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Litter origins, accumulation rates, and hierarchical composition on urban roadsides of the Inland Empire, California

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Litter origins, accumulation rates, and hierarchical composition
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E-mail: wincowger@gmail.com**Keywords:** anthropogenic litter, plastic pollution, mismanaged waste, environmental planning, environmental policy, solid waste managementSupplementary material for this article is available [online](#)

Abstract

Urban areas are the primary source of human-made litter globally, and roadsides are a primary accumulation location. This study aimed to investigate how litter arrives at roadsides and determine the accumulation rate and composition of roadside litter. We monitored select roadsides in the Inland Empire, California, for litter abundance (count) and composition (material, item, and brand type). Receipt litter with sale time and location information was used to investigate whether wind, runoff, or human travel were dominant transport agents. Only 9% of the receipts could have experienced runoff, and wind direction was not correlated with receipt transport direction. However, human travel and receipt transport distances were similar in magnitude and distribution, suggesting that the displacement of litter from the place of purchase was predominantly affected by human travel. The median distance receipts traveled from the sale location to the litter observation location was 1.6 km, suggesting that most sources were nearby to where the litter was found. Litter accumulation rates were surprisingly stable (mean 40 349 (33 255–47 865) # km⁻¹ yr⁻¹ or 1170 (917–1447) kg km⁻¹ yr⁻¹) despite repeated cleanups and the COVID-19 stay-at-home orders. A new approach was employed to hierarchically bootstrap litter composition proportions and estimate uncertainties. The most abundant materials were plastic and paper. Food-related items and tobacco products were the most common item types. The identified branded objects were from the primary manufacturers (Philip Morris (4, 2%–7%), Mars Incorporated (2, 1%–3%), RJ Reynolds (2, 1%–3%), and Jack in The Box (1, 1%–3%)), but unbranded objects were prevalent. Therefore, identifiable persistent labeling on all products would benefit future litter-related corporate social responsibility efforts. High-resolution monitoring on roadsides can inform urban litter prevention strategies by elucidating litter source, transport, and accumulation dynamics.

1. Introduction

Urban areas are the primary sources of anthropogenic litter that damages aquatic and terrestrial environments (Jambeck *et al* 2015, Rech *et al* 2015, Lebreton *et al* 2017, Cowger *et al* 2019). The source of all anthropogenic litter is at the production location (Araújo and Costa 2019). Production lines transform

litter into various forms and transport it to a sale location. Consumers purchase the litter from the sale location and transport it further (Kawecki and Nowack 2019). At any point across this system, there can be a loss of litter to the urban environment. Roadsides are the primary litter accumulation location within urban areas (Kawecki and Nowack 2019). In the United States, the major roadside litter supply

processes are suspected to be individual littering, illegal dumping, and improper household waste disposal (Müller *et al* 2020). Although these mechanisms are typically associated with consumer actions, the entire supply chain and governing bodies need to be engaged to solve litter pollution (Borrelle *et al* 2020). Producers can create more reusable or less environmentally harmful products (Altman 2021), and governments can pass ordinances to regulate products and improve waste management strategies (Borrelle *et al* 2020). This study focuses on roadside litter in the Inland Empire and aims to develop a strategy for assessing litter transport processes, identifying factors that control litter accumulation rates, and advancing litter composition quantification to inform litter prevention.

After a human mismanages litter and it escapes into the environment, it can be transported by wind (Zylstra 2013) or runoff (Mellink *et al* 2021) to other locations or removed by cleanup activities or degradation. Litter observed during roadside monitoring campaigns will reflect an integration of these processes. Recent policy research has highlighted the importance of local action (Rochman *et al* 2020) and source identification (Provencher *et al* 2020) on ending litter accumulation. A strategy for identifying which sources are pertinent to a region could be a critical decision-making tool. Receipts are a novel piece of litter that often have location and time information about the sale location they originated. The first goal of this study was to use receipt trajectories to unravel the relative importance of runoff, wind, and human transport mechanisms and describe the proximity of litter sources to litter observations.

Identifying prevention strategies to end the accumulation of roadside litter is a critical step for improving urban environmental quality and avoiding the financial costs of cleanup (Wagner and Broaddus 2016). A common observation in littering behavior research is that people are more likely to litter in littered areas (Schultz *et al* 2013). We hypothesized that removing litter from roadsides to keep them clean would decrease litter accumulation throughout the study duration. During the COVID-19 pandemic, studies observed decreases in other types of pollution (Dutheil *et al* 2020). We hypothesized that litter accumulation would decrease as a result of the pandemic. The second goal of this study was to determine if frequent cleanup or the COVID-19 pandemic would reduce litter accumulation at our monitoring sites.

Roadside litter composition informs hazard identification and fate assessment and assists in identifying litter sources (Morales-Caselles *et al* 2021). Typically, material type (resource) and item type (shape) compositions of the litter are described. Brand information directly ties litter to a producer and is less often measured. Therefore, studying litter brands is a novel approach (Roper and

Parker 2006, Muñoz-Cadena *et al* 2012, Ballatore *et al* 2021) that can inform the producers and corporate social responsibility initiatives, such as voluntary and mandatory actions to improve environmental quality (Landon-Lane 2018). Litter composition is often reported as a total proportion of litter classes (material, item, brand types) without any uncertainty metrics (Morales-Caselles *et al* 2021). Recently, a new relational and hierarchical classification system (Trash Taxonomy) was developed to thoroughly assess litter composition by material, item, and brand (Hapich *et al* 2020). The third goal of this study was to quantify uncertainty in the litter composition at our sites and assess gaps in current litter classification strategies, focusing on how they might impact corporate social responsibility initiatives.

