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Plastics, Microplastics, and Per- and Polyfluoroalkyl Substances

Abundance and Composition Across Water Resources: Estimation and Uncertainty

A dissertation submitted in partial satisfaction of the
requirements for the degree Doctor of Philosophy
in Environmental Science and Management

by

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June 2026

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Plastics, Microplastics, and Per- and Polyfluoroalkyl Substances
Abundance and Composition Across Water Resources: Estimation and Uncertainty

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by Rebecca M. Reynolds

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This work is dedicated to my grandparents, Saeed and Zahrah Behshid, and to my parents, Thomas and Soheila Reynolds. Your sacrifice, guidance, and love made it possible for me to pursue this degree, and the magnitude of that privilege is not lost on me. Thank you for pushing me to recognize my full potential and for showing me, through your own excellence, that a person really can change their stars.

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ABSTRACT

Plastics, Microplastics, and Per- and Polyfluoroalkyl Substances Abundance and Composition Across Water Resources: Estimation and Uncertainty

by

Rebecca M. Reynolds

Plastic trash, microplastics, and per- and polyfluoroalkyl substances (PFAS) are co-occurring, ubiquitous, and persistent urban pollutants with demonstrated adverse impacts on human and ecosystem health. Though their sources may differ, urban runoff is a major transport pathway for all three of these pollutants into surface waters. Given emerging regulatory and legislative responses at federal and state levels, accurately estimating these pollutants' loads with measures of variance is critical to monitoring, determining risk, informing policy design, and ensuring compliance with remediation requirements. However, field campaigns to directly measure plastic trash, microplastics, and PFAS are time- and cost-intensive, resulting in data limitations. In the case of plastic trash, current single-pass surveying methods are known to underestimate environmental loads, and lack measures of effort and variance, preventing cross-study comparisons. Surface waters receiving plastic trash, microplastics, and PFAS via urban runoff may interact with groundwater, an important drinking water resource. Yet, studies measuring microplastics in groundwater are rare, and studies measuring both microplastics and PFAS in groundwater as well as in

potentially interacting surface waters are rarer still. This dissertation addresses these limitations and knowledge gaps.

In Chapter II, we demonstrate that multiple-pass removal surveys with depletion modeling, a well-established method in fisheries ecology, can be adapted to estimate plastic trash abundance with quantified variance and standardized sampling effort, enabling both the quantification of single-pass survey underestimation and cross-study comparison of plastic trash loads. In Chapter III, we compare plastic trash abundance estimates and standard errors from multiple-pass removal surveys with depletion modeling to those derived from a mark-recapture surveying approach, another well-established fisheries ecology method, to determine whether the two methods converge on similar estimates when applied to the same plastic trash within the same transect. In Chapter IV, we evaluate agreement between depletion-modeled trash mass estimates and qualitative trash level categories assigned using the On-Land Visual Trash Assessment method, California's primary single-pass trash assessment protocol. We also use Empirical Bayesian Kriging Regression Prediction to interpolate spatially explicit estimates of total trash mass, stratified by Priority Land Use across the sidewalk networks of three neighboring watersheds, with quantified uncertainty. In Chapter V, we determine the concentration and composition of microplastics and PFAS in municipal production well water and surface waters potentially interacting with the source aquifer in the same study area as Chapter IV. Together, these studies provide actionable insights for stormwater and water resource managers navigating plastic trash, microplastic, and PFAS regulations.

