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Characterizing plastic disorder in consumption systems: A statistical entropy analysis to target circular economy interventions

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ABSTRACT

Addressing plastic pollution requires understanding of the drivers shaping material flows and waste generation. This study applies Statistical Entropy Analysis to evaluate its potential as a circular economy metric to quantify disorder within plastic systems and identify its drivers.

Santa Cruz Island in the Galápagos Archipelago, was used as a bounded system to empirically test Statistical Entropy Analysis within a real-world plastic consumption system. A mixed methods approach combined maritime imports data, shop audits, litter transects, recycling characterization and human movement tracking. Statistical analyses were used to examine the relationships between system characteristic and plastic systems, followed by Statistical Entropy Analysis to assess system disorder.

Results showed that packaging, particularly multi-material, is a major contributor to low circularity and increased system disorder. Litter distribution was more strongly associated with area characteristics rather than with human movement, with higher accumulation in commercial and recreational areas, while the presence of bike paths was linked to reduced littering. Statistical Entropy values were highest in leaked plastic systems, especially in urban areas, and lowest in recycling streams due to material separation. Supermarkets' products exhibited higher statistical entropy due to packaging complexity.

System disorder is shaped by spatial context, retail format, product design and consumption preferences, highlighting the need for targeted upstream and downstream interventions. Compared with conventional circular economy metrics focused on resource efficiency, statistical entropy analysis captures material dispersion and mixing, providing a complementary and comparable indicator of circularity across contexts. This study supports the design of policies and business strategies for circularity.

1. Introduction

Plastic demand is rapidly increasing, largely driven by single use plastics (Geyer et al., 2017). Hundreds of polymer types exist on the market, with commodity polymers such as polypropylene, polyethylene, polyethylene terephthalates, polystyrene, polyvinylchloride, produced in multiple grades and used across diverse products with varying lifespans and geographical distribution (Dumon, 2025). This diversity and

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material mixing increase the complexity of traceability, recovery and reintegration into the economy. As a result, current waste management systems remain insufficient, leading to significant plastic leakage. In 2020, 49% of discarded plastic ended up in landfills, 22% mismanaged, 20% incinerated and only 9% recycled (Dokl et al., 2024). These trends highlight the need to transition toward circular production and consumption systems that reduce environmental and health impacts (Schuyler et al., 2021).

Plastic pollution is not only a waste management problem, but a systemic challenge shaped by socio-ecological processes. Previous research has shown that inland plastic leakage is better explained by factors such as land use, infrastructure, income, socioeconomical and site variables than by population density alone (Schuyler et al., 2021; Schuyler et al., 2022). Designing effective circular interventions therefore requires understanding the system drivers, barriers and enablers such as new technology adoption, the regional context where it occurs, the diversity of society and cultural habits (Bell et al., 2011). Interventions that fail to consider system complexity may lead to unintended consequences. For example, plastic bag bans, in some cases, increased impacts associated with alternative materials and encouraged cross-border smuggling of plastic bags (Muposhi et al., 2022). These challenges highlight the need for tools capable of capturing systems complexity to better target circular economy (CE) interventions.

Current CE metrics at city, national or regional level commonly use Material Flow Analysis and Life Cycle Assessment to develop indicators, such as recycling rates, resource productivity, industrial waste disposal, and total material consumption (Wang et al., 2018; Munonye, 2025). Additional indicators explored in CE research include resource efficiency, waste generation and reclamation, industrial solid waste utilization, and construction waste recovery rates (Wang et al., 2018). Similarly, frameworks such as the Circularity Gap Report and the Ellen MacArthur Foundation indicators evaluate aspects of resource circularity and material use efficiency (Voukkali et al., 2023). The Circularity Assessment Protocol further supports a systemic understanding of plastic circularity through community-level data on products sold, stakeholder attitudes, product design, reuse practices, end-of-life management, and leakage (Circularity Informatics Lab, 2021a), helping identify potential intervention points. While these approaches provide valuable insights into material management and CE performance, most of them do not fully capture the degree of material dispersion, mixing, or disorder within the system, nor how processes capture, sustain or create value (Geng et al., 2012; Munonye, 2025). A comparable indicator to benchmark and understand the drivers of plastic circularity disorder across different contexts is needed.

In this context, entropy has gained attention in CE as a concept to assess the degree of disorder or randomness in a system (Korhonen et al., 2018; Velázquez Martínez et al., 2019; Parchomenko et al., 2020; Rondinel-Oviedo and Keena, 2023; Martinez-Alier, 2022; Compart and Gräbner, 2024). As material transformations across value chains involve unavoidable losses of material and energy (Velázquez Martínez et al., 2019), keeping materials with the maximum functionality, reducing mixing of different materials, contamination and complexity, are essential for enabling CE (Parchomenko et al., 2020).

Statistical Entropy Analysis (SEA) offers a promising approach to operationalize this concept by quantifying the degree of disorder within material systems. It enables the assessment of how different interventions concentrate or disperse polymers across the system (Parchomenko et al., 2020). Statistical entropy (SE) decreases when materials are concentrated, and it increases when materials are diluted or dispersed, for example, through environmental leakage (Parchomenko et al., 2020). Similarly, products composed by materials in equal concentrations increase the SE, as it reduces their potential for reintegration into productive systems (Roithner et al., 2022). SEA can be a valuable indicator for assessing how system disorder varies across contexts, including cities, stages of the value chain and CE interventions such as reuse, recycling and refurbishment.

Although SEA applications have focused mainly in substances in systems such as copper (Rechberger and Graedel, 2002), nitrogen in crop farming (Sobańtka et al., 2012), phosphorus (Laner et al., 2017), lithium-ion battery waste (Velázquez Martínez et al., 2019) and vehicles (Parchomenko et al., 2020). Recent studies have extended the system to packaging waste flows and downstream interventions such as recycling, incineration and landfilling (Lipp and Lederer, 2025), optimization of waste management technologies (Korotenko et al., 2025), recyclability assessment of deli packaging (Moyaert et al., 2022) and life cycle of a plastic packaging product (Skelton et al., 2022). Also, Nimmegeers and Billen (2021) developed a modified multilevel SEA to quantify the separation complexity of plastic waste by incorporating an additional multiproduct system level. Using empirical data from Belgium the authors applied the method to determine which types of plastic packaging contributed most to the complexity and effort required for waste separation. Moreover, based on statistical entropy, joint entropy, has been proposed to evaluate the quality of post-consumer plastic bottles in the collection stage (Liu et al., 2021).

Despite its potential, the application of SEA to analyse the circular system complexity and its underlying drivers remains limited. This may be attributed to its labour and data intensive requirements, as well as the need of harmonised datasets, consistent system boundaries and standardised equations to enable meaningful comparisons across systems (Skelton et al., 2022).

This study investigates the use of SEA to evaluate spatial disorder. It investigates how socio-ecological dynamics shape local plastic systems and their entropy through the application of SEA. The approach is used to assess system disorder, identify intervention hotspots, and support the design of targeted CE strategies. By doing so, this study seeks to evaluate SEA as a methodological approach for assessing circularity and system disorder within plastic consumption systems.

Santa Cruz island in the Galápagos Archipelago is used to apply this approach due to its well-defined system boundaries enabling a detailed analysis of product import, consumption and waste generation. While geographically specific this study intends to inform strategies to reduce plastic pollution, while developing a transferable approach for other systems.

To achieve this aim, this study addresses two research:

RQ1: What are the factors influencing inland plastic systems?
RQ2: How does system configuration affect SE and what are the implications for plastic CE interventions?

To address the questions, a mixed-method approach was employed. Data on plastic systems and its characteristics were collected through import characterization, grocery shop audits, kerbside transect surveys, recycling waste characterization and human movement monitoring. The variables influencing plastic systems were analysed using non parametric tests and multivariate statistical methods. Finally, SEA was applied to quantify the degree of system disorder and propose targeted interventions.

2. Materials and methods

2.1. Area of study: Santa Cruz, Galápagos Archipelago

Santa Cruz Island, in the Galápagos Archipelago (Fig. 1), was selected to analyse plastic dynamics and disorder within consumption systems, and to test SEA to evaluate circularity and inform interventions. Due to their geographical isolation, the islands can be treated as a relatively bounded system in which plastic inflows and outflows can be systematically identified, enabling detailed analysis of consumption and waste drivers. The bounded nature of island systems provides an opportunity to test the applicability of Although islands are not major producers of plastic, they are highly vulnerable to its impacts, making the Galápagos Archipelago an ecological important system for study

