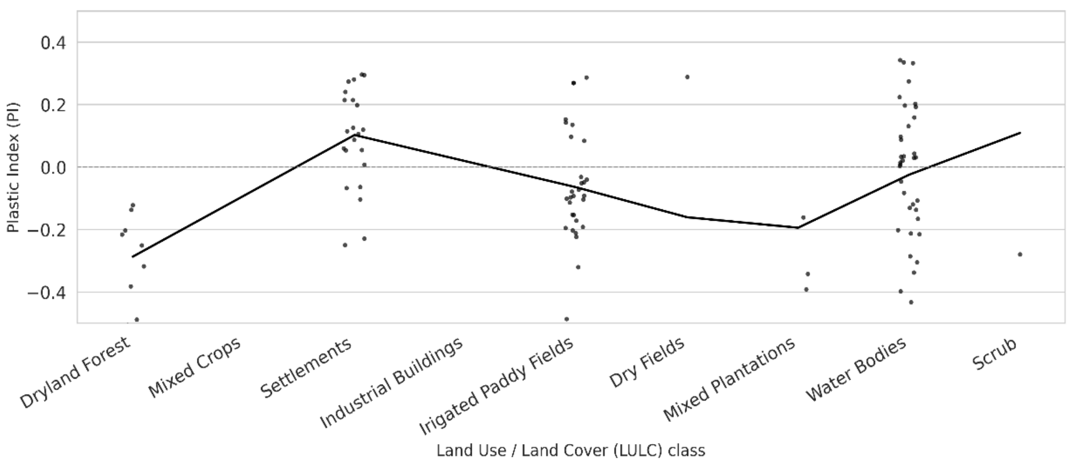


Fig. 13. Relationship between Plastic Index (PI) and Land Use/Land Cover (LULC).

The LOWESS curve exhibits an initial increase from Dryland Forest (PI ≈ -0.30) to a pronounced maximum at Settlements (PI ≈ +0.10 to +0.15), representing an increase of approximately 0.40 to 0.45 units across this transition. This sharp gradient underscores the fundamental role of residential and commercial areas as primary point sources of plastic pollution in the study landscape. The elevated PI values observed in settlement areas are consistent with previous studies demonstrating the correlation between population density, inadequate municipal solid waste management infrastructure, and environmental plastic loads (Jambeck et al., 2015; Lebreton et al., 2017). The considerable scatter of individual observations around Settlements (ranging from approximately -0.05 to +0.30) suggests significant intra-class heterogeneity, likely attributable to variations in waste management practices, population density, and socioeconomic factors across different settlement types within the study area.

Following the peak at Settlements, the LOWESS trend exhibits a declining trajectory through Irrigated Paddy Fields, reaching a local minimum at Mixed Plantations (PI ≈ -0.20 to -0.35). The negative PI values observed in Irrigated Paddy Fields (median PI ≈ -0.10) indicate relatively low plastic contamination despite their position in the agricultural production landscape. This pattern may reflect the combined influence of regular water management practices that facilitate plastic transport and removal, as well as the lower intensity of plastic-generating activities compared to settlements. The further decline toward Mixed Plantations demonstrates the buffering capacity of plantation systems, where dense vegetation cover and reduced anthropogenic disturbance limit plastic accumulation through physical interception and reduced waste inputs (Browne et al., 2011; Eerkes-Medrano et al., 2015)

A notable secondary increase in the LOWESS curve occurs at Water Bodies, where the smoothed trend approaches near-neutral values (PI ≈ -0.05 to 0.00). However, this class exhibits the greatest dispersion of individual observations, with values spanning the entire analytical range from -0.45 to +0.35. This extreme variability reflects the dual nature of aquatic systems as both transport corridors and accumulation sinks for plastic debris (Ballent et al., 2016; Van Emmerik & Schwarz, 2020). The presence of substantial positive outliers (PI > +0.20) indicates that specific water bodies within the study area function as significant plastic accumulation hotspots, likely resulting from convergent flow patterns, proximity to upstream pollution sources, limited flushing capacity, or the presence of physical retention features such as debris dams or low-energy depositional zones. Conversely, negative PI values in other water bodies suggest effective transport and removal processes, potentially associated with higher flow velocities, greater hydrological connectivity to downstream systems, or isolation from direct pollution inputs. This heterogeneity underscores the importance of site-specific assessment rather than class-level generalizations when evaluating plastic contamination in aquatic environments.