We found that, on average, single-pass surveys underestimated plastic trash count and mass by 72% (SD $\pm 12\%$) and 53% (SD $\pm 17\%$) respectively when conducted across a variety

of transect types in a coupled human and natural system, and by 48% (SD $\pm 18\%$) and 46% (SD $\pm 16\%$) respectively when conducted across more uniform transect types along an urban sidewalk network. When plastic trash was surveyed in the same transect using both a mark-recapture approach and multiple-pass removal survey with depletion modeling, we found that estimated plastic trash counts and associated standard errors were very similar: 268 (SE ± 75) and 313 (SE ± 73), respectively. We found that On-Land Visual Trash Assessments meaningfully distinguished sites categorized as "Not Littered" from those categorized as "Slightly Littered" and "Littered," but did not distinguish trash mass between "Slightly Littered" and "Littered" transects. Empirical Bayesian Kriging Regression Prediction revealed that trash density patterns were not consistent with Priority Land Use designations in one of three watersheds of interest, and that location-specific effects beyond Priority Land Use designations alone may suggest the need for watershed-wide intervention. Finally, microplastics and PFAS were detected in the majority of waters sampled, with plastic plumbing infrastructure identified as a potential source of microplastics in municipal production well water samples.

Together, this body of work quantifies single-pass trash survey underestimation and offers managers two novel methods for estimating trash abundance with measures of variance. We also provide a spatially explicit methodological framework to interpolate trash mass at the watershed scale, determine agreement between mass-based trash loads and current primary statewide trash assessment categories, and characterize microplastic and PFAS concentrations across water resources, all within the same urban system.

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GLOSSARY OF TERMS

Plastics: A diverse suite of materials, consisting of synthetic or semi-synthetic organic polymers that are moldable when soft, that become rigid or only slightly elastic once set, and that are shaped by the process of flow during their production (Millican, 2021; Sorenson, 2022).

Trash or Litter: California code defines litter as, “all improperly discarded waste material, including, but not limited to, convenience food, beverage, and other product packages or containers constructed of steel, aluminum, glass, paper, plastic, and other natural and synthetic materials, thrown or deposited on the lands and waters of the state, but not including the properly discarded waste of the primary processing of agriculture, mining, logging, sawmilling or manufacturing [...]” (California Code Title 7.97 Section 68055.1.).

Both the United States Environmental Protection Agency (US EPA) and the California State Water Resources Control Board (SWRCB) use either “litter” or “trash” in documents pertaining to its regulation under the Federal Clean Water Act and the California State Porter Cologne Water Quality Control Act (California State Water Resources Control Board, 2015; United States Environmental Protection Agency, 2024).

Life cycle: The combined stages of production, consumption, and waste management of a product (Nielsen, 2020).

Microplastics: No standard definition for microplastics currently exists (Rochman, 2019).

However, in 2022 the California SWRCB defined microplastics in drinking water as “...Solid polymeric material to which chemical additives or other substances may have been added, which are particles which have at least three dimensions that are greater than 1

nanometer and less than 5,000 micrometers. Polymers that are derived in nature that have not been chemically modified (other than by hydrolysis) are excluded.”

Perfluoroalkyl and Polyfluoroalkyl Substances (PFAS): The US EPA Toxic Substances Control Act defines PFAS as, “...Synthetic organic compounds that do not occur naturally in the environment...[and that] contain at least one of the following three structures: (1) R-(CF₂)-CF(R')R'', where both the CF₂ and CF moieties are saturated carbons, (2) R-CF₂OCF₂-R', where R and R' can either be F, O, or saturated carbons, and (3) CF₃C(CF₃)R'R'', where R' and R'' can either be F or saturated carbons.” Under the Safe Drinking Water Act, the US EPA set limits for five specific individual PFAS known as GenX Chemicals: PFOA, PFOS, PFNA, PFHxS, and HFPO-DA, and set hazard index levels for mixtures of two or more of the following four PFAS: PFNA, PFHxS, HFPO-DA, and PFBS.