1.1. Survey region

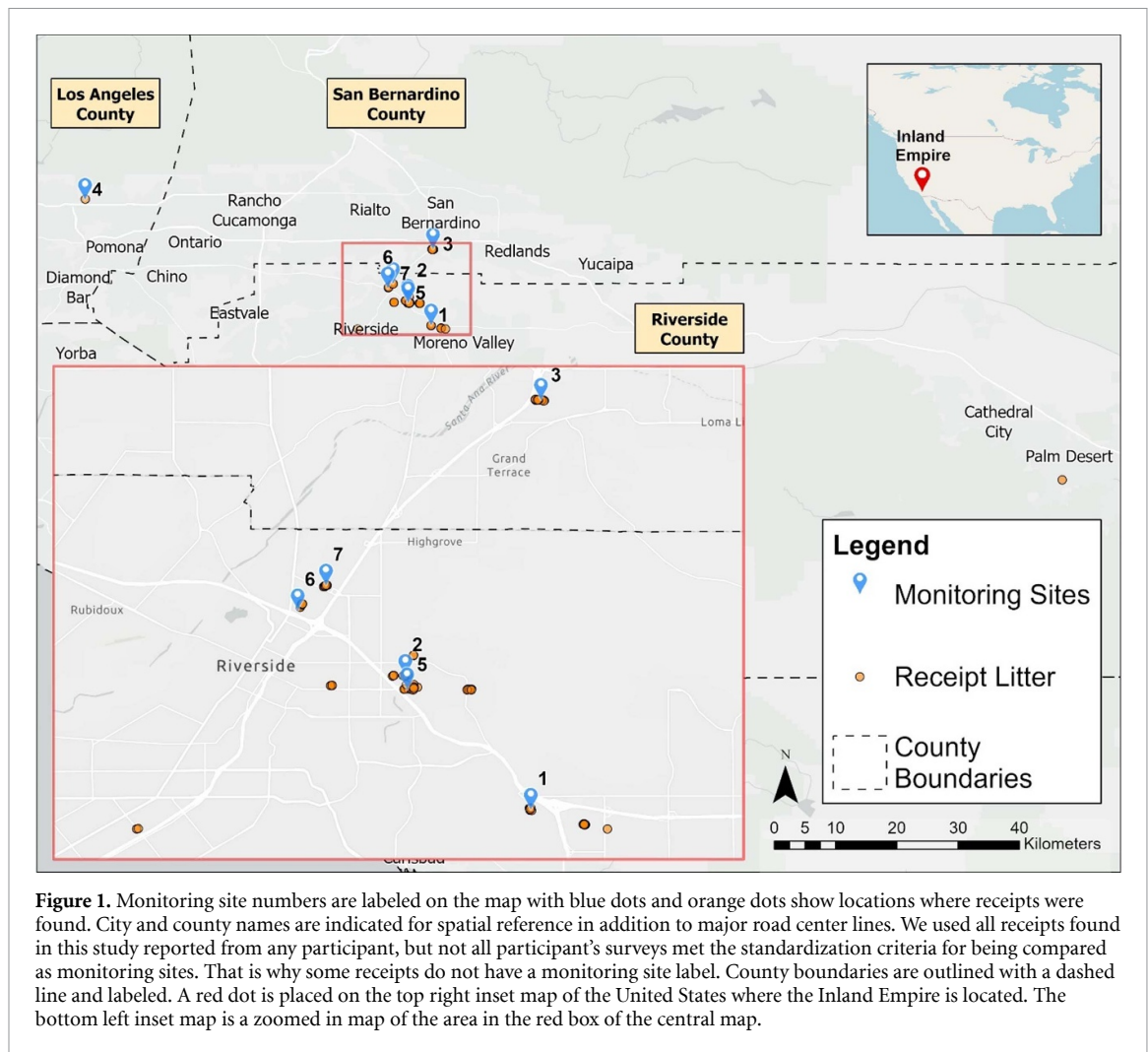
The Inland Empire includes San Bernardino County and Riverside County, California, United States (figure 1). The Inland Empire was chosen because most researchers were based there. The topography of the area includes mountains and valley regions, and major land uses are natural vegetation (>90%), developed (2%–5%), and agricultural (1%–4%) areas (Agriculture and Natural Resources U of C 2021). The region has a mean population density of 60 people km⁻² (Census 2021a). The climate is Mediterranean with 50 cm of average annual precipitation, primarily falling as rain in winter and dry summers. Wind is typically low intensity (mean daily 8.3 km h⁻¹) and moves north to south. In the fall and spring, when this study was conducted, strong winds and rain were generally rare, which led us to hypothesize that the primary mode of litter transport would be human transport. The Inland Empire has a robust waste management system that includes municipal and private street-side collection of three recovery streams (landfill, recycling, and yard waste), street sweeping, litter capture devices in storm drains, and frequent manual cleanups.

2. Methods

This study monitored roadside litter in the Inland Empire, California, using a crowdsourced methodology with high-resolution surveying of litter accumulation and composition.

2.1. Survey methods

Eighteen researchers each surveyed a unique ~100–1000 m length of roadside for litter 1–3 times per week for 2–4 weeks in Fall 2018, Fall 2019, or Spring 2020 in the following Inland Empire cities: Riverside, Moreno Valley, Loma Linda, San Dimas, and Palm Desert using a standardized methodology (supplemental information, figure 1 available online at stacks.iop.org/ERL/17/015007/mmedia). Sites were



selected based on convenience due to the crowd-sourced nature of the surveying. Thus, our observations were not necessarily generalizable to the entire Inland Empire area. Differences in survey duration occurred due to the differences in the amount of time that the researchers could provide.

Before beginning surveys, all surveyors were trained in person during two 1 h sessions and joined a group called Our Clean Community in Litterati, a crowdsourcing litter cellphone app (Litterati 2021) for data collection. Although we used the Litterati application in this study, Open Litter Map (Lynch 2018) or geolocated images on any phone could produce the same results.

During the surveys, both sides of the road were surveyed at each site, including the curb, sidewalk, and sidewalk margin. Private property was not entered. Site length depended on litter abundance, and researchers were instructed to survey until approximately 100–1000 pieces of litter were observed during their first survey. This strategy was used to ensure a low likelihood of non-detect. Each researcher recorded the litter observations and any changes to the methodology. To maintain safety, researchers generally stayed on the sidewalk out of the road.