The final segment of the LOWESS curve demonstrates a sharp decline to strongly negative values at Scrub (PI ≈ -0.30). Scrubland areas, characterized by low anthropogenic pressure and moderate vegetation cover, consistently exhibit low plastic accumulation. The relatively constrained scatter of observations within this class indicates more homogeneous environmental conditions and reinforces the role of semi-natural vegetation as an effective barrier to plastic transport and deposition. The non-linear relationship revealed by the LOWESS analysis has important implications for understanding landscape-scale plastic pollution dynamics. The oscillating pattern, with distinct peaks at Settlements and Water Bodies separated by troughs at vegetated land covers (Dryland Forest, Mixed Plantations, Scrub), demonstrates that plastic accumulation cannot be adequately described by simple linear models or uniform urban-to-rural gradients. Instead, the spatial distribution of plastic pollution reflects a mosaic pattern determined by the specific characteristics of each land use type, their spatial configuration, and the connectivity pathways that facilitate plastic transport between source and sink areas.

From a management perspective, these findings highlight three priority intervention points: (1) enhanced solid waste management and behavioral change programs in Settlement areas to reduce plastic inputs at the source; (2) strategic preservation and expansion of vegetated buffer zones, particularly Mixed Plantations and Scrubland, to intercept plastic transport pathways; and (3) targeted monitoring and remediation efforts in high-accumulation water bodies identified through the substantial positive outliers observed in Water Bodies. The strong buffering effect demonstrated by vegetated land covers (Dryland Forest, Mixed Plantations, and Scrub) supports nature-based solutions approaches that integrate riparian vegetation management and green infrastructure into broader plastic pollution mitigation strategies.

The LOWESS regression analysis of the relationship between precipitation and plastic index (PI) reveals a complex, non-monotonic pattern that deviates substantially from simple linear assumptions **(Fig. 14)**. The smoothed trend line demonstrates multiple inflection points across the precipitation gradient, suggesting that the influence of rainfall on plastic accumulation operates through multiple, competing mechanisms that vary in dominance across different precipitation regimes. At the lower end of the precipitation spectrum (0-10 mm), the LOWESS curve exhibits moderate positive PI values (approximately +0.05), followed by a sharp decline to a local minimum at approximately 10 mm (PI ≈ -0.15). This initial negative trend may reflect the threshold mobilization effect, whereby moderate rainfall events possess sufficient energy to initiate plastic transport from terrestrial surfaces but insufficient volume to facilitate long-distance transport or dilution. The substantial scatter of individual observations within this range (spanning from approximately -0.40 to +0.35) indicates high spatial variability in local hydrological conditions, surface characteristics, and proximity to plastic sources.