Priority Land Uses: The California SWRCB Trash Provisions states that priority land uses are, “those developed sites, facilities, or land uses (i.e., not simply zoned land uses) within the MS4 permittee’s jurisdiction from which discharges of trash are regulated [and which include]: (1) High-density residential: all land uses with at least ten (10) developed dwelling units/acre. (2) Industrial: land uses where the primary activities on the developed parcels involve product manufacture, storage, or distribution (e.g., manufacturing businesses, warehouses, equipment storage lots, junkyards, wholesale businesses, distribution centers, or building material sales yards). (3) Commercial: land uses where the primary activities on the developed parcels involve the sale or transfer of goods or services to consumers (e.g., business or professional buildings, shops, restaurants, theaters, vehicle repair shops, etc.) (4) Mixed urban: land uses where high-density residential, industrial, and/or commercial land

uses predominate collectively (i.e., are intermixed). (5) Public transportation stations: facilities or sites where public transit agencies' vehicles load or unload passengers or goods (e.g., bus stations and stops).”

Epistemic uncertainty: the “uncertainty associated with knowledge of the state of a system [including] uncertainty due to limitations of measurement devices, insufficient data, extrapolations and interpolations, and variability over time or space” (Regan, 2002).

Epistemic uncertainty can be classified into measurement error, systematic error, natural variation, inherent randomness, model uncertainty, and subjective judgment.

I. Introduction

A. Background

Plastics may enter the environment in the form of material feedstocks, or as partially or fully finished products; plastic loss to the environment is largely due to process inefficiencies and general materials mismanagement (Geyer, 2017; Nielsen, 2020; Schwarz, 2023; Ryberg, 2019). Total global loss of plastic to the environment was estimated to be 9.2 million metric tons (Mt) in 2015, and microplastics comprised 33% of this mass (Ryberg, 2019). A Materials Flow Analysis of regionally divided global plastic production and consumption data estimated that the greatest loss of plastic occurs during the use and disposal stages, which account for 36% and 55% of plastic losses, respectively (Ryberg, 2019). During the disposal stage, the mismanagement of municipal solid waste and littering are estimated to be the largest sources of plastic loss to the environment (Ryberg, 2019; Geyer 2017). Approximately 4.1 Mt of plastic enters the environment via mismanaged municipal solid waste, and 0.8 Mt via littering (Ryberg, 2019).

Ninety percent of plastics lost to the environment are "packaging plastics" (Schwarz, 2023; Geyer 2017). This aligns with the fact that 42% of all non-fiber plastic made since 1950 has been utilized as packaging material (Geyer, 2017). Plastic packaging is predominantly composed of polyethylene, polypropylene, and polyethylene terephthalate; however, the largest percentage of plastic losses to the environment are from polymers of unknown identity (23%), while the second largest losses are from polypropylene (19%) (Geyer, 2017; Ryberg, 2019).

Notably, non-aquatic terrestrial compartments accumulate the majority of plastics lost to the environment (Schwarz, 2023). Researchers estimate that, each year, the amount of plastic released to terrestrial compartments is 4–23 times greater than what is released to the ocean (Hurley, 2020). Yet, terrestrial plastic waste is relatively understudied compared to marine debris and aquatic trash (Malizia, 2019; Schwarz, 2023). Malizia et al. (2019) suggest that terrestrial plastic waste is less studied relative to plastic waste in marine systems due to the relative complexity and heterogeneity of inland plastic waste transport pathways and distribution patterns and hypothesize that "plastics are likely more hidden beneath vegetation and within soils inland, and less detectable than in the oceans" (Malizia, 2019).

Building on these observations, it is essential to examine terrestrial source-pathway-receptor chains of plastic and microplastic pollution. Litter is one of two important sources of plastics and microplastics to terrestrial systems based on observations from regional-scale empirical studies (Blasing, 2018; Braun, 2023; Okoffo, 2021; Liu, 2021). Plastics are littered directly onto soils or are transported from impervious surfaces to receiving soils via wind or surface runoff (Mellink, 2022). Car tire rubber particles are a second important source of plastics and microplastics to terrestrial systems (Blasing, 2018; Braun, 2023; Okoffo 2021; Liu, 2021). Surface runoff is the main transport pathway for car tire particles, conveying particles deposited by car tire wear on impervious surfaces to nearby soils (Okoffo, 2021; Liu, 2021). Plastics and microplastics from personal care products, household products, and textiles originate as non-point source pollutants through human activity in developed areas connected to centralized wastewater treatment systems (Alimi, 2018). These plastics enter the sewer system and are conveyed to the receiving wastewater treatment plant (Alimi, 2018). Due to their physicochemical properties, approximately 95%–99% of these plastics