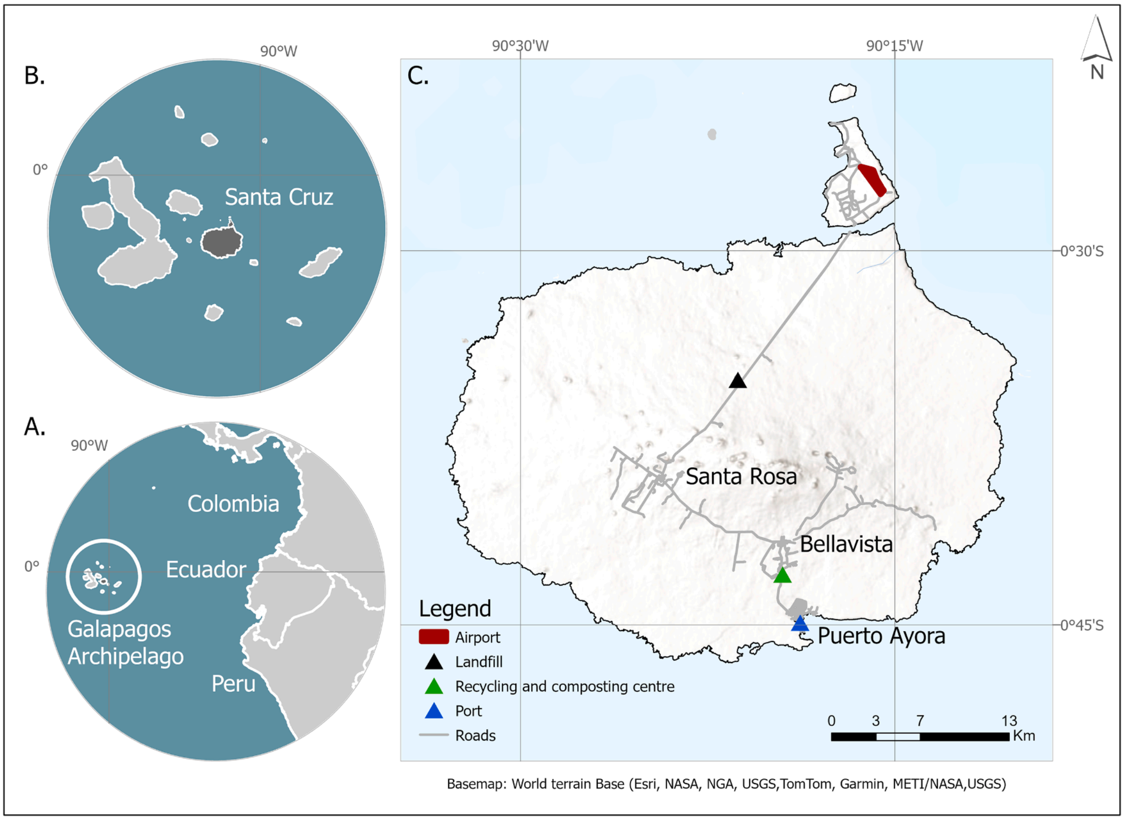

Fig. 1. A) Galápagos archipelago location, in relation to mainland Ecuador B) Santa Cruz island, location in the Galápagos archipelago C) Santa Cruz island with their three towns, Santa Rosa, Bellavista and Puerto Ayora. Basemap: World terrain Base, ArcGIS Pro. Additional data: roads network and airport were obtained from IGM (2013).

(Flor et al., 2025).

Santa Cruz island is the second largest and most populated island, has 17233 habitants (2022) across three towns: Puerto Ayora (12737 habitants), Bellavista (3933) and Santa Rosa (563) (INEC, 2022b). Approximately 88% of the land is managed by the National Park and 12% is privately owned (Pike et al., 2022). It generates the highest volume of waste in the archipelago, mainly organic (43%) and plastic (14%) (Veolia, 2019). Although most waste is separated and managed through municipal systems, including recycling, compost and landfill, (INEC, 2022a; INEC, 2022c), a large share remains non-recyclable (Martin et al., 2021).

The economy is largely driven by tourism (INEC, 2017). Tourists' arrivals have almost double between 2007 and 2024, reaching 281,000 tourists in 2024 (Parque Nacional Galápagos, 2025). Despite ongoing conservation efforts, the Galápagos islands face increasing pressures from population and tourism growth (Mena et al., 2020; Sampedro et al., 2020; Burbano et al., 2022).

Plastic pollution is a key concern, particularly in the Galápagos archipelago, where debris, often transported by currents, pose a risk to terrestrial and marines species such as marine iguanas, sea turtles and Galápagos penguins (Jones et al., 2021; Muñoz-Pérez et al., 2023; McMullen et al., 2024). Despite initiatives such as coastal clean-up and efforts to reduce single-use plastics, municipalities still face significant challenges with plastic waste that remains in the islands (Martin et al., 2021).

2.2. Methodological approach

To address RQ1: What are the factors influencing inland plastic systems? An import characterization was conducted to identify major plastic inflows. This was followed by grocery shops audits to assess the products origin, packaging types, plastic content in top selling products, and existing practices aimed to reduce plastic waste. To assess plastic leakage and the influence of the socio-ecological dynamics on litter type and quantity, kerbside transect surveys and human monitoring using sensors were conducted. In addition, the recycling stream was characterized to identify plastics entering this pathway. Statistical analyses, including Spearman correlation, Kruskal-Wallis, Multiple Correspondence Analysis and the negative binomial regression were then applied to identify the factors shaping plastic systems. To answer RQ2: How does system configuration affect SE and what are the implications for plastic CE interventions? SEA was applied to quantify entropy across plastic leakage, recycling and grocery shops systems An overview of the methodology is presented in Fig. 2.

2.2.1. Import characterization

A registry from maritime imports data (January-June 2022) provided by the main authority in the Galápagos Islands, *"Consejo de Gobierno del Régimen Especial de Galápagos"* (CGREG), was processed. The CGREG registers weights and classifies imports entering the Galápagos into 111 types of products. These categories were reviewed, standardized, and reclassified according to Supplementary material S1. Based on the CGREG information, 58% of imports were allocated to Santa Cruz. In cases where categories contained multiple product types, imports were divided equally by weight. The lifespan of products containing plastic were assigned based on Geyer et al. (2017). Data were pro-rated over a 12-month period and plastic waste generation was assumed to occur linearly over the product's lifetime.

2.2.2. Kerbside transect surveys

Litter from kerbside transects was collected, classified and quantified, and polymer type was identified. Surveys were performed from 08/

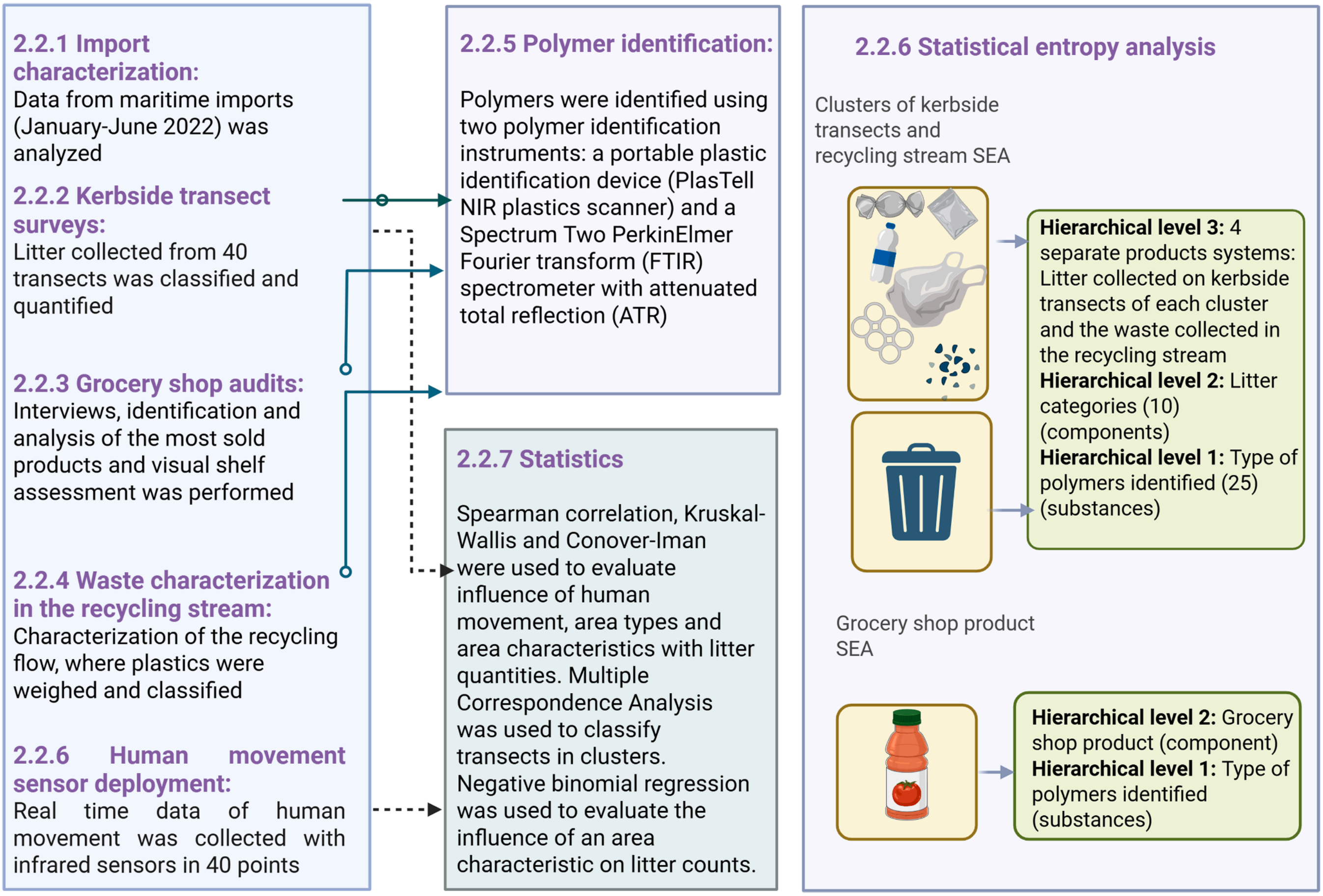

Fig. 2. Overview of the methodological framework used to address the research question.