Observations indicated that most litter was concentrated near the sidewalk curb and along the sidewalk margin. All litter (>1 cm length) was recorded and removed from the study location during each survey. Researchers used Litterati to photograph litter and record the material, item, and brand type. The cellphone app recorded location, date, and time simultaneously with each image (figure 2). Digital images of each object were taken within 1 m of where the object was found (figure 2(A)) while ensuring branding marks were visible in the image (figure 2(C)). Receipts were flattened so that all information on the receipt was viewable in the image (figure 2(A)). If multiple objects of the same type or fragments from a single object were found, those objects were logged together in one image. If researchers found any bags full of litter, they reported them as a bag full of trash. However, if a loose pile of litter was found, it was deconstructed and each object was reported individually. Large (too large for a single person to carry) or hazardous (e.g. chemicals, sanitary products) objects were left at the site and only photographed on first observation. Images were retaken if blurry. Material and item types were categorized in Litterati (figure 2(C)) using the most

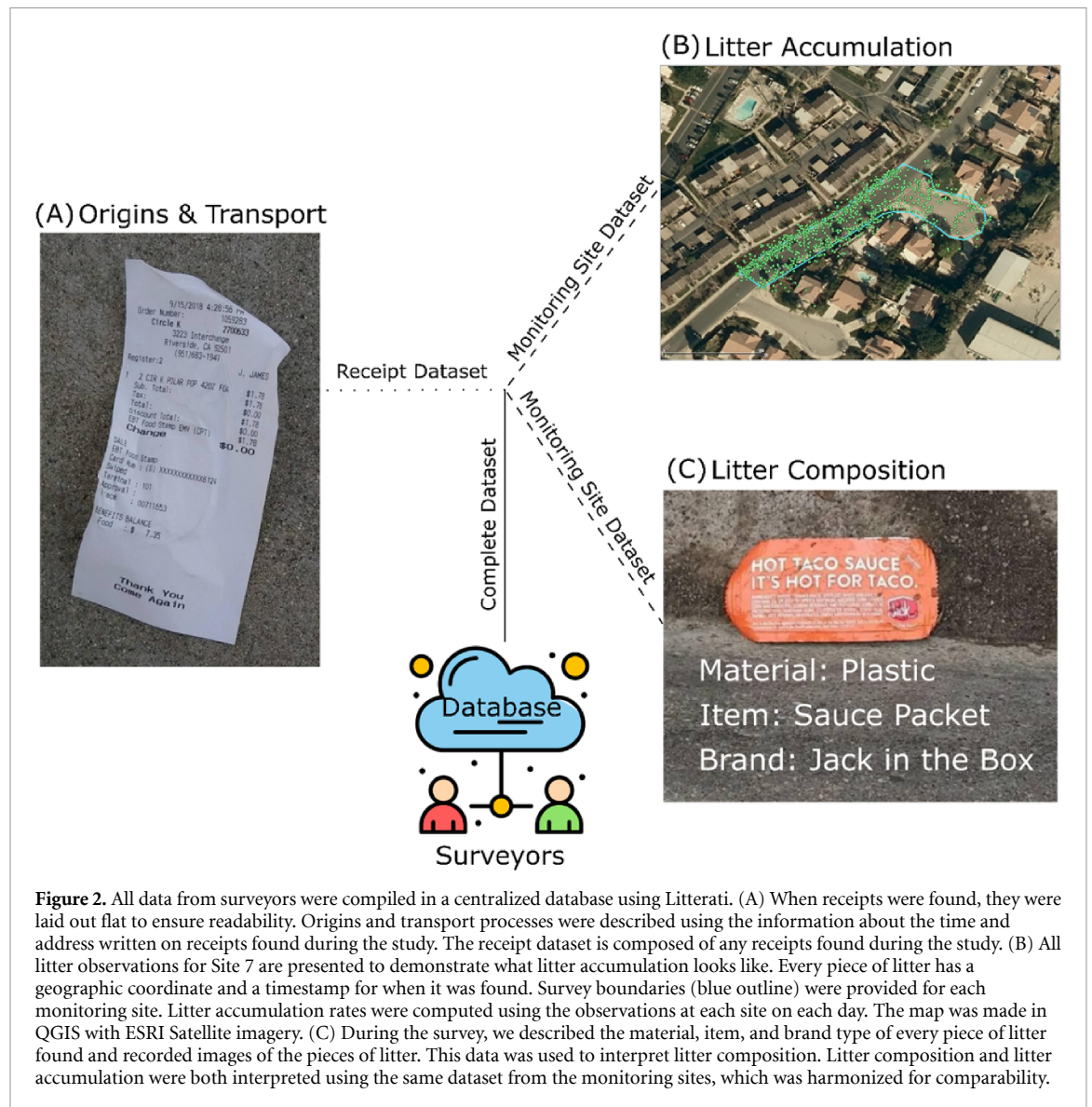


Figure 2. All data from surveyors were compiled in a centralized database using Litterati. (A) When receipts were found, they were laid out flat to ensure readability. Origins and transport processes were described using the information about the time and address written on receipts found during the study. The receipt dataset is composed of any receipts found during the study. (B) All litter observations for Site 7 are presented to demonstrate what litter accumulation looks like. Every piece of litter has a geographic coordinate and a timestamp for when it was found. Survey boundaries (blue outline) were provided for each monitoring site. Litter accumulation rates were computed using the observations at each site on each day. The map was made in QGIS with ESRI Satellite imagery. (C) During the survey, we described the material, item, and brand type of every piece of litter found and recorded images of the pieces of litter. This data was used to interpret litter composition. Litter composition and litter accumulation were both interpreted using the same dataset from the monitoring sites, which was harmonized for comparability.

up-to-date version of the Trash Taxonomy classes (Hapich *et al* 2020) (supplemental information). Using the Trash Taxonomy, our classes were compatible with classes used in other studies (Intergovernmental Oceanographic Commission 2009, Lippiatt *et al* 2013, Institute for Environment and Sustainability 2014). When a litter class did not exist in the Trash Taxonomy, a new class was created to describe the litter. Brands were recorded when found on an object.