and microplastics settle into the solids phase of wastewater (Alimi, 2018), and a majority remain in these solids even after treatment. Thus, wastewater treatment plants are considered a point source of plastic and microplastic pollution to receiving terrestrial systems, with the main transport pathway from the point of release to the terrestrial environment being the application of soil amendments that use treated and untreated sewage sludge as a feedstock (Hurley, 2020; Okoffo, 2021). The most common polymers entering soils from these sources are polypropylene, polyethylene, polyester, and polyamide (Okoffo, 2021; Horton, 2017; Ren, 2024; Adhikari, 2024). Studies most frequently observe microplastic fibers, films, and fragments in soil samples (Adhikari, 2024; Liu, 2021).

Terrestrial systems not only receive plastics and microplastics but also release them into other environmental compartments. Land-based plastic pollution originating as mismanaged waste and litter is transported via wind and surface runoff into aquatic and marine compartments, which are the major surface water receptors of plastic and microplastic pollution from terrestrial systems (Malizia, 2019; Chassignet, 2021; Ding, 2021; Alimi, 2018; Mellink, 2022; Biermann, 2020; Hale, 2020). Jambeck et al. (2015) reported that an estimated 4.8 to 12.7 Mt of plastic pollution entered the ocean from its point of terrestrial generation in coastal cities in 2010 (Jambeck, 2015). Schwarz et al. predicted relatively lower plastic emissions from land-based systems to the ocean (1.8 Mt), and higher emissions from land-based systems to surface freshwater systems such as lakes and rivers. Plastic items littered on the beaches and banks of freshwater lakes are hypothesized to be the main source of plastic pollution to these aquatic systems and are commonly composed of single-use packaging and cigarette butts (Davidson, 2023; van Emmerik, 2022). High- and low-density polyethylene, polyethylene terephthalate, polypropylene, polystyrene, polyvinyl

chloride, and polyamide are six major types of microplastics detected in freshwater samples (Ding, 2021; Davidson, 2023). In September 2024, the on-land density of estimated escaped trash was mapped by the US EPA's Trash Free Waters Program using a Bayesian hierarchical mixed model to predict the density of land-based litter at risk of entering waterways across the United States (Jambeck, 2024). That analysis found that the ten most common litter items across the US include plastic and foam fragments, cigarettes and cigars, plastic caps and lids, plastic food wrappers, plastic bottles, plastic bags, aluminum and tin cans, straws, foam or plastic cups and plates, and metal bottle caps or tabs (Jambeck, 2024). In addition to terrestrial litter, car tire particles transported from impervious road surfaces into nearby receiving waters via runoff are hypothesized to be a major source of microplastics in surface waters (Hale, 2020). Treated wastewater effluent is another significant source of microplastics to surface waters, transporting the 1%–5% of microplastics that neither settled into sewage solids nor were removed during treatment into receiving marine and freshwater systems (Alimi, 2018).