07/2023 to 18/07/2023. A stratified random sampling approach based on population count categories (high, medium-high, medium and low) derived from the LandScan dataset[1] (Fig. 3), was applied using ArcGIS Pro 3.0.1 (Youngblood et al., 2022). The dataset was processed to generate a ~1 km^2 grid within the area of interest. Within this layer, ten random points per population count category were generated. Each point served as the starting coordinate of a 100m x 2m transect, oriented east, west, north or south depending on the street direction and the random selection process. Points that were far from streets or not in populated areas were moved to the closest street or to a close and accessible protected area. In total, 40 kerbside transect surveys were conducted in the sampling points (Fig. 3). Litter was collected in labelled bags (date, time and transect ID) and site characteristics were recorded, including the presence of houses, nature/vegetation, recreational services (hotels, restaurants, bars), farmland, industries, services (public institutions buildings, banks, schools, others) and shops, unmanaged waste, bike paths, construction site, pavement, and highway. Litter was then classified, counted and weighed based on a wet basis according to the modified categories and subcategories from Youngblood et al. (2022) and National Geographic Society (2021) (Supplementary material S2).

2.2.3. *Grocery shop audits*

Grocery shops audits combined interviews with managers or owners, the identification of the most sold products and visual shelf assessment to evaluate plastic consumption patterns. A sample of 13 grocery shops was selected. Sampling aimed to randomly select two shops per population count category ($n = 8$), as no data was found regarding the total number of shops in Santa Cruz. As no shops were found in the low population count category, these were replaced with nearby medium-low population count category. To capture variation by retail type (small, medium, large shop and open market), the sample also included two large supermarkets and three open market stalls (Supplementary Material S3)

During the audits, 126 products were purchased and analysed. These products were selected based on interview responses identifying the 20 most sold products (initially 240, later refined based on availability and duplication). Each shop contributed 18–20 products, except open market stalls which had fewer (2,7 and 9). Products were characterized by name, weight based on a wet basis, packaging weight, parent company, manufacture location, manufacture date and polymer type.

2.2.4. *Waste characterization in the recycling stream*

Based on municipality collection schedules and availability, waste characterization was conducted on three days:19/11/2024, 22/11/2024 and 25/11/2024. Each day, eight recyclable waste bags (two per collection route) were randomly selected by municipal staff, weighed on a wet weight basis, and emptied onto a tarpaulin. Hazardous and sanitary risk waste were removed and not further analysed. The remaining material was divided into quadrants and one quadrant retained for analysis. From a total of 66.1 kg collected, 7.5 kg (11.3%) was characterized. Items were classified and weighed using the same categories as the transect surveys, with plastics separated to identify the polymer type.

[1] LandScan provides ambient population with a spatial resolution of 30 arc-seconds and a temporal resolution of 24 h average, based on remote sensing (Oak Ridge National Laboratory, 2022). A 30 arc-seconds resolution represents the distance crossed on the earth surface in one second (ESRI, 2022).

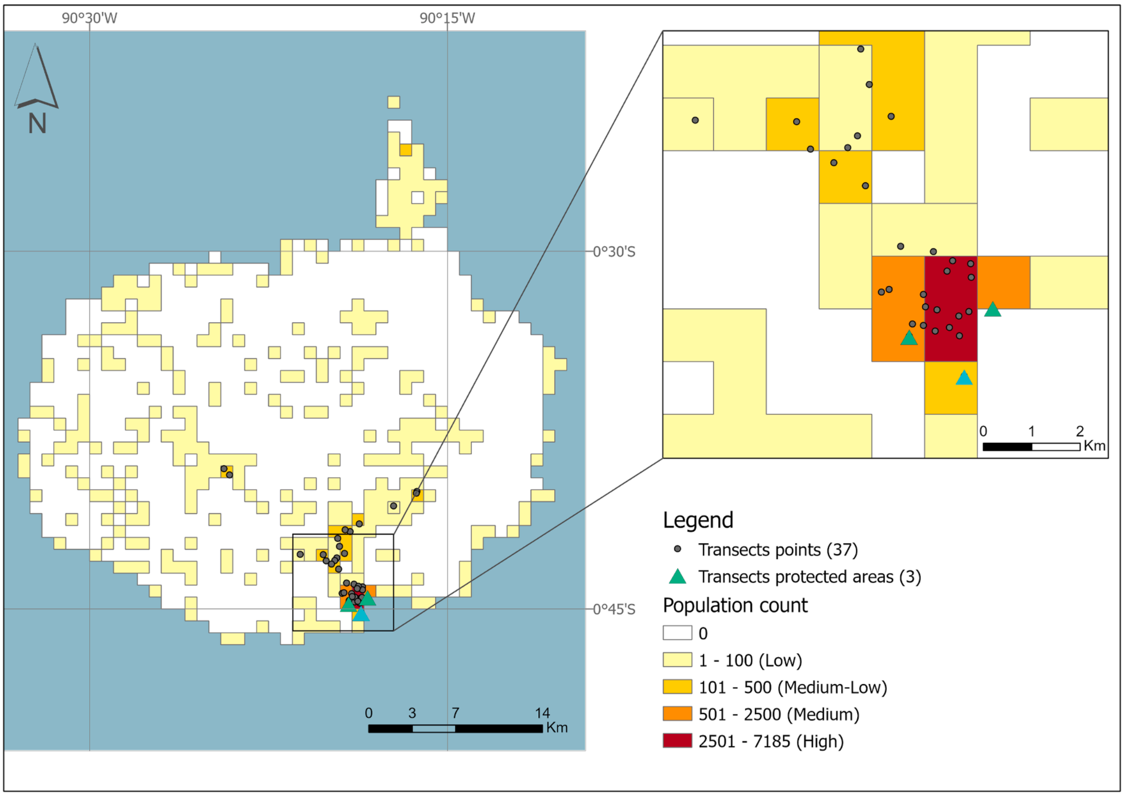

Fig. 3. Sampling points (transects) selected for each population count: low, medium-low, medium and high.

2.2.5. *Polymer identification*

Plastics from grocery shops and kerbside transect surveys were analysed using two complementary polymer identification methods. A portable plastic identification device (PlasTell NIR plastics scanner, desktop version, Matoha Instrumentation Ltd.) equipped with a transmittance-reflectance NIR spectroscopy, 1550–1950 nm - 2NIR lamps built-in and a Spectrum Two PerkinElmer Fourier transform infrared (FTIR) spectrometer with an attenuated total reflection (ATR) attachment to identify the polymers (measuring in a wavelength range from 650 to 4000 to cm^{-1} and a resolution 4 cm^{-1}).

The obtained spectra from the FTIR-ATR were compared with the Perkin-Elmer FTIR-ATR of Polymers Library, stablishing a minimum match score of 60%. Additionally, the spectra of scanned polymers were visually compared with the reference spectra from the library to ensure the best match. In some cases, if the score did not reach the 60% minimum, the scanned was repeated. If after three repetitions a better score was not reached, the polymer with the best score was recorded (representing 4% of the total sample)

Plastics from the recycling flow were identified using only the hand held PlasTell device, as it allowed an on-site polymer identification, and it was proven in the previous polymer identification (grocery shops products) suitable for polymer identification (77% match). The first identified polymer was recorded. If unsuccessful, up to two additional scans were conducted by cleaning, repositioning or folding the item (Supplementary Material S4)

2.2.6. *Human movement sensor deployment*

Real time data of human movement (movement of people, cars, motorbikes and bikes) was gathered using Pyro Evo sensors, which are passive infrared sensors that detect movement based on temperature changes. These long-range sensors identify movement up to 15 m in both directions. Information was stored in the device and then exported and visualized in the software eco-link^{evo} v2.6.4. Sensors were installed at the 40 transects identified in Section 2.2.2, data were collected from 8pm to 3pm the following day.

2.2.7. *Statistics*

To evaluate the influence of human movement (sensors data) with litter quantities per transect, the Spearman Correlation coefficient was obtained. Differences across area types (urban, rural or protected) were evaluated using Kruskal-Wallis and Conover-Iman test.

Furthermore, Multiple Correspondence Analysis (MCA) was performed to identify patterns in area characteristics by representing points in a multidimensional space (Costa et al., 2013). The analysis was performed using the R package for MCA {FactoMineR}. Area characteristics included presence of houses, natural area or significant vegetation around, recreational services (e.g. bars, restaurants and hotels), farmland, industrial area, services and shops, bike paths, construction site, pavement and highway. Each characteristic was coded binarily (1 = presence, 0 = absence). Then hierarchical clustering was applied using the first five dimensions which together explained 76.3% of the variance, resulting in three clusters. Finally, Kruskal-Wallis test followed by Conover-Iman post-hoc test was used to assess significant differences in litter quantity between clusters.