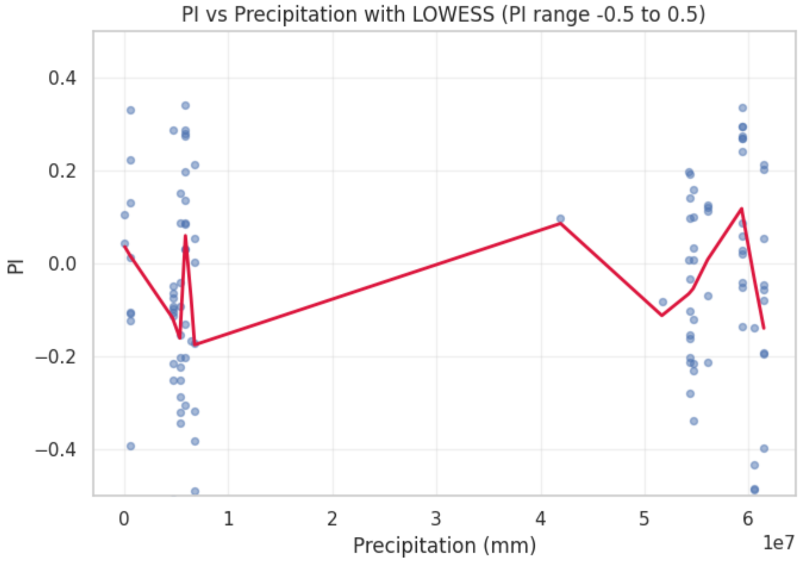


Fig. 14. Relationship between Plastic Index (PI) and Precipitation.

The trend line subsequently exhibits a gradual increase from the 10 mm minimum through the mid-range precipitation values (10-40 mm), reaching a secondary peak at approximately 40-45 mm (PI ≈ +0.10). This ascending limb of the curve suggests that moderate-to-high precipitation events may enhance plastic accumulation through several potential mechanisms. First, increased runoff volume during substantial rainfall events can transport plastics from diffuse upland sources to convergent flow paths and depositional zones within the landscape (Hurley et al., 2018). Second, higher precipitation totals may be associated with longer-duration storm events that facilitate the breakdown of larger plastic items into smaller fragments through physical abrasion, thereby increasing detection probability via spectral indices such as PI (Corcoran et al., 2009). Third, areas receiving moderate rainfall may support land use practices that generate plastic waste, such as intensive agriculture with plastic mulching or greenhouse cultivation (Steinmetz et al., 2016).

Following this secondary maximum, the LOWESS curve displays a pronounced decline to near-zero or slightly negative values at approximately 50 mm (PI ≈ -0.10), followed by another sharp increase to a tertiary peak at approximately 60-65 mm (PI ≈ +0.10 to +0.15). This oscillating pattern in the high precipitation range is particularly intriguing and may reflect the complex interplay between transport capacity, dilution effects, and spatial patterns of land use. High-precipitation areas may experience enhanced flushing of plastic materials through well-developed drainage networks, leading to reduced local accumulation but increased downstream transport (Van Emmerik et al., 2018). Alternatively, the positive PI values observed at the highest precipitation levels could indicate areas where intense rainfall concentrates transported plastics in specific depositional environments, such as floodplains, retention basins, or coastal zones that serve as terminal sinks.

The substantial vertical scatter of observations throughout the precipitation gradient, particularly evident in the 0-20 mm and 55-65 mm ranges, underscores the importance of factors beyond precipitation in determining plastic accumulation patterns. This variability likely reflects the confounding influences of land use intensity, population density, waste management infrastructure, topography, soil characteristics, and vegetation cover all of which modulate the relationship between rainfall and plastic transport-deposition dynamics (Horton et al., n.d.; Windsor et al., 2019).

From a process-based perspective, the non-linear relationship revealed by this analysis suggests that plastic mobilization and accumulation across precipitation gradients cannot be adequately described by simple hydrological transport models. Instead, the data indicate threshold-dependent behaviors and regime shifts that likely correspond to distinct hydrological states: (1) a low-precipitation regime characterized by limited transport capacity and localized accumulation near sources; (2) a moderate-precipitation regime where enhanced runoff facilitates both mobilization and redeposition; and (3) a high-precipitation regime where competing processes of transport efficiency, dilution, and concentrated deposition produce spatially heterogeneous outcomes.