Post survey, each researcher delineated their study area on a map using Google Maps (figure 2(B)). Litter location accuracy was calculated as the mean distance from all points recorded outside the study area to the surveyed boundary resulting in ± 7 m (figure 2(B)). Each researcher cleaned their data by removing duplicate or inaccurate images, correcting incorrect tags, noting when multiple objects were in one image, and identifying any data points that were not for this study. In total, 18 locations were surveyed, and 146 receipts were found.

Data were archived by Litterati and made accessible through their data portal (Litterati 2021). Data included images, user input labels, time stamps, latitude, and longitude coordinates of every piece of litter (supplemental information, figure 2). Further refinement of the complete dataset resulted in two datasets structured for our specific study objectives. The first dataset (Receipt dataset) includes 146 receipts found at all 18 of the survey locations. Receipt observations were extracted from the total dataset by searching the tags for the keyword 'receipt'. The second dataset (Monitoring site dataset) focused on data from survey locations with comparable quality control procedures (see section 2.3) to compare litter accumulation and composition across sites.

2.2. Receipt dataset

We calculated transport metrics for receipts, including time and distance traveled and corresponding precipitation, wind, and human transport metrics. Of the 146 receipts, 72 had both time and location

information for the sale transaction, 85 had at least sale location information, and 75 had at least sale time information. If a receipt had an address, travel distances were calculated as Haversine distance (straight line) from the latitude and longitude coordinates where the object was found to the address listed. Haversine distance was divided by the time between when the receipt was created and when it was found to determine the transport rate (m d^{-1}). We compiled wind (mean daily wind direction (0° – 360°), mean daily wind speed (m s^{-1})) and precipitation (mm, total daily) data for the entire observation period from a weather station (KRAL) near the center of our study region using the Midwestern Regional Climate Center's cli-MATE application (MRCC 2021). If a receipt had a timestamp and sale location on it, mean daily wind directions were vector averaged with daily wind speed for the receipt's potential duration in the environment to estimate the vector mean wind direction the receipt could have experienced. The receipt transport direction was calculated as the straight direction from the address on the receipt to where the receipt was found. Receipts with sale addresses were collected from 16 September 2018 to 18 November 2019, and all were found in Riverside and San Bernardino counties. Data on human trip distances from 01 January 2019 to 31 December 2019 in San Bernardino and Riverside Counties were acquired from the Bureau of Transportation Statistics (Bureau of Transportation Statistics 2021). Trip data was only available from 01 January 2019 onward, but we think this represents the temporal domain of the receipt dataset. The Bureau of Transportation created the binned human trip distance data by using smartphone tracking and aggregating them to daily and county levels (e.g. 100 human trips occurred between 1 and 10 km in San Bernardino County on 01 February 2019). Trips were defined as movements with a stay of longer than 10 min. We made the data continuous by randomly sampling the distance range bins with uniform probability distributions ranging from the smallest to largest value for the bin.

2.3. Monitoring site dataset

All survey sites included in the monitoring site dataset needed to have data cleaned by the researcher (described in section 2.1) and trash removed from the entire site at least once during the study to ensure high quality and comparable data. Only seven of the 18 locations met these criteria, and the others were excluded (figure S2). One site was unable to be fully cleaned during the first 2 d of the study, so the data for those first 2 d were omitted from the monitoring site dataset. A technical malfunction disrupted data logging at one site during one survey, but the litter was manually tallied outside Litterati and added to the database without a timestamp or latitude and longitude information.

One site was surveyed on two separate occasions to test the hypothesis that COVID-19 stay at home orders would decrease litter accumulation. First, a year before the COVID-19 pandemic and second, during the 2020 stay-at-home orders issued by California Governor Gavin Newsome effective 19 March 2020. The activity of walking around the neighborhood (essential for conducting this study) was permitted by the stay-at-home order. The stay-at-home order continued throughout the second survey period.

Socio-geographical information was compiled for each site. Demographic data were extracted for each location by merging Census tracts with the 2015 Census tract planning database (Census 2021b). Population density per Census tract was calculated by dividing the population in the tract by the tract area. Population density in the study area was an average of $920 \text{ people km}^{-2}$, while the Inland Empire was $60 \text{ people km}^{-2}$. Monitoring sites were only comprised of urban land use areas (primarily residential and mixed commercial-residential). As a result, our sites were biased toward urban high population density regions of the Inland Empire. Road length was calculated in Google Earth by tracing the centerline of the road in the monitoring site. Road widths ranged from 10 to 25 m, and road lengths ranged from 121 to 483 m.

Litter accumulation rates ($\# \text{ d}^{-1} \text{ km}^{-1}$) were calculated for each survey by dividing the number of litter observed by the total number of days since the previous survey and by the length of the surveyed road. Litter mass accumulation ($\text{kg d}^{-1} \text{ km}^{-1}$) was computed by conducting a literature review to find the average mass of each litter object (Wijzer 2015, Ballatore *et al* 2021, Ocean Conservancy 2021). When a reasonable estimate for an object's mass was unavailable, we used the suggested 82.5 g estimate (Wijzer 2015). The mass conversion table was applied to every object (supplemental information).

Litter composition was assessed using the Trash Taxonomy. Data were merged to the most up-to-date Trash Taxonomy material, items, and brand alias, and hierarchy tables. Datasets were reconciled to the Trash Taxonomy (Hapich *et al* 2020) tables using Open Refine (Openine 2021) and reconcile-csv (Open Knowledge Foundation 2021). This procedure makes the data compatible with the 69 other litter surveys incorporated in the Trash Taxonomy. Litter composition was computed for each survey day by dividing the total number of pieces observed for an individual category by the total number of pieces observed.