A negative binomial regression was performed in R to analyse the influence of an area characteristics, on litter counts. This method was selected as the data consisted of count variables, exhibited overdispersion and contained no zero values (Zhang et al., 2018; Elhai et al., 2008). Litter counts (the dependent variable) had a skewness value of 1.17 and a kurtosis value of 1.07, values that violated normality assumptions, therefore models of General Linear Models (GLMs) were not used (Elhai et al., 2008). A Poisson regression model was initially fitted, but overdispersion was detected (30.82). A likelihood ratio test indicated that the negative binomial regression provided a significantly better fit than the Poisson regression mode (LR χ^2 = 732.58, p = 2.2exp^{-16}) (Elhai et al., 2008). Overdispersion (1.21) and McFadden's Pseudo R (0.11) further confirmed that the Negative Binomial Regression was an appropriate fit for the data.

2.2.8. Statistical entropy analysis

SEA is based on Shannon's Statistical Entropy, which measures the variability of elements within a set and how different they are between each other (Eq. 1) (Carcassi et al., 2021). Shannon's Statistical Entropy is used in computer science and communication theory and is conceptually distinct from Boltzmann entropy. Whereas Shannon's Statistical Entropy describes the variability of elements within each set, Boltzmann entropy focus on the thermodynamic state (Shutler and Cheah, 1998; Carcassi et al., 2021). In this study Shannon's Statistical Entropy is used to understand the concentration or dispersion of materials, rather than a measure of thermodynamic entropy.

$$H_{(p)} = -\sum_{i=1}^{n} p_i \log p_i \tag{1}$$

p_i represents the fraction of an object in a set

This study adapted the multilevel Statistical Entropy analysis proposed by Parchomenko et al. (2020) and Nimmegeers and Billen (2021) to quantify the distribution and complexity of polymers across the components of a defined system, to answer RQ2: How does system configuration affect SE and what are the implications for plastic CE interventions?. The methodology was adapted by redefining the hierarchical levels according to the characteristics of each system (i.e. spatial clusters or grocery shop product) while preserving the hierarchical structure of the original framework. This study does not perform an MFA across the island, it rather focuses on composition of polymers per type of waste category in transects and the recycling stream, and the composition of polymers in grocery shop products. Two independent SEA analysis were performed. The first analysed waste collected in three clusters identified through MCA together with the recycling stream, while the second analysed grocery shop products. For the litter collected in transects across the clusters and the recycling stream SE describes how polymers are distributed across the sampled waste categories and polymer types. For grocery shop products it describes the diversity and distribution of polymers and other materials within each individual product. A higher SE indicates a more compositionally heterogenous system, in which polymers are distributed across greater number of categories or polymer types. This can show that there is a greater potential of complexity in later stages for sorting and separation. Lower SE values indicate that polymers are concentrated in fewer categories or polymer types. Each cluster and recycling stream were treated as the highest hierarchical level (product) analogous to the product level described by Parchomenko et al. (2020). Within each product waste categories represented the component level, and polymer types represented the substance level. Plastic parts detached from the original item (e.g. labels and lids) were excluded, and only the predominant component of each item with its predominant polymer was considered.

To allow comparison between the SE of the clusters and the recycling stream H^{c}_{max} (Eq. 5) was calculated using the overall polymer distribution across all four products (clusters 1–3 and the recycling stream). This ensured that all products were evaluated against the same reference basis. Absolute SE was used for comparison as suggested by Nimmegeers and Billen (2021), as relative product entropy would normalize each product against a different maximum, reducing its comparability. Absolute values non-negative and may equal zero when there is one material concentrated in a single waste category or product. Absolute SE does not have a universal fixed range. Consequently, whether and SE value is considered high or low can only be determined by comparison with systems that have similar hierarchical structures.

For the grocery shop analysis, the individual component-level statistical entropy was adapted to assess the distribution of polymer and material types within each product. In this analysis each grocery shop product was treated as the component-level unit, while the substances corresponded to the polymers or materials identified in its packaging. This approach was used because individual product parts, such as lids, bottles and labels, were generally represented by a single polymer or material, which would result in zero entropy if analysed using 3 hierarchical levels. Absolute SE were compared among individual grocery products. Subsequently, the mean product SE of the sampled products was calculated for each grocery shop and used to compare compositional complexity among shops.

Table 1 presents the equations used and the methodological considerations for each analysis. An example of the intermediate calculations of SEA is provided in Supplementary Material S5. For the cluster and recycling stream analysis, polymer identification from the PlasTell device was used to enable direct comparison. The corresponding SE results and methodology based on FTIR-ATR identification are also provided in the Supplementary Material S5 and Excel file. For the grocery shop product analysis, only the polymer identification obtained from the FTIR-ATR was used.

3. Results

This section presents the results addressing RQ1 and RQ2. To address RQ1, Section 3.1 examines imported goods to identify the main plastic inflows into the system. Section 3.2 presents the findings from the kerbside transect surveys, Section 3.3 reports the results of the grocery shop audits and packaging characterization and Section 3.4 presents the results of the waste composition of the sampled recycling stream. Building on these findings, Section 3.5 examines the relationship between socio-ecological factors and plastic through statistical analyses identifying the variables most strongly associated with presence of plastic. To address RQ2, Section 3.6 presents and compares the SE results for the analysed systems, integrating relevant findings from the preceding subsections to support their interpretation.

3.1. Inflows of goods imported

An estimated 34,154 t of goods enter Santa Cruz annually as maritime imports, of which 1979 t (or 5.8%) corresponds to plastic contained in goods either as packaging or embedded. Of this, approximately 70% (1370 t) is expected to become waste within one year. Most plastic is associated with food packaging (65.5%), reflecting both the short shelf life of these products and its essential role in preserving products during transport and storage, with goods taking an average of 15 days to arrive (Nieto-Vasco, 2020). In contrast, building and construction materials represent 31.4% of annual plastic imports, and their longer lifespans contribute to lower annual plastic waste generation (Fig. 4).

3.2. Littering and plastic leakage: kerbside transects

Transects litter abundance ranged from 0.03 to 2.12 items/ m^2, and 0.01 to 5.13 g/m^2 with the highest accumulation observed in Puerto Ayora, consistently with human movement data showing greater activity in this area (Fig. 5). Food plastic, other plastics and plastic fragments (Fig. 6) were the main contributors to litter, while the most common items found per subcategory included food plastic packaging, cigarette butts and hard plastic fragments. The predominant polymer detected were HDPE, PP, CPE and anthropogenic cellulose (See supplementary material S7).

3.3. Grocery shop audits and packaging characterization

To further explore food packaging, grocery shop audits were conducted ($n = 13$) to owners or managers. Interviews and data collected from the most sold products showed that 83% of products are imported and being manufactured (based on the label) in mainland Ecuador (76.6%), Colombia (7%), with the remainder (10.4%) in Chile, Perú, United States and Greece. Only 6% of products are manufactured in Galápagos. The average plastic content per product was 9.7% by weight. Packaging was dominated by polypropylene (PP) (36.53%), high density polyethylene (HDPE) (29.52%), BP adhesive (5.17%), poly (ethylene

Table 1
Methodological considerations to calculate SE.

Selected system for SEA	Description	Hierarchical levels defined	Equations
Litter collected in the 3 clusters and in the recycling stream.	This analysis was performed to define the distribution of polymers over the different waste categories within each cluster and the recycling stream and compare them.	Level 3 Product (highest hierarchical level): Four products analysed individually corresponding to the waste collected in Cluster 1-3 and the recycling stream. Level 2 components: Waste categories (12): Construction and demolition materials E-waste (Electrical waste) Fishing gear Food plastic Paper Personal care products Glass Metal Other plastics Plastic fragments Level 1 substances using data from PlasTell device (25): Type of polymers Acrylonitrile Butadiene Styrene (ABS), ABS or Polystyrene (PS), PS, Polyamide (PA), Polycarbonate (PC), PC or ABS, Polyethylene (PE), Polypropilene (PP), PE or PP, Polyether Ether Ketone (PEEK), Poly (Ethylene Terephthalate) (PET), PET or PC, Polylactic Acid (PLA), Polymethylmethacrylate, acrylic (PMMA), PLA or PMMA, Polyurethane (PU), Polyoxymethylene, Acetal (POM), Poly (Vinyl Chloride) (PVC), Poly (Vinylidene Fluoride) (PVDF), Silicone rubber (SIL), PLA or PU, PMMA or ABS, PU or PP	H^P is the statistical entropy and P represents the number of the cluster (i.e 1,2,3) and the recycling stream $H^P\left(c_{n,p},\ H_n^c, rel\ \left(c_{i,n}, m_n^c\right)\right) = -\sum_{n=1}^{N} log_2\left(c_{n,p}\right) H_{n,\ rel}^c\left(c_{i,n},\ m_n^c\right)$ **Eq. 2** (Parchomenko et al., 2020) To apply the Eq. 2, first the component statistical entropy was calculated (H_n^c) **(Eq. 3)**. The components correspond to the waste categories. $H_n^c\left(c_{i,n}, m_n^c\right) = -\sum_{i=1}^{I} m_n^c c_{i,n} log_2\left(c_{i,n}\right)$ **Eq. 3** Where, $c_{i,n}$ is the concentration of substance *i* within component *n,* calculated as the number of items composed of polymer *i* in a waste category, divided by the total number of items belonging to component n (waste category) within each product m_n^c is the mass fraction of each waste category and all the categories in each P. Then the relative statistical entropy (H_n^c, rel) of each waste category was calculated using the following equations: $H_n^c, rel\left(c_{i,n}, m_n^c\right) = \frac{H_n^c\left(c_{i,n}, m_n^c\right)}{H_{max}^c}$ **Eq. 4** $H_{max}^c = -\sum_{i=1}^{I} c_{i,tot} log_2\left(c_{i,tot}\right)$ **Eq. 5** Where, $c_{i,tot}$ is the concentration of polymer *i*, across the complete waste system, calculated as the total number of items composed of polymer i across the three clusters and the recycling stream divided by the total number of items across all four products. Finally, $c_{n,p}$ in Equation S5.1 corresponds to the concentration of component n in the cluster, calculated using: $c_{n,p} = \frac{q_n}{N_{tot}}$ **Eq. 6** Where q_n is the number of items in component *n* in this case the number of items in the waste category and N_{tot} is the total number of items in the product (each cluster or the recycling stream).
Products sold in grocery shops	A total of 126 products were individually analysed using the SE. This was used to analyse how substances are distributed over the different products.	Level 2 component (highest level): Product in grocery shops Level 1 substances using data from the FTIR-ATR: Type of polymers and materials (32) HDPE, PP, PET, PCT, PS, PE, Anthropogenic cellulose, PA, BP adhesive, PEO, CSM, PDMS, PBT, PCL, Propylene Glicol Ricinoleate (PGR), OTHER, PEMA, PMMA, CPVC, CPE, Methyl Acetyl Ricinoleate (MAR), SBS, POLY (1-BUTENE), PVCVA-VOH, PBMA, PVC, EVA, PEA, Poly (Vinyl Acetate) (PVAc), metal, glass, paper/ cardboard.	The following equation was used: $H_{n,\ indiv}^c\left(c_{i,n}\right) = -\sum_{i=1}^{I} c_{i,n} log_2\left(c_{i,n}\right)$ **Eq. 7** Where, $H_{n,\ indiv}^c\left(c_{i,n}\right)$ is the individual component level statistical entropy $c_{i,n}$ is the concentration of substance *i* in the component *n,* in this case the concentration was calculated by the weight of the polymer or material in the product divided by the weight of all the packaging materials