As with terrestrial systems, surface waters both receive and release plastic and microplastic pollution. There is empirical evidence that microplastics pollute surface waters known to recharge underlying groundwater aquifers, and that microplastics penetrate soils to depths several meters below ground surface. Despite this, few studies have experimentally determined the concentration and composition of microplastics in groundwater. A 2024 systematic review identified only 24 experimental studies reporting field results on microplastic occurrence in groundwater samples (Lee, 2024). Major transport pathways of microplastics into groundwater are consequently relatively understudied, but are thought to include untreated stormwater and irrigation water infiltration and percolation, sewage from

exfiltrating pipes and leaking septic systems, leachate from landfills, and direct injection for aquifer recharge, all of which are matrices known to contain microplastics and to enter aquifers (Gundogdu, 2023; Arat, 2024). Due to the diversity of microplastic properties and the complex heterogeneity of soils and sediments, microplastic transport models are developing (Ren, 2021). Results from column experiments suggest that microplastics accumulated in sandy soils have the potential to penetrate to subsurface depths of up to 5.24 m (95% CI = 2.78–7.70 m), exposing subterranean aquifer systems to microplastics over a 100-year timescale (O'Connor, 2019). As such, groundwater is vulnerable to microplastic contamination from surface water recharge and transport through soil and sediment (Ren, 2021; Ranjan, 2023). Fibers are the most common microplastic shape identified in groundwater samples (Ren, 2021). Additional empirical data are needed to better understand the concentration and composition of microplastics in groundwater, particularly in municipal production wells used for drinking water, as drinking water is a known primary microplastics exposure pathway for people (Rochman, 2019). New sources of microplastic contamination of well water may also be identified when well construction materials are known, as well casing has been identified as a potential source of microplastic contamination of well water (Viaroli, 2024).

Finally, plastics and microplastics, particularly those made of polyvinyl chloride, polystyrene, and high-density polyethylene, contain toxic additives, including per- and polyfluoroalkyl substances (PFAS), that can leach into water (Whitehead, 2023). However, many other sources of PFAS exist, including major point sources such as wastewater treatment plants, military bases, airports, and industrial manufacturers (Rafiei, 2023). PFAS are also known to accumulate on impervious surfaces as diffuse pollutants, deposited by

transport infrastructure, automotive emissions, and industrial deposition, and are mobilized into surface waters and groundwater via urban runoff (Bouarafa, 2026). Modeling efforts by Tokranov et al. (2024) used groundwater PFAS concentration data collected by the U.S. Geological Survey between 2019 and 2022 to predict PFAS occurrence in groundwater at drinking water supply depths, and to determine the effect of variables such as percent urban land use, well depth, and soil characteristics on PFAS occurrence predictions (Tokranov, 2024). The authors found that different variables are important predictors in different areas of the country, underscoring the importance of local empirical measurements where sampling is feasible. Where sampling is possible, measuring the abundance and composition of plastics, microplastics, and PFAS, and analyzing how concentrations and compositions correlate with variables like well chemistry, well lithology, percent urban land use, and concentrations in connected surface waters, can help identify local pollution sources and guide source-control solutions for managers.

Accurately characterizing the occurrence and abundance of plastic trash, microplastics, and PFAS in the environment requires confronting multiple, compounding sources of uncertainty. Regan et al. (2002) provide a taxonomy of uncertainty relevant to ecology, including epistemic uncertainty, or uncertainty in determinate facts. Of the six categories of epistemic uncertainty Regan et al. identify, three are particularly relevant to the research presented in this dissertation: measurement error, systematic error, and model uncertainty.

Measurement error results from imperfections in observational techniques. This includes both operator error and instrument error, and manifests as apparently random variation in measurements of a quantity (Regan, 2002). In the context of litter surveys, trash is challenging to detect based on its physical characteristics, location in the transect, and the