2.4. Statistical analysis

Statistics were calculated in *R* with hypothesis tests determined as significant or insignificant using the significance level of 0.05.

2.4.1. Origins and transport processes

We tested three potential litter transport mechanisms: runoff, wind, and people. We used precipitation as a proxy for runoff potential. Receipts that had time difference data (75) were used for precipitation analysis. If precipitation occurred between when the receipts were created and found, we considered runoff a possible transport mechanism. Receipts that had time and location data (72) were used in the wind direction correlation analysis. If the vector mean wind and receipt transport directions were correlated by circular correlation (Agostinelli and Lund 2017) (abs-correlation > 0.2 and $p < 0.05$), we would consider wind a possible important transport mechanism. We also implemented a spoke plot (Hussain *et al* 2010) for visualizing circular correlations, which was not implemented elsewhere in R to our knowledge. The cumulative distributions of litter transport distances and human trip distances were assessed for similarities and differences for the 85 receipts with location data. Quantiles were derived for the receipt and human transport distance distributions at 0.01–0.99 for a 0.01 step size, and an ordinary linear regression was performed between the two \log_{10} transformed distributions to assess the offset and goodness of fit.

2.4.2. Litter accumulation rates

The effect of persistent cleanup and COVID-19 stay-at-home orders were tested as potential interventions to litter accumulation. Each monitoring site's litter accumulation time series was assessed using linear regression to determine if the accumulation rate increased or decreased over the study period. We expected a large difference in mean litter accumulation rate between pre-COVID-19 and during COVID-19 stay-at-home orders because of the abrupt shift in outdoor activities. Mean litter accumulation confidence intervals were generated by bootstrapping (resampling with replacement, $n = 10\,000$) to assess significant mean differences in pre-COVID-19 and during COVID-19 based on overlap in 95% confidence intervals.

Post hoc power analysis was conducted in R to determine what shifts in the mean litter accumulation rate could be visible if future repeat studies were conducted. The mean litter accumulation rate from all monitoring site observations, the total sample size, and the sample standard deviation were used in a t-test power analysis to determine the Cohens d effect size, which would be necessary to achieve a power of 0.8 and a p value of 0.05 if the same study were repeated.

2.4.3. Litter composition

Differences between litter class proportions were assessed statistically using confidence intervals calculated with bootstrapped (resampling with replacement, $n = 10\,000$) mean proportions. Sunburst plots were generated with the plotly package (Sievert 2020)

and the data.tree package (Glur 2020) to hierarchically display clustered proportions and their confidence intervals. Any material or item class with a mean proportion less than 10% was considered non-essential to display. Any brand class with a mean proportion of less than 1% was considered non-essential to display.

3. Results

3.1. Origins and transport processes

Three plausible mechanisms could transport receipts in the Inland Empire: runoff, wind, and people. The median receipt transport rate was 290 m d^{-1} , and 50% of the data fell between 147 and 1497 m d^{-1} . Although we do not estimate litter transport rates over land due to wind or runoff, we suspect the observed transport rates were much faster than those processes. Nevertheless, we rigorously tested the likelihood of wind and runoff transport. Based on the precipitation data during the receipt's potential duration in the environment, we determined that 68 out of 75 receipts (91%) did not experience any precipitation (figure 3(A)). Using Pearson's product-moment circular correlation, we compared the vector mean wind direction the receipt could have experienced to the mean transport direction (figure 3(B)). No correlation between wind direction and receipt transport direction was observed (correlation -0.1 , p -value 0.357). The receipt transport distances followed a similar cumulative distribution function (log-normal) to the human trip distance distribution but were offset to smaller distances (figure 3(C)). Of the 85 receipts with sale locations, the maximum transport distance was 136 km, and the minimum was 27 m (three times as large as the estimated mean location uncertainty (7 m)) (figure 3(C)). Half of the receipts originated from less than 1.67 km away from where they were found. Linear regression fit to \log_{10} transformed data between the paired quantile values revealed that the offset between receipt and human trip distances increased by 1.1 times per unit of human trip distance and had a y -intercept of -0.9 (figure SI 1).

3.2. Litter accumulation rates

Did cleanup or COVID-19 stay-at-home orders affect accumulation rates? The majority of monitoring sites had relatively stable litter accumulation rates throughout the sampling period (figure 4). The total mean annual accumulation rate estimate is $40\,349$ ($33\,255$ – $47\,865$) $\# \text{ km}^{-1} \text{ yr}^{-1}$ or 1170 (917 – 1447) $\text{kg km}^{-1} \text{ yr}^{-1}$ for the survey region. Site mean litter accumulation rates varied over an order of magnitude, ranging from 0.021 to 0.25 m d^{-1} . Most observations at sites were within half an order of magnitude of one another (figure 5). We did not find a steady drop in the litter accumulation rate at