terephthalate) PET (4.43%), poly (1.4-cyclohexadimethylene terephthalate) (PCT) (4.43%) and oxidized polyethylene (PE) (3.69%). When expressed as percentage by weight, HDPE (27.27%) and PP (26.37%) were the dominant, followed by PET (15.83%) and PCT (14.46%). Nearly half (47%) of the flexible packaging and sachets explored consisted in multilayered materials combining different polymers.

Plastic reduction initiatives at shop level focused on reusing and recycling tertiary packaging (47% and 41%, respectively), whereas actions aimed at reducing plastic consumptions, such as refusing plastic (6%) or adopting alternative materials (6%) were less common. Differences in plastic bag consumption were also observed across shop types, with higher usage in small shops (1753 bags per month) and open market (3200) than in a medium shop (365) and a supermarket (300), associated with the sale of bulk products (See Supplementary information S6)

3.4. Plastic disposal: waste characterization

In the recycling stream, the largest fraction consisted of paper (34% of the number of items), food plastics (30%) and other plastic (21%), with food wrappers and packaging representing most of the plastic items. The predominant polymers identified were PE, PP and PET accounting for 63% of the total polymers detected.

3.5. Understanding the factors influencing littering and type of littering

There was a weak correlation between human activity and number of litter items (Spearman correlation coefficient: 0.0611, $p = 0.711$) with similar results observed for litter weight (Spearman correlation coefficient: -0.3070, $p = 0.0573$). In contrast, litter quantity differed significantly according to area type (urban, rural and protected). There was a significant difference between rural and urban areas ($p = 0.0064$) and between protected and urban areas ($p = 0.0026$). On average, urban transects contained 168 ± 110 items compared with 69 ± 60 items in rural areas and 25 ± 14 items in protected areas. Litter weight also varied across area types, with significant differences between urban and protected areas ($p = 0.0069$), although differences between urban and rural areas were not significant ($p = 0.1374$). Rural area items had a higher weight average (3.87 ± 4.19 g per item) than urban (2.41 ± 3.77 g) and protected area (0.39 ± 0.55 g), reflecting the presence of larger and heavier waste items in rural areas such as car parts and construction materials.

To further examine the influence of area characteristics on type of litter, MCA followed by hierarchical clustering was used to classify transects into three clusters (Fig. 7). Cluster 1 is characterized by

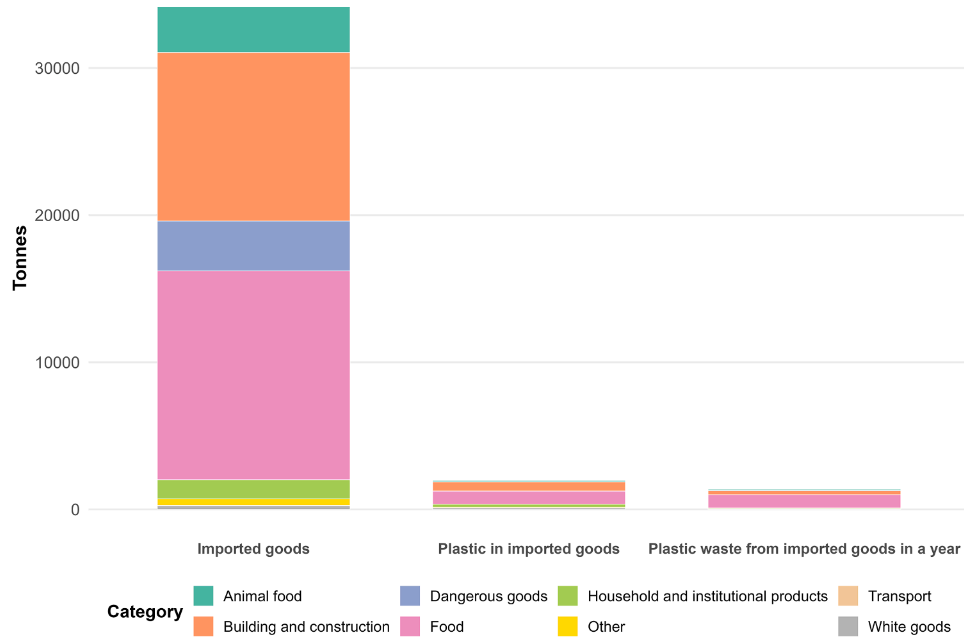

Fig. 4. Goods imported through maritime transport, plastic in imported goods (contained in packaging or embedded) entering Santa Cruz, and the potential of plastic waste generation from imported goods in a year per category.

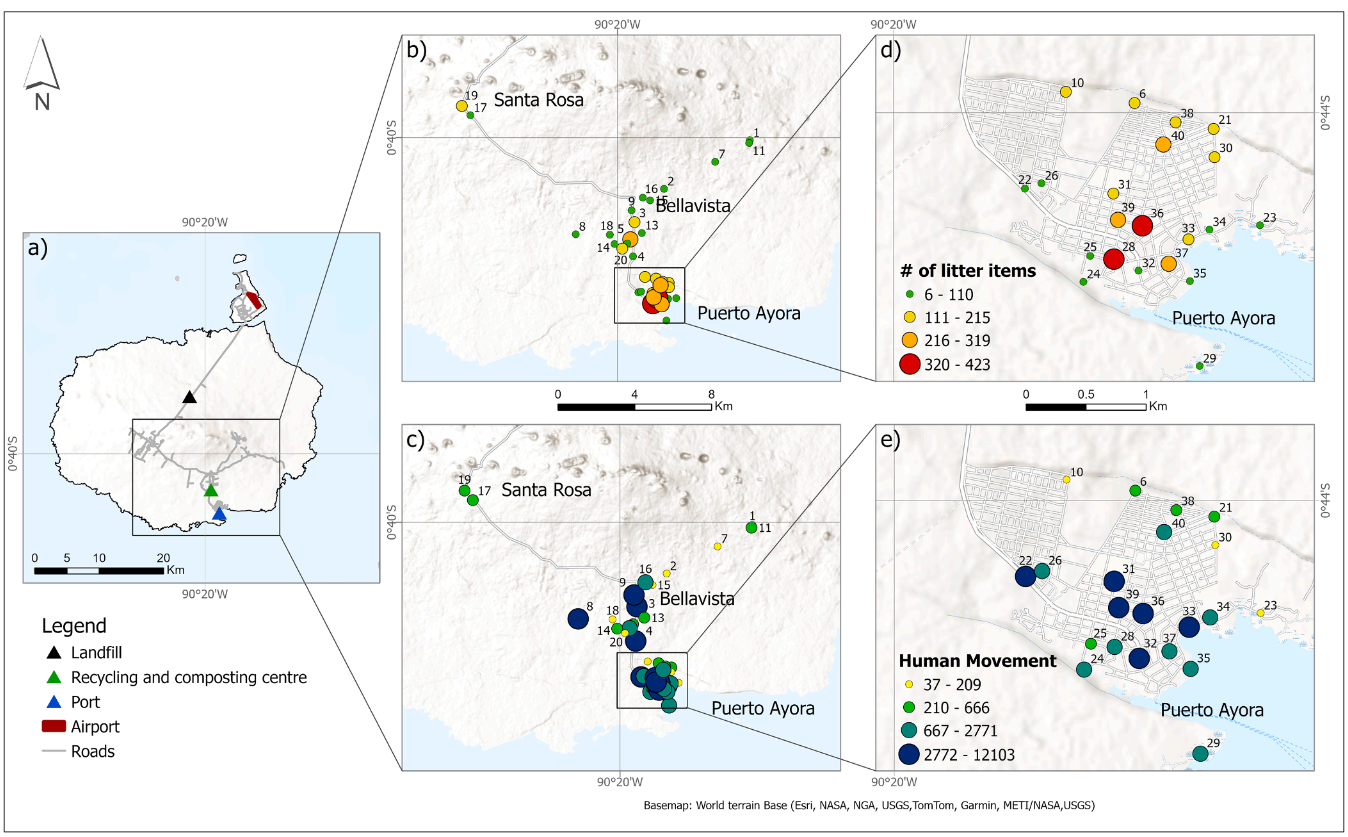

Fig. 5. Total litter items found per transect (# of items) and human movement (# of movement of people, cars, motorbikes and bikes) per transect. Basemap: World terrain Base, ArcGIS Pro. Additional data: roads network and airport, Instituto Geográfico Militar del Ecuador (IGM, 2013).