transect's complexity. This results in random variation in the quantity of trash recovered across varying survey efforts. Similarly, microplastic analysis by micro-Fourier transform infrared spectroscopy (μ FTIR) and PFAS analysis by liquid chromatography-tandem mass spectrometry (LC-MS/MS) are subject to measurement error arising from instrument detection limits, spectral matching thresholds, background contamination, and analyst interpretation of ambiguous spectra or peaks, all of which introduce apparently random variation into concentration and composition measurements. Systematic error, by contrast, occurs as the result of bias in the measuring equipment or sampling procedure. It is defined as the difference between the true value of the measured quantity and the value to which the mean of the measurements converges as sample sizes increase. Unlike measurement error, is not apparently random. Measurements subject to systematic error do not vary about the true value (Regan, 2002). Single-pass litter surveys represent a systematic error in trash abundance estimation: because observers remove or count only what is visible in a single pass, and because some fraction of trash is consistently obscured, the method produces estimates that are biased downward relative to true abundance. This bias is not random; it is a predictable consequence of the survey design, and its magnitude and direction can be estimated and corrected for. Model uncertainty arises from the use of mathematical or computational representations of physical and biological systems. It is challenging to quantify and impossible to eliminate (Regan, 2002). Empirical Bayesian Kriging Regression Prediction (EBKR), used in this dissertation to interpolate litter mass across urban sidewalk networks, is subject to model uncertainty inherent in the choice of semivariogram model, the spatial extent of the calibration dataset, and the assumptions of local stationarity and spatial continuity.

The research presented in this dissertation directly addresses each of these sources of epistemic uncertainty through the development of novel methods and the acquisition of new empirical data. Repeated-pass removal surveys with depletion modeling and mark-recapture provide estimates of true litter abundance with quantified standard errors, reducing measurement error relative to single-pass approaches and directly quantifying the systematic error introduced by single-pass survey methods including the On-Land Visual Trash Assessment (OVTA), California's primary trash monitoring protocol under the Clean Water Act Trash Amendments. Empirical Bayesian Kriging Regression Prediction with propagated measurement uncertainty, validated using a modified Bland-Altman-like approach, explicitly incorporates and communicates model uncertainty in spatially explicit litter mass estimates. Measurement uncertainty in microplastic and PFAS analyses is addressed through rigorous contamination controls, field and laboratory blanks, and reporting conventions that distinguish detections from quantified concentrations.

While the number of studies focused on plastics, microplastics, and PFAS contamination is growing rapidly, several knowledge gaps remain:

Current single-pass survey methods underestimate the true abundance of trash and introduce systematic error into litter abundance estimates (SFEI, 2021; Reynolds, 2025; McGruer, 2025). These methods rarely provide measures of uncertainty or standardized surveyor effort, preventing cross-study comparisons and limiting their utility for trash load reduction.

The agreement between depletion-modeled true litter mass estimates and qualitative OVTA rankings has not been established, nor have spatially explicit, mass-based estimates

of litter loading by Priority Land Use type and watershed been produced for California municipalities working toward Clean Water Act Trash Amendment compliance.

Additional empirical data are needed to better understand the concentration and composition of microplastics and PFAS in groundwater, particularly in deep municipal production wells used for drinking water supply, and in surface waters known to interact with underlying source aquifers.

The research outlined in this dissertation addresses these knowledge gaps, as described in the following section.

B. Objectives and Significance

This research accomplished the following aims:

Chapters II and III: Demonstrated the novel application of two surveying methods: multiple-pass removal surveys with depletion modeling and mark-recapture. Both methods are adapted from well-established methods in fisheries ecology to estimate the true abundance of land-based plastic trash with measures of uncertainty and standardized surveyor effort.

Chapter IV: Assessed agreement between depletion-modeled estimates of terrestrial trash abundance and California's primary trash surveying protocol, the On-Land Visual Trash Assessment, and produced spatially explicit estimates of litter mass loading by Priority Land Use type across three urban watersheds using Empirical Bayesian Kriging Regression Prediction with quantified prediction uncertainty.

Chapter V: Determined and compared the concentration and composition of microplastics and PFAS in municipal production well water and potentially interacting

surface waters, including urban creek water, reclaimed wastewater, and untreated wastewater, within the same urban study area where litter loads were estimated.

These aims address the following objectives:

Chapters II and III: Enhance the accuracy and precision of plastic litter measurements by quantifying and correcting for the systematic error inherent in single-pass survey methods, improving data comparability and supporting managers in monitoring, predicting, and reporting trash discharges from Priority Land Use areas toward Clean Water Act Trash Amendment compliance.