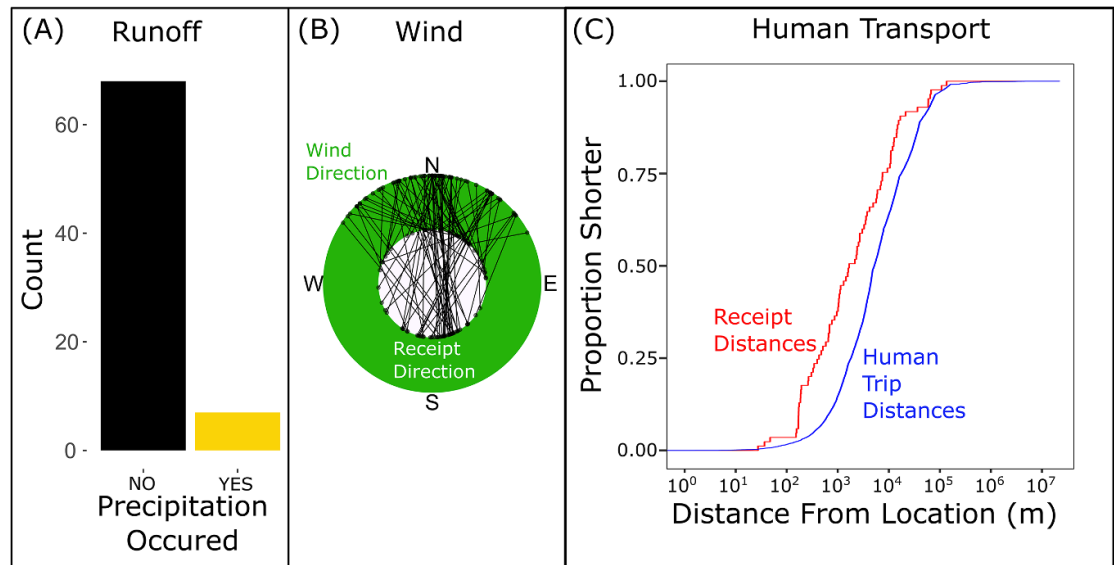


Figure 3. (A) Precipitation occurring during the receipts potential time in the environment. YES stands for the receipt could have experienced precipitation, NO means the receipt could not have experienced precipitation. We found precipitation could not be a dominant process transporting the receipts. (B) A spoke plot displaying the circular correlation between direction receipts came from (inner circle), and vector mean wind directions (outer circle). North (360°) is up. The lines connecting the points represent the paired directions for a single receipt. The plot can roughly be interpreted as similar directions when the line does not cross the central circle and different directions when the line does cross the central circle. The Pearson product-moment circular correlation is -0.1 and p -value 0.357 . There is no correlation between wind direction and receipt travel direction. (C) Empirical cumulative distribution function (ECDF)s of distance to receipt address (red) and the human trip travel distance (blue) from the Bureau of Transportation. Receipts were slightly shifted to lower distances than the trips. Human travel appears to be the most probable mechanism for the majority of observed receipt transport.

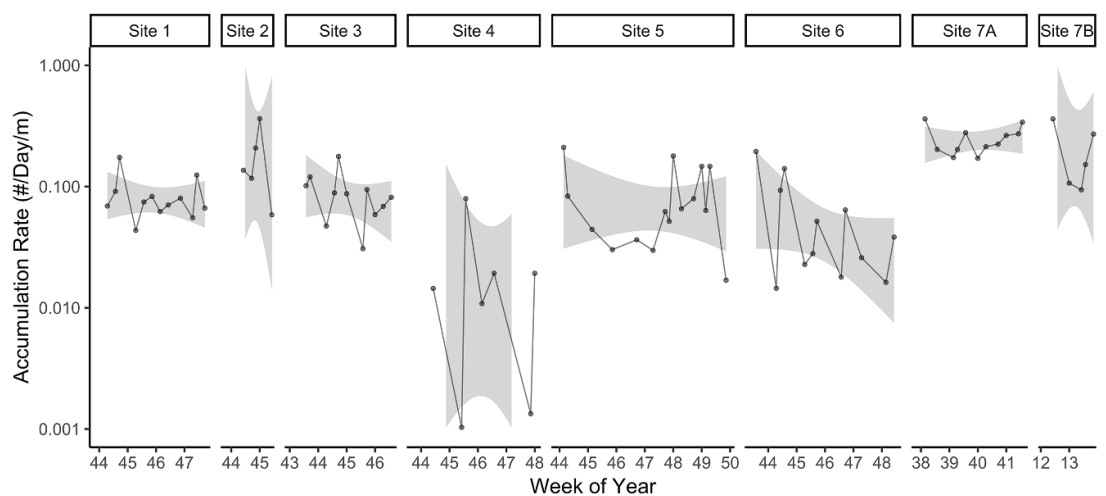


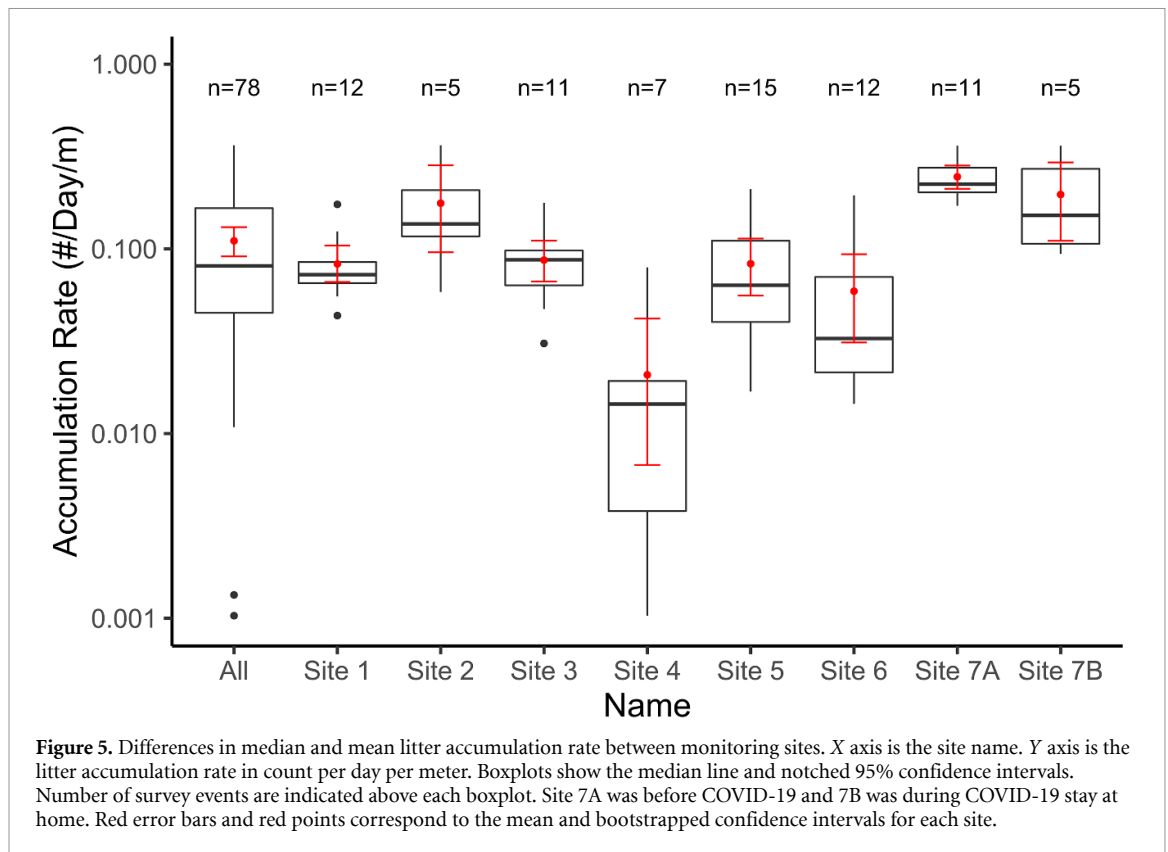
Figure 4. Litter accumulation rates for each monitoring site observation (count per day per meter). Site name is indicated on the top axis. The total count observed during each sample date and a plot showing comparisons between sample days are indicated in the supplemental information (figure S2). Sample dates (x -axis) were reported as week numbers for the year and differed between sites. Confidence intervals (95%) for linear regressions were plotted for the time series to assess the effectiveness of persistent cleanup on litter accumulation. None of the sites show significant trends in litter accumulation.