highways, bike paths and surrounding natural areas or abundant vegetation. Cluster 2 included areas with limited pavements and services, and small to medium shops with usage of plastic bags and bulk products. Cluster 3 was characterized by presence of pavement, with higher concentration of services, greater diversity of shops, with high usage of plastic bags and packaged products, and recreational services (See supplementary material S8).

A Kruskal-Wallis test showed significant differences in litter abundance between the clusters (p-value= 0.001283). Post hoc test indicated significant differences between cluster 1–3 (p-value= 0.0004) and

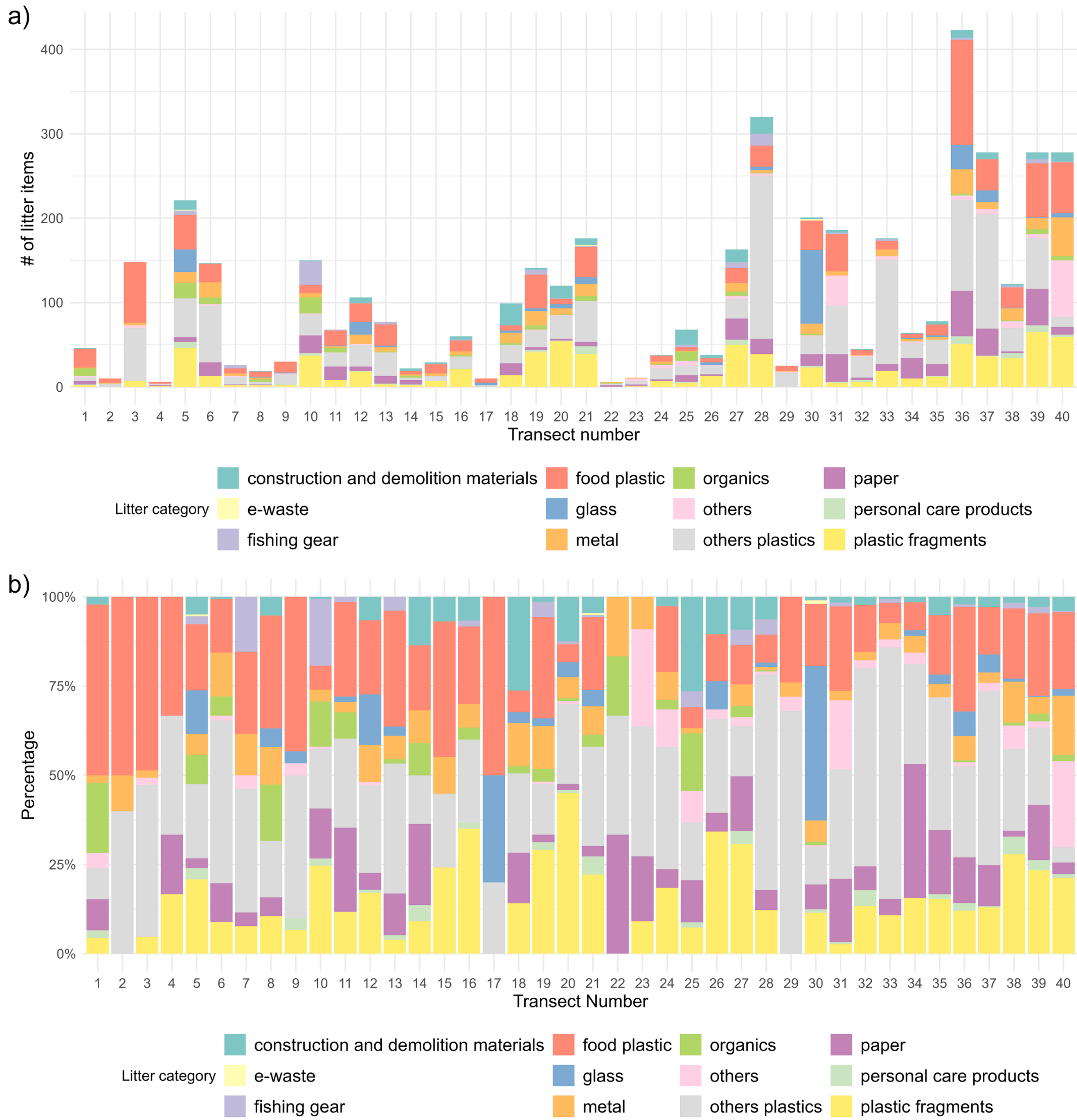

Fig. 6. a) Number of litter items found in each transect. b) Percentage of each litter category per transect. In total $n = 4514$ litter items were found of which $n = 3343$ (74%) litter items contained plastic. See supplementary material Table S7.2.

between cluster 2–3 (p value=0.0027). Cluster 3 exhibited the highest litter abundance (207 ± 119 items) but the lowest average weight per item (1.54 ± 1.23 g) suggesting the predominance of lightweight packaging waste. In contrast cluster 1 and 2 contained fewer (40 ± 61 and 85 ± 64 items, respectively) but heavier litter items, with average items weight of 3.22 ± 4.83 g and 3.79 ± 3.55g, respectively.

To further assess the influence of specific area characteristics on litter abundance, a negative binomial regression was performed. Results showed that having houses (+1.69), industrial installations (+1.51), services and shops (+0.61) was associated with increased litter quantities. In contrast, the presence of bike path (−1.13) was associated with reduced litter abundance.

3.6. Statistical entropy analysis

The polymer types present and their distribution across waste categories or grocery shop products influenced the observed SE values. Four analytical systems were initially evaluated: the three clusters of kerbside transects and the recycling stream. All four systems were analysed using the same hierarchical structure, polymer and waste categories, equations and a common H^{c}_{max} thereby enabling direct comparison. Absolute SE does not have a specific range of values. The values are interpreted

Fig. 7. Factor map of the three clusters identified, using MCA. Note: Cluster 1 is characterized by highways and bike paths with natural areas or abundant vegetation in the surroundings. Cluster 2 characterized by few pavements, services and shops. Cluster 3 characterized by presence of pavement, services, shops and recreation services.

comparatively within the four harmonised systems in this study.

Based on polymer identification using the PlasTell device, cluster 3 had the highest absolute SE (1.58), followed by cluster 2 (1.44), the recycling stream (0.78) and cluster 1 (0.61) (See supplementary material S8 and Excel file for details). The higher SE values observed in Clusters 2 and 3 indicate that polymers were more diverse and more widely distributed across waste categories than in cluster 1 and the recycling stream. This reflects greater compositional dispersion and potential separation complexity within these clusters. These differences are consistent with the greater diversity of area characteristics and socio-ecological dynamics. The recycling stream had lower SE (0.78) than Clusters 2 and 3, indicating that polymers were more concentrated within fewer waste categories, reflecting the effectiveness of separation initiatives in concentrating plastics within this stream.

Grocery shops products were evaluated in a separate SEA application, using a different hierarchical structure and concentration basis. Consequently, their SE were not compared directly with the results obtained from clusters or the recycling stream. For grocery shop analysis, absolute SE was first calculated for each product, then a mean product SE for each type of retail format was calculated. Open markets had the lowest mean product SE (0), followed by small shops (0.27), medium shops (0.39) and supermarkets (0.67). A SE value of zero indicates that the analysed product was composed of a single polymer or material category. Higher values indicate that the product contained a greater diversity of polymers and materials distributed in more similar proportions, suggesting greater potential complexity for material separation.

Open markets and small shops primarily sold bulk products or products supplied in simple, single polymer bags, resulting in lower mean SE values. However, these shops also reported greater monthly bag use. In contrast, supermarkets had the highest mean product SE because they sold a greater proportion of imported and multicomponent packaged products. Products with high SE included ketchup and mayonnaise sachets, fabric softener, jelly and multicomponent food products such as yogurt with cereal. Further details are provided in the supplementary information S8 and Excel.

4. Discussion

This section discusses the findings in relation to the drivers of inland plastic systems and the role of consumption systems configuration in shaping SE and CE interventions. It further assesses system circularity and demonstrates the potential of SEA as a tool to target interventions.