The management implications of these findings are significant. The positive association between certain precipitation ranges and elevated PI values suggests that plastic pollution monitoring and mitigation efforts should be intensified in areas experiencing moderate-to-high rainfall, particularly following significant storm events when transport and redeposition processes are most active. Furthermore, the high variability observed across all precipitation levels indicates that precipitation alone is insufficient to predict plastic accumulation patterns; effective management strategies must integrate hydrological factors with comprehensive land use planning, improved waste collection systems in high-rainfall areas, and strategic placement of sediment and debris retention structures to intercept transported plastics before they reach sensitive aquatic environments.

The oscillating LOWESS pattern also raises important methodological considerations for future research. The presence of multiple local maxima and minima suggests potential threshold effects or regime shifts that warrant investigation through more sophisticated statistical approaches, such as segmented regression or mixture models, which can explicitly test for discontinuities in the precipitation-PI relationship. Additionally, temporal considerations such as antecedent moisture conditions, rainfall intensity versus duration, and seasonal patterns may further refine our understanding of how precipitation influences plastic accumulation dynamics.

5. DISCUSSION

Although the analysis was conducted over a relatively short observation period of 13 days, the results remain meaningful for interpreting the spatial distribution of plastic waste in relation to land use and land cover (LULC) characteristics. This is because LULC configuration represents a relatively stable structural control that governs plastic accumulation patterns, particularly along river corridors and adjacent built-up areas. While seasonal variability may influence the magnitude and mobility of plastic waste under different rainfall regimes, the underlying spatial relationships between plastic accumulation hotspots and dominant land-use types are expected to persist over time. Wet-season conditions are likely to enhance plastic transport and redistribution through increased runoff, whereas dry-season conditions may promote localized exposure and accumulation within river channels. Consequently, the short observation window primarily limits temporal generalization rather than spatial inference.

The complex oscillating pattern observed in the precipitation Plastic Index (PI) relationship (**Fig. 14**), characterized by multiple local maxima and minima without a consistent directional trend, likely reflects this temporal constraint. The pronounced vertical scatter across the precipitation gradient further indicates that temporal factors such as antecedent moisture conditions, rainfall intensity versus duration, and seasonal hydrological processes may exert a stronger influence on plastic transport dynamics than spatial precipitation totals alone. These findings suggest that precipitation effects on plastic distribution are event-driven and season-dependent rather than spatially uniform.

In addition to temporal limitations, the spatial resolution of Sentinel-2 imagery (10–20 m) constrains the detection of small plastic fragments and the precise delineation of narrow riparian zones, as illustrated in Figure 3. Pixel-level aggregation may obscure sub-pixel heterogeneity in heterogeneous riverine environments, where localized plastic accumulation can be highly variable. Mixed pixels containing both contaminated and uncontaminated surfaces may yield intermediate PI values, potentially underestimating localized contamination and contributing to the residual scatter observed in the Random Forest model (**Fig. 5**; $R^2 = 0.8892$). Future studies should therefore integrate higher-resolution satellite data (e.g., PlanetScope at 3–5 m, WorldView at 0.3–2 m) or UAV-based multispectral imagery to improve spatial detail, detection accuracy, and the characterization of fine-scale plastic accumulation patterns.

Spectral confusion with similar materials remains a challenge. Dried vegetation, bright soil surfaces, sand deposits, construction materials, and light-colored substrates may exhibit reflectance characteristics that partially overlap with plastic materials. While the Random Forest model incorporating multiple spectral indices (NDVI, NDWI, NDBI, TI) achieves high overall accuracy ($R^2 = 0.8892$), residual spectral confusion cannot be entirely eliminated. Some positive PI values shown in Figure 3, particularly in areas with mixed land uses, may reflect spectral confusion rather than actual plastic accumulation. This issue is compounded for weathered or degraded plastics, which exhibit altered spectral properties compared to fresh materials. Future work should employ hyperspectral imaging to discriminate materials based on narrow-band spectral features and develop comprehensive spectral libraries of interfering materials under varying environmental conditions.