any monitoring site (figure 4). Instead, trends in litter accumulation rates seemed random throughout each survey, and none were significant (figure 4). We observed a small decrease (20%) in the mean litter accumulation rate during COVID-19 stay-at-home orders at Site 7 ($0.2, 0.11\text{--}0.29 \text{ \# m d}^{-1}$) compared to before COVID-19 ($0.24, 0.21\text{--}0.26 \text{ \# m d}^{-1}$), but the means were not significantly different (two sided t test, $p = 0.42$). Power analysis revealed that

a Cohen's d effect size of 0.45 (small-medium effect) amounting to a shift of 37% from the current mean accumulation rate of the full monitoring site dataset (figure 5) would be required to attain a power of 0.8 and p value of 0.05 for future repeat studies.

3.3. Litter composition

The most common material types found in the litter surveys were plastic (mean proportion: 56,



53%–59%) and paper (33, 30%–35%) (figure 6(A)). Food-related items (38, 35%–42%) and tobacco-related items (14, 11%–17%) were the most abundant litter item types (figure 6(B)). Correspondingly the top four brands were all cigarette and food producers: Philip Morris (4, 2%–7%), Mars Incorporated (2, 1%–3%), RJ Reynolds (2, 1%–3%), and Jack in The Box (1, 1–3%) (figure 6(C)). The majority of objects were unbranded (66, 62%–70%), and many brands (13, 11%–15%) were identifiable but could not be merged with the Trash Taxonomy.

4. Discussion

4.1. Origins and transport processes

We found that human trips were the primary transport mechanism of the receipts in our study sites. There is an offset between human trip distances and litter transport, which is likely due to the differences in the calculation of human trips (travel path) and receipt transport distances (as the crow flies), and the acquisition and/or deposition of litter within a given trip rather than at the trip endpoints. Receipt addresses were slightly further away than the nearest potential receipt address on average (figure S3). This result may indicate that litter item purchase occurs at convenient locations along personal and work commutes. Additionally, human trip distance distributions could be a good proxy for estimating litter transport distances using regression on paired quantiles (figure S1). Although this research focuses on receipts

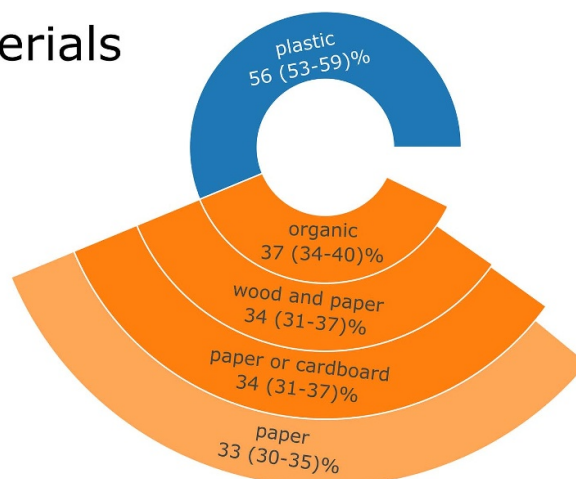
in the Inland Empire, we expect that these metrics apply to similar litter morphologies and sources on roadsides in the United States with similar human trip distributions, climate, and waste management practices. Future studies should assess other types of litter in different regions to better understand global litter transport and incorporate a social science component to determine the societal drivers of litter accumulation.

Most of the receipts found on roadsides in this study originated less than 1.6 km away. Local action has been proposed as a strategy to combat litter accumulation (Rochman *et al* 2020). If local actions in the Inland Empire targeted prevention of receipt-like litter from sale locations within 1.6 km to litter hotspots, they would likely account for half of the sources supplying the litter.