Chapter IV: Provide managers with a spatially explicit, mass-based methodological framework for assessing litter loading by Priority Land Use type at the watershed scale, with quantified prediction uncertainty to support informed management decisions.

Chapter V: Establish baseline measurements of microplastics and PFAS in municipal production well water and potentially interacting surface waters, providing managers with actionable insights for source identification and contamination mitigation as state and federal regulations governing these contaminants continue to develop.

The significance of this work is as follows:

Chapters II and III: The quantification of single-pass survey underestimation provides the first empirical basis for correcting a systematic error that is embedded in primary approaches for monitoring trash. The surveying methods demonstrated here are adaptable to a variety of transect types, accessible to non-experts, and fully reproducible in open-source software, lowering the barrier to adoption by municipal managers and community science practitioners alike.

Chapter IV: The comparison of depletion-modeled trash mass estimates to On-Land Visual Trash Assessment categories represents the first empirical evaluation of California's primary trash monitoring protocol against quantitative trash mass measurements on urban sidewalks. The spatially explicit litter mass estimates produced at the watershed scale provide a previously unavailable management tool for prioritizing institutional controls and source reduction efforts by Priority Land Use type.

Chapter V: The microplastic and PFAS concentration data collected across interacting water resources, from production wells to surface waters to reclaimed and untreated wastewater, provide an empirical foundation for understanding contaminant pathways and exposure risks in a region where such data have not previously existed, at a time when the regulatory landscape governing these contaminants is actively developing.

II. Estimating plastic litter load using K-pass surveys in coupled natural and human systems

A. Introduction

Plastics, defined as synthetic materials composed of organic polymers, are found ubiquitously across both built and natural environments (Wang, 2022; Nizamuddin, 2024). Their widespread use began approximately 75 years ago, and primary production has since followed a second-order polynomial growth trend (Geyer, 2020). Between 1950 and 2017, a total of 9.2 billion tonnes of fossil fuel-based plastic were produced, half of which was manufactured after 2004 (Geyer, 2020). As of 2016, the global rate of plastic production was second only to that of cement and steel (Geyer, 2017).

In 2015, global plastic losses to the environment were estimated at 9.2 million tonnes, approximately one-third of which consisted of microplastics, defined as plastic particles between 5 mm and 100 nanometers in size (Ryberg, 2019). The greatest losses of plastic materials occurred during the use and disposal stages of their life cycle, accounting for an estimated 36% and 55% of total losses, respectively (Ryberg, 2019). During disposal, mismanaged municipal solid waste and littering were the primary sources of environmental plastic release (Ryberg, 2019; Geyer, 2017). Littering alone contributed approximately 0.8 million tonnes of plastic to the environment in 2015 (Ryberg, 2019). By 2020, littering had become the largest source of plastic debris emissions in high-income countries, where waste collection coverage approached 100% (Cottom, 2024).

Non-aquatic terrestrial compartments are observed to accumulate the majority of plastics lost to the environment (Schwarz, 2023). Each year, an estimated 4–23 times more

plastic is released to terrestrial systems than to the ocean (Hurley, 2020). Plastic litter is a persistent and mobile pollutant, progressively fragmenting into microplastics and nanoplastics (<100 nm) mainly due to photo-oxidation and mechanical abrasion, and dispersing via wind and surface runoff (Schwarz, 2023; Mellink, 2022; Ibrahim, 2024; Hartmann, 2019). Plastic pollution remains one of the most pressing environmental challenges due to its ubiquity, persistence, mobility, and harmful effects on ecosystems (MacLeod, 2021).