Critical hydrological parameters were not incorporated into the analysis. The absence of river discharge and flow velocity data limits mechanistic interpretation of plastic transport dynamics and the extreme variability observed in Water Bodies (**Fig. 12**: PI ranging from -0.45 to +0.35). As discussed in the LOWESS analysis of Water Bodies **(Fig. 14)**, the presence of substantial positive outliers (PI > +0.20) likely reflects convergent flow patterns, limited flushing capacity, or physical retention features. However, without discharge and velocity measurements, distinguishing between high-accumulation sites resulting from natural hydrological convergence versus those influenced by anthropogenic alterations remains challenging. Additionally, unmapped hydraulic structures (dams, weirs, check dams, water gates) may create artificial accumulation hotspots by altering flow regimes and creating zones of reduced velocity where plastics settle. The extreme positive PI outliers identified in certain water bodies may partially reflect the influence of such unmapped structures rather than solely natural processes. Future research should integrate continuous hydrological monitoring, comprehensive infrastructure mapping, and process-based modeling to develop mechanistic understanding of plastic transport pathways and retention mechanisms.

The study did not differentiate plastic types, sizes, or polymer compositions. The aggregate PI values shown in Figures 11-12 represent a composite measure that cannot distinguish between macroplastics (>5 mm), mesoplastics (5-1 mm), and microplastics (<1 mm), which exhibit fundamentally different mobility patterns and environmental behaviors. Different polymer types possess distinct density, buoyancy, and degradation characteristics that influence transport dynamics and spatial distribution. As noted in the precipitation analysis **(Fig. 14)**, enhanced runoff during substantial rainfall events may facilitate breakdown of larger items into smaller fragments through physical abrasion. However, without size and polymer differentiation, these processes cannot be quantified. Future research should incorporate field sampling and spectroscopic analysis (FTIR, Raman spectroscopy) for detailed plastic characterization and source attribution.

Socioeconomic variables (income levels, waste collection coverage, population density, behavioral factors) were not integrated but likely explain substantial intra-class variability. As demonstrated in Figure 11, Settlements exhibit a wide PI range (-0.05 to +0.30), with considerable scatter around the class median. The LOWESS analysis **(Fig. 13)** further confirms this heterogeneity through the substantial vertical scatter of individual observations around Settlements, which we attributed to "variations in waste management practices, population density, and socioeconomic factors across different settlement types." However, without high-resolution infrastructure data (locations of waste collection points, landfills, informal dump sites), the specific neighborhood-level factors driving this variability cannot be identified. The discussion of management implications emphasized targeting "densely populated settlement zones exhibiting the most extreme positive PI values," but operationalizing this recommendation requires socioeconomic data integration. Future studies should incorporate census data, municipal waste management records, and participatory mapping to explain intra-settlement variability and provide actionable policy insights.

Missing data for Mixed Crops, Industrial Buildings, Dry Fields, and Plantations limits landscape-scale comprehensiveness. As noted in both **Figures 12-14**, only 6 of 10 LULC classes contain observations, creating gaps in understanding the complete spectrum of LULC-plastic relationships. Industrial Buildings are of particular concern, as they are expected to exhibit elevated PI values based on their association with manufacturing activities and packaging waste. The absence of these classes creates uncertainty regarding total anthropogenic contribution and may affect the management recommendations, which currently focus on Settlements as the primary intervention target without assessing industrial contributions. Future studies should employ stratified sampling designs ensuring adequate representation of all major LULC classes, particularly those with high anthropogenic activity.

The spatial pattern analysis, while revealing non-linear relationships between PI, LULC, and precipitation, does not address the connectivity pathways that facilitate plastic transport between source and sink areas. The LOWESS analysis **(Fig. 13)** demonstrates an oscillating pattern with peaks at Settlements and Water Bodies separated by troughs at vegetated areas, suggesting a mosaic distribution pattern. However, understanding how plastics move from settlement sources through the landscape matrix to accumulate in specific water bodies requires spatial connectivity analysis incorporating topography, drainage networks, and flow routing. The management recommendation to establish "vegetated buffer zones to intercept plastic transport pathways" presumes knowledge of these pathways, yet the current analysis does not explicitly map them. Future research should employ landscape connectivity modeling and network analysis to identify critical transport corridors and optimal buffer placement locations.