4.2. Litter accumulation rates

We were surprised by the persistence of litter accumulation rates despite our efforts to keep the sites clean and COVID-19 stay-at-home orders. Litter behavior studies have noted that keeping areas clean affects the aptitude of people to litter, but that effect is generally small (Schultz *et al* 2013). We may not have had a long enough study period to detect the effect of cleanup. Although only a small number of observations (5) were collected during stay-at-home orders, these data (and the prevalence of essential goods in the composition i.e. food items) point toward the idea that litter accumulation may be tied to essential everyday

(A) Materials



(B) Items



(C) Brands

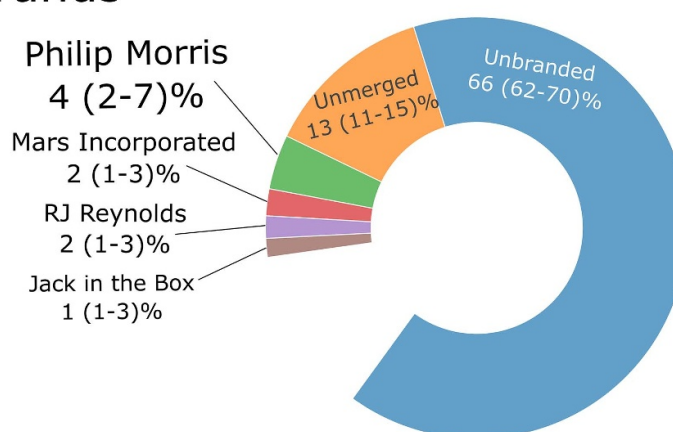


Figure 6. Sunburst plots show the relative composition of litter clustered by the hierarchy from the Trash Taxonomy. The hierarchy displayed here is essential for thorough comparison with other studies who use different classification schemes. Categories closer to the center of the circle are parent categories in the hierarchy of the child categories which are further from the center. Each category lists the percent composition of that category to all litter found during the study, and uncertainties around the mean percent were bootstrapped (resampling with replacement, $n = 10,000$) and listed. Figure (A) shows the material composition, any category less than 10% of the total was removed from the figure for visualization. Figure (B) shows the item types, any category less than 10% of the total composition was removed from the figure. Figure (C) shows the manufacturer names, any category less than 1% was removed from the figure.

activities, which were continued during the stay-at-home order. Additionally, Seco Pon and Becherucci (2012) found that litter standing stock on roadsides in Argentina was stable throughout the seasons of the year without removing any of the litter, similar to the first observations of standing stock at Site 7, which were both around 200 pieces (figure S2). Litter accumulation may be generally balanced by litter removal at these monitoring sites. Site 4 stood out as having a significantly lower litter accumulation rate than most other sites (figure 5). Site 4 also had the lowest Cal EnviroScreen score (an index of environmental burden) of all the sites (supplemental information, OEHHHA 2021). Future work could assess if any of the variables in the Cal EnviroScreen are strong determinants of litter accumulation.

The stability of the litter accumulation rates indicates that this method may be valid for future investigation into interventions. Since the cleanup did not impact the litter accumulation, this method would be valid to test other prevention strategies without removing the effect from the measurement itself. To further support our approach for regional analysis, the city of Riverside (central to where much of the survey monitoring occurred) estimated a litter accumulation rate of $2855 \text{ kg km}^{-1} \text{ yr}^{-1}$ in 2010 with street sweeping data (Riverside City 2021), while our estimate was $1170 (917\text{--}1447) \text{ kg km}^{-1} \text{ yr}^{-1}$ in 2018–2020, which were within a factor of two. However, future studies should randomize monitoring sites throughout the Inland Empire for a more robust regional inference. Based on power analysis, future repeat studies should expect an intervention capable of producing a shift in the mean accumulation rate greater than $\pm 37\%$ or collect more data to quantify a statistically robust effect at the sites.

4.3. Litter composition

Plastic, food items, cigarette products, and brands with high market prevalence were also known to be the most prevalent litter objects in environmental compartments around the world (Roper and Parker 2006, Muñoz-Cadena *et al* 2012, Ballatore *et al* 2021, Morales-Caselles *et al* 2021). In another study in Southern California, Marlboro and Jack-in-the-box were also prevalent brands on beach litter (Moore *et al* 2001). Solutions have been proposed to decrease single-use plastic product availability and engage corporations through corporate social responsibility initiatives (Landon-Lane 2018). The approach we have developed for measuring the uncertainty in the proportion of objects attributed to manufacturers should assist in developing effective corporate social responsibility strategies. We would like to see the most prevalent manufacturers of litter found at our sites take an active role in decreasing the abundance of their waste. Future studies could employ this monitoring technique to measure their efficacy.

Unmerged and unbranded categories were prevalent, not useful, and resulted from a limitation of our current classification capabilities for litter. Unmerged categories were not in the Trash Taxonomy (Hapich *et al* 2020) and should be added to the Trash Taxonomy in future work. Most objects were unbranded and therefore nearly untraceable to their producer. This discrepancy hampers corporate social responsibility initiatives for the producers of unbranded products. We advocate for improving material fingerprinting and branding policies that increase the identifiability of manufacturers who created the products (Almroth *et al* 2021).

5. Conclusions

In this study, we advance science relevant to government entities, individuals, and corporations so that all can work together to end litter by advancing the science of litter transport processes, accumulation rates, and composition in the Inland Empire of California. This study was the first of its kind to conduct high-resolution surveys of litter accumulation rates on roadsides and identify human transport as a primary mechanism for litter transport. Roadsides are a significant input of litter to the environment, and this work reports a methodology for monitoring litter on roadsides and measuring the efficacy of interventions to litter accumulation there. The hierarchical litter composition and uncertainty analysis used here has vast implications for thoroughly interpreting litter compositions and brand composition assessment which could be instrumental in driving future corporate social responsibility initiatives. Removing litter from the study locations made our efforts impactful in its own right, although this intervention did not reduce littering as we expected.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: <https://osf.io/82dqk/>.

The entire data analysis procedure was version-controlled and documented on Github (CC BY 4.0) (<https://github.com/wincowgerDEV/OurCleanCommunity>).

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Author contributions

W Cowger: conception, data collection, data analysis, write up of publication. A Gray: conception, data analysis, write up of publication. H Ajami: data analysis, write up of publication. S Singh: data collection, data analysis, write up of publication. All others: data collection, write up of publication.

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Conflict of interest

None to declare.

Author confirmation

The authors have confirmed that any identifiable participants in the study have given their consent for publication.

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