Plastics constitute a heterogeneous contaminant class due to the broad variability in size and chemical composition, ranging from meter-scale debris to nanoscale particles composed of diverse polymers and additives. Microplastics represent a physically and chemically diverse subset of plastic pollution and should be treated as a complex contaminant suite (Rochman, 2019). Most plastics contain chemical additives in addition to their polymer backbone, including known toxins such as bisphenol A, phthalates, and per- and polyfluoroalkyl substances (PFAS), which can leach under environmental conditions (Groh, 2019; Rillig, 2021; Weis, 2023). Consequently, humans, wildlife, and plants experience concurrent exposure to both particulate and chemical pollution from plastics and their additives. Experimental studies indicate that these co-exposures can produce additive or synergistic toxic effects in biota (Cassio, 2021; Soltanighias, 2024).

Major human exposure pathways to microplastics include ingestion, inhalation, and dermal contact (Domenech, 2021). Microplastics enter the human body through contaminated food and drinking water (Yee, 2021), and have been shown to accumulate in tissues such as the gut, liver, and kidneys, where they induce inflammation (Covello, 2024; Obeng, 2025; Nihart, 2025). Desorption of toxins, specifically polychlorinated biphenyls

(PCBs), from microplastics has been observed during simulated human digestion processes (Tang, 2025). Polystyrene microplastics have demonstrated the ability to cross the blood–brain barrier in mice, and micro- and nanoplastics of various chemistries have been detected in human cerebrospinal fluid (Shan, 2022; Cho, 2024; Xie, 2024). Exposure to microplastics and their additives has been linked to inflammatory, endocrine-disrupting, and carcinogenic effects in humans (Tyc, 2025).

Given ingestion as a major human exposure pathway, plastic pollution enters food webs through wildlife, livestock, and crops in coupled natural–human systems. Notably, marine wildlife commonly ingest plastics, leading to physiological harm as well as tissue contamination and potential trophic transfer to humans (Rochman, 2015; Lusher, 2013). Free-roaming livestock may also ingest plastic waste in their grazing areas (Haddy, 2025). Agricultural environments are increasingly impacted by plastic pollution due to the incomplete removal of agricultural plastic films and the application of synthetic fertilizers which contain plastic fibers. Plastic pollution accumulates in agricultural soils, negatively affecting crop health (Pivnenko, 2016). Crops such as lettuce and carrots have been shown to absorb microplastics, introducing them into the food chain (Rios-Mendoza, 2020). Overall, plastic contamination in humans occurs primarily through the consumption of contaminated seafood, as well as products derived from livestock (e.g., milk and meat) that have ingested plastic particles (Galloway, 2017). Plastic pollution is widely distributed across terrestrial landscapes and large geographies through erosion and runoff (Browne, 2011), followed by aquatic transport in rivers and ocean currents (Lechner, 2014; Cozar, 2014). Plastics that enter surface freshwater systems pollute these major drinking water supplies, as evidenced by the World Health Organization (2019) reporting the pervasive

presence of microplastics in both treated and untreated drinking water, underscoring the global scale of human exposure. Considering land-based plastic litter as a significant source of plastic and microplastic pollution in coupled natural-human systems, the need for accurate plastic litter abundance measurements is critical for understanding exposure and designing effective remediation strategies.

In regions where plastic trash is a regulated pollutant, established methodologies exist for monitoring, reporting, and predicting trash levels (Harris, 2018; Reynolds, 2025; Jambeck, 2024; USEPA ETAP, 2021). Researchers have also developed methods for surveying trash as part of scientific investigations (Conley, 2022), while numerous non-profit and community organizations conduct volunteer-based clean-up programs following their own organizational protocols. In terrestrial systems, boots-on-the-ground surveys are among the most common of these methods, with single-pass surveys being the norm (Harris, 2018). In a single-pass survey, an individual or team surveys an area once, recording, and often removing, the litter observed.

Single-pass surveys have been central to quantifying environmental plastic litter loads, removing debris, and informing policy. However, there is evidence to suggest that single-pass surveys underestimate plastic litter abundance. An evaluation of the Southern California Stormwater Monitoring