4.1. Systems configuration effect on plastic systems and statistical entropy

Plastic leakage mirrored the composition of plastic items entering the islands and individual consumer preferences and consumption patterns strongly shape litter generation. Compared with the most common macroplastics identified in beach surveys, such as caps/lids, rope/string/cords, drink bottles, plastic fragments and bottle rings (Jones et al., 2021), inland transect surveys showed a higher presence of plastic food packaging and cigarette butts. This difference reflects built-environment dynamics, where short-lived items such as packaging are discarded and accumulated, whereas beaches tend to retain items more easily transported and less prone to fragmentation by currents.

These results are consistent with global trends, such as in Europe, where packaging represents one of the largest waste streams after paper and cardboard (Somlai et al., 2023). Similar patterns have been reported in other regions, including the Ganges River Basin, Vietnam, and Panama where food packaging dominate retail and street litter, while often holding limited recycling value (Youngblood et al., 2022; Circularity Informatics Lab, 2021a; Circularity Informatics Lab, 2021b). Despite these similarities, overall litter density (litter per m^2) was lower in Santa Cruz, reflecting ongoing protection and waste management efforts.

This study shows that area characteristics have a stronger influence on plastic systems than human movement, challenging approaches that estimate plastic leakage primarily based on population size (Jambeck et al., 2015, Lebreton and Andrady, 2019; Mai et al, 2020). Instead, the results indicate that land-use configuration plays a key role, with urbanized areas exhibiting the highest level of plastic litter. In contrast, the presence of natural vegetation and bike paths is associated with lower litter levels.

These findings support previous research showing that environmental context and infrastructure influences littering behaviour. For instance, areas with higher baseline litter tend to accumulate more waste, as observed in retail and shopping centres (Schuyler et al., 2022). Similarly, individual's perceived value of the surroundings can affect levels of litter, with residential areas, beaches and parks generally showing less litter levels compared to industrial areas (Schuyler et al., 2021). In addition, perceived risk of reprisal may shape littering behaviour, as lower perceived risk of being observed has been associated with increased littering (Bator et al., 2011; Schuyler et al., 2022). Together, these mechanisms help explain the lower litter levels observed in protected areas compared to urban settings.

However, litter quantity alone does not capture the diversity and complexity of plastic waste within an area, limiting the identification of intervention hotspots and the estimation of resources required for material recovery and reintegration. This limitation is addressed through SEA.

Results showed that areas with more mixed land-use characteristics exhibited higher absolute SE. Upstream actions and product characteristics also strongly influence system SE at the system level. Retail formats shape both the types of litter found within transects and the overall disorder of plastic systems. In particular large retail formats, such as supermarkets, show higher SE, driven by greater product diversity and the prevalence of complex packaging designed not only for food conservation but also for marketing and information (Marsh and Bugusu, 2007). Cluster 3 characterized by high retail diversity and mixed land-use, showed the highest SE value. This suggests that mixed commercial offer a broader range of packaged products and generate more diverse plastic systems, thereby increasing system disorder and complicating CE implementation. As system complexity increases, greater effort is required to recover and reintegrate materials (Roosen et al., 2020), further challenging CE strategies.

In contrast, smaller retail formats with more limited product variety are associated with lower disorder. The proximity of these shops in Clusters 1 and 2 may have contributed to the lower absolute SE observed in these areas. Findings also showed that small shops and open markets have the potential to decouple products from packaging through the sale of bulk products, although this practice is currently driven more by affordability than by environmental considerations. These findings suggest that retail formats and supply chain configurations represent important leverage points for reducing packaging use. However, factors such as consumer preferences, tourism demand and expectations regarding product variety must also be considered particularly in tourism-intensive areas.

Overall, SE is strongly shaped by upstream system dynamics, including product design, import dependency, retail practices, and consumption patterns transferred from mainland, which may not align with the environmental and infrastructural constraints of island system. Plastic pollution is not only a waste management issue but a systemic outcome of the production and consumption system.

4.2. Current state and interventions to reduce plastic pollution

The island continues to operate under a predominantly linear economy. Most of the products are imported, and packaging, the highest contributor to plastic waste ends up primarily in the landfill. Separation efforts reduce the SE but it does not solve the system and material disorder. The high diversity of imported products and the lack of specific packaging rules for their importation increase SE. Systems driven by imported rather than local/bulk products contribute to higher SE levels, particularly in commercial and tourist areas where product variety and packaging complexity is greater.

Current interventions to reduce plastic waste in the Galápagos islands have focused primarily on banning single-use plastics, repurposing plastic and recycling (Martin et al., 2021). In grocery shops interventions are centred on reusing and recycling tertiary packaging. However, no interventions were identified targeting product packaging itself, or to reduce the quantity of packed products.

The law prohibiting single-use plastics was enacted in 2015 and allowed the use of biomaterials for products such as straws. As a result, sugarcane-based straws are now commonly available in restaurants. However, kerbside transect surveys revealed these types of straws are leaking into the urban areas and do not appear to be biodegrade under normal conditions. The FTIR-ATR spectra showed that these straws are made of PP, suggesting a blended material containing sugarcane fibres and PP. The limited biodegradability of products poses risks to both terrestrial and marine environments, through increasing the likelihood of ingestion by fauna (Jones et al., 2021).

Interventions targeting specific single-use plastics can influence system entropy differently. For example, eliminating the handled plastic bags increased the use of the roll bags, which were present in transect surveys. Although their increased use may still contribute to plastic pollution, they are typically composed of a single material and used for bulk products, resulting in lower entropy compared with more complex packaged alternatives, suggesting better material management is needed. In contrast, replacing petroleum-based straws with partially plastic-based "eco-friendly" alternatives did not necessarily reduce system SE, partly due to unclear regulations regarding the materials allowed for import, which can result in more complex products.

Although repurposing initiatives were not directly assessed in this study, they may also influence entropy dynamics. For example, transforming dispersed marine plastic waste into handicrafts may help concentrate materials removed from the environment into new products, and therefore reduce entropy in the system. However, if multiple polymer types are mixed within these products, entropy at the product level may remain high even if overall system disorder is reduced (Martin et al., 2021). Reusing interventions in the islands may have helped maintain materials concentrated within the product for longer periods, reducing the probability of dispersion into the environment and potentially lowering system disorder.

Moreover, Galápagos has placed strong emphasis on recycling as a strategy to reduce plastic pollution. Most households and commercial sites sort their waste, which is then transported to the recycling centre, for further sorting before being sent either to mainland Ecuador for recycling or to landfill (GAD Municipal Santa Cruz, 2025). As mentioned before, recycling interventions, help concentrate polymers, reducing the SE of the system. This supports previous research showing that material separation reduces the SE and improve recycling potential (Skelton et al., 2022), However, this reliance on recycling and outsourcing of waste can also shape local perceptions of solutions. In Santa Cruz and other islands recycling is often prioritized over upstream interventions and other interventions such as reducing and refurbish are less frequently applied (Praet and Guézou, 2025; Flor et al., 2025).

Still, despite the reduced entropy within the recycling stream, a substantial proportion of packaging ends up in landfill rather than being recycled, contributing to capacity pressure and the need for new disposal sites (Martin et al., 2021). This highlights that sorting alone is insufficient to achieve circularity. The final disposal method ultimately determines the system disorder. For example, plastic incineration represents a state of maximum SE as substances are irreversible dissipated into the atmosphere (Lipp and Lederer, 2025).

Even with effective material recovery, the recyclability of plastics remain highly context dependent. Products designed for recycling in one system may not be recyclable in another due to differences in infrastructure and market conditions. For instance, in mainland Ecuador, flexible and multi-material plastics are difficult to process and are often landfilled. Materials separated in Galápagos may ultimately follow linear disposal pathways.

Moreover, impurities can hinder material recovery (Roosen et al., 2020). For example, while PE and PP with high carbon content can be used for pyrolysis, residues such as food residues, labels or caps can disrupt the process, despite advance cleaning techniques (Roosen et al., 2020). Similarly, mixing PET bottles and PET trays can make recycling blends unfeasible due to differences in material composition. PET bottles can contain ethylene vinyl acetate (EVA) as a sealing polymer, whereas PET trays typically use PET as the outer layer for water and gas barrier properties and PE as the inner layer for sealing performance and cost-effectiveness (Roosen et al., 2020).

Similar conditions were observed in this study, where a product such as a ketchup within a sachet contained three different types of polymers (HDPE, PET and PCT) distributed across five components (the main sachet, lid, tape, metal lid and tester sachet). While the sachet itself contained two different types of polymers, i.e. HPE and PCT, this packaging complexity increased product SE, making recycling more difficult.

4.3. Opportunities to transition

The transition towards a more circular system depends on understanding the systemic drivers shaping plastic systems within their specific socio-ecological context. This study demonstrates how system infrastructure, product design, retail configuration and land-use activities influence both plastic systems and entropy. Accessibility to a wider variety of products in commercial and tourism-intensive areas, can shape consumption patterns, thereby influencing system SE and downstream plastic pollution. At the same time, consumer preferences and demand for imported products, particularly in areas with higher tourism activity, may also influence the type of products and packaging offered in local markets.