Future research should prioritize systematic multi-temporal monitoring to better capture seasonal dynamics and precipitation-driven plastic transport processes. Quarterly or seasonal time-series analyses would allow robust comparisons between wet and dry periods and improve understanding of temporal variability in plastic accumulation patterns. In addition, rainfall-event–based analyses focusing on extreme precipitation and high-runoff events are strongly recommended, as such events are likely to dominate plastic redistribution within river systems. Integrating remote sensing–derived plastic indices with hydrological modeling including discharge estimation, flow routing, and hydraulic structure characterization would further enable process-based interpretation and predictive assessment of plastic transport pathways.

Beyond these core priorities, methodological improvements should include the use of higher spatial resolution data (e.g., UAV platforms or ≤5 m satellite imagery) to enhance detection of small plastic fragments and narrow riparian zones, as well as hyperspectral imagery and spectral library development to reduce false positives from spectrally similar materials. Additional advances may be achieved through plastic characterization by polymer type, size class, and degradation state via combined field sampling and laboratory analysis; integration of high-resolution socioeconomic and infrastructure datasets to explain intra-class variability and identify intervention priorities; stratified field sampling ensuring representation of all LULC classes, particularly Mixed Crops and Industrial Buildings; and spatial connectivity analysis incorporating topography and drainage networks to map plastic transport pathways. Scenario-based modeling, evaluating the effectiveness of management interventions such as improved waste collection, debris interception structures, and riparian buffers under varying land-use and hydrological regimes, would further enhance the applicability of remote sensing-based plastic monitoring frameworks.

6. CONCLUSIONS

This study demonstrates that the spatial distribution of plastic waste in Kendal Regency is predominantly governed by land use and land cover (LULC) characteristics rather than by precipitation dynamics. Plastic Index (PI) values exhibit clear gradients across LULC types, with the highest concentrations occurring in settlement areas reflecting intensive human activity, inadequate waste management infrastructure, and strong source zone characteristics. Water bodies function as dynamic transport corridors and accumulation zones, displaying extreme variability due to differences in hydrological connectivity, flow conditions, and proximity to upstream anthropogenic inputs. In contrast, vegetated landscapes such as dryland forests, mixed plantations, and scrub consistently exhibit negative PI values, confirming their role as natural buffer zones that limit plastic transport and deposition.

The LOWESS analyses further reveal that the relationship between precipitation and PI is highly non-linear, characterized by multiple inflection points and substantial scatter, with no significant or consistent trend. These patterns indicate that short-term rainfall totals measured independently of hydrological processes such as flow velocity, runoff pathways, and storm intensity do not exert a dominant influence on plastic accumulation within the study period. Instead, plastic distribution is shaped by spatially explicit drivers, including land cover configuration, river connectivity, and localized human pressures.

The integration of Sentinel-2 imagery, CHIRPS rainfall data, and Random Forest modeling results in a robust remote-sensing–based framework for detecting and analyzing riverine plastic pollution. Model performance was consistently strong ($R^2 = 0.8892$), confirming the utility of multispectral indices and machine learning for mapping plastic waste at landscape scales. However, the pronounced intra-class variability especially in settlements and water bodies emphasizes the need for higher-resolution spatial data, improved hydrological characterization, and incorporation of socioeconomic factors in future research.

Overall, the findings underscore that effective mitigation strategies in Kendal Regency should prioritize land-based interventions in densely populated and industrially influenced areas, strengthen waste management systems, and protect or expand vegetated riparian buffers to intercept plastic transport. Since precipitation alone does not predict plastic accumulation, integrated land-use planning, targeted source reduction, and hydrologically informed monitoring are essential to reducing downstream plastic flows and safeguarding riverine and coastal ecosystems.

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