These findings indicate that context-specific interventions can reduce both plastic pollution and system disorder. In residential areas leveraging from existing infrastructure (such as small shops) promoting bulk purchasing systems and reusable bags may significantly reduce packaging waste. In more commercial and tourism intensive areas, interventions could focus on reducing packaging complexity and encouraging retail formats based on refill and bulk distribution systems, particularly within supermarkets where entropy levels were highest. Refill models have proven effective in reducing packaging demand (Antad et al., 2024). Scaling-up these interventions may require product diversification, partnerships with companies and waste management organizations (Antad et al., 2024)

This study showed that the presence of vegetation and natural areas in the surroundings was associated with lower litter levels and SE. Similarly, the Galápagos islands, due to their unique biodiversity and conservation status, exhibited lower litter densities compared with other urban areas reported in the literature (Youngblood et al., 2022). These conditions provide a strong foundation for interventions aimed at reducing plastic leakage. Initiatives such as regreening urban spaces may encourage environmental responsible behaviour and reduce littering, and they may also influence how services such as restaurants and hotels are designed and operated, for example by promoting reusable packaging systems or products with less packaging (Schuyler et al., 2021). However, public awareness and environmental education is needed, as citizen's attitudes can strongly influence littering behaviour and sustainable practices (Nejadsadeghi et al., 2024).

Systemic interventions, including strengthening local economic development by enhancing local capacity and infrastructure, has been identified as important pathways to increase circularity in island systems (Flor et al., 2025). Enhancing local production could reduce dependency on imported goods and the associated packaging required for long distance transport. However, current production in the Galápagos islands does not meet local demand. Agricultural production has been constrained by a shift of labour toward the tourism sector (Sampedro et al., 2020), water scarcity and regulations for the use of agrochemicals (Freire et al., 2018).

Shifting toward more circular production-consumption systems requires greater emphasis on upstream strategies aimed at reducing plastic complexity and limiting problematic plastics, thereby decreasing system disorder at end-of-life stages and increasing material reintegration potential. Findings showed that most imported products are manufactured in mainland Ecuador making upstream interventions more feasible. For example designing valorised and simpler packaging for take-back schemes, can reduce impacts and entropy, and guarantee a correct reinsertion into the system (Bassani et al., 2024). Deposit Refund Systems with incentives to consumers, can enhance material recovery while reinforcing the Extended Producer Responsibility. These systems already show high return rates, for example 97% recovery in Germany and 89% in Norway for PET bottles, but aspects such as environmental gains and impacts still require thorough evaluation (Picuno et al., 2025). They also reduce cross-contamination thereby lowering entropy and energy demand in subsequent processing stages (Picuno et al., 2025).

Alternative materials, such as biobased and biodegradable plastics can be considered as substitutes, particularly for packaging applications (Moshood et al., 2022). In import dependent systems such as the Galápagos Islands, these alternatives may help reduce the number of petroleum-based polymers currently entering the islands, especially where eliminating packaged imported products is not feasible. However, their effectiveness depends on actual displacement of conventional plastics, simplification of the materials and appropriate disposal. In some cases, environmental impacts can increase, as the production of biomaterials or biobased products adds to rather than replace the impacts associated with petroleum-based plastic production (Zink and Geyer, 2017). In addition, consumers perceptions of these materials as environmentally friendly, can undermine efforts to reduce single-use product consumption (Chang and Hung, 2022).

4.4. SEA as a tool for driving a CE

Most common CE indicators focus on resource efficiency and material management. Incorporating SEA adds a new dimension to circularity assessment by enabling the comparison of system disorder based on the diversity, concentration and dispersion of material within the system. SEA helped identify which systemic factors or interventions contribute to increasing or reducing disorder, thereby supporting the identification of leverage points for plastic waste reduction.

CE interventions do not necessarily reduce entropy. Some strategies, such as introducing alternative materials while maintaining existing consumption patterns, may unintentionally increase disorder by adding material diversity, and therefore SE, rather than reducing or replacing the problematic plastic products. Therefore, by capturing material mixing and system complexity across different contexts and scales, SEA can help identify priority areas where interventions may generate the greatest reductions in disorder.

Testing SEA as a complementary tool for CE assessment provided useful insights in this study. By expressing polymer distribution through a common indicator, SEA enabled comparison among the three litter clusters and the recycling stream, helping to identify systems with greater compositional dispersion and potential separation complexity. SEA also enabled comparison among individual grocery products and retail formats, showing the ones that need more urgent action due to its complexity on the different type of polymers. SEA adds information not captured by waste, litter or product counts; it helps identify which type of combination and distribution of materials increases the complexity of the system.

SEA supported the identification of key intervention points to reduce entropy and plastic pollution such as, regulating imported products from the mainland, promoting local production and encouraging bulk sales, and reducing packaging diversity. Targeted interventions should be context specific, for instance, rural areas can strengthen bulk sales, while urban areas should aim to limit product and packaging diversity. This tool can be used to track changes in system disorder overtime following the implementation of interventions.

Moreover, SEA has potential for application across multiple stages of a product's life cycle, where it can be used to identify optimal pathways to reduce disorder. Additional dimensions, such as energy and impacts can also be integrated, as SEA alone does not capture all the dimensions of circularity. However, integrating SEA along with MFA may be more appropriate than analysing individual systems separately, as undertaken in the present study.

Finally, combining SEA with socio-ecological analysis enables a deeper understanding of how the built environment and the consumption system shape plastic consumption and leakage, providing valuable insights to inform future urban policies and behavioural interventions.

4.5. Study limitations

Several limitations should be considered for future studies:

- Litter outside defined transects was not included, although illegal dumping in vegetated areas was observed.
- Estimates of plastic waste generation and imports were based on a standard product lifespans and 7 months data, extrapolated to 12 months.
- SEA can provide a useful complementary analytical tool. However, meaningful comparisons between systems require consistent system boundaries, hierarchical levels, component categories and substances. Therefore, its applicability depends on the availability of harmonised and sufficiently detailed data, which limits its application as a universal indicator across systems. This was already noted by Skelton et al. (2022), where sensitivity to material categorization was analysed, showing that it can influence the results.
- SEA values comparability may also be affected by whether systems are assessed independently, as in the present study, or analyzed as interconnected flows within MFA.
- Compiling and analyzing harmonized data can be time-consuming and resource intensive, potentially limiting the feasibility of applying SEA for continuous monitoring and reporting.
- SEA focuses primarily on material concentration and dispersion, and may therefore overlook other important aspects such as energy use and environmental impacts may be overlooked (Lipp and Lederer, 2025). Several authors have sought to address these methodological limitations by combining SEA with complementary indicators. For example, Nimmegeers et al. (2021) incorporated energy consumption because, although SEA provides insight into material mixing and compositional complexity, it doesn't measures the required efforts for separating those materials. Similarly, Compart & Gräbner (2024) combined SEA with indicators such as carbon footprint and economic.

5. Conclusion and future research

This study introduced an innovative approach to analysing how system dynamics influence plastic systems and disorder. To the authors' knowledge this is the first application of SEA to assess how the dynamics of a system dynamics and area characteristics influence plastic pollution and SE. Findings showed that area characteristics exert stronger influence on plastic systems than human movement. The SE levels were highest in areas with large shops and mixed land-use characteristics where greater diversity and packaging complexity make CE interventions more challenging.

The application of SEA proved valuable for assessing plastic systems and identifying interventions that can reduce entropy and foster circularity. By providing a common indicator, SEA also enables the prioritization of context-specific interventions. The findings can support decision makers in advancing the transition toward a CE by identifying leverage points for systemic change, particularly in the context of the Global Plastics Treaty.

Based on these findings, future research should investigate alternative packaging that minimize the use of composite materials and evaluate restrictions on products associated with high SE. CE models capable of reducing SE, such as bulk product systems, should be explored. In addition, future studies could analyze entropy across the entire lifecycle. Future research could also focus on applying SEA specifically to CE interventions by measuring entropy changes in the different loops.

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

During the preparation of this work the author(s) used ChatGPT to improve readability of the text and troubleshooting in R code. After using it, the authors reviewed and edited the content and take full responsibility for the content of the published article.

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Ethics approval statement

The scope, methodology and data management process were approved by the FHLS Biosciences Ethics Committee (Application ID: 1741069). All the participants signed consent forms.

CRediT authorship contribution statement

Daniela Flor: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Andrea Osorio Baquero:** Writing – review & editing, Visualization, Software, Methodology, Investigation. **Lara M. Pinheiro:** Writing – review & editing, Methodology, Investigation. **Ceri N. Lewis:** Writing – review & editing, Supervision, Funding acquisition. **Penelope K. Lindeque:** Writing – review & editing, Investigation. **Estelle Praet:** Writing – review & editing, Investigation. **Ricardo Zambrano:** Writing – review & editing, Investigation. **Angelica Aguirre-Sanchez:** Writing – review & editing, Investigation. **Fiona Charnley:** Writing – review & editing, Investigation. **Jen S. Jones:** Writing – review & editing, Validation. **Ramzy Kahhat:** Writing – review & editing, Validation. **Simron Singh:** Writing – review & editing. **Tamara S. Galloway:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

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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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.rcradv.2026.200378.

Data availability

Data supporting this publication is available at the Environmental Information Data Centre at:

https://doi.org/10.5285/b6076854-c526-44b2-9e5a-4fa4f8df4b21
https://doi.org/10.5285/f2e7292f-d36d-4f1f-aa70-2f76ce9dea11
https://doi.org/10.5285/f7ae5395-8ed8-4046-acbd-4bdc699340e3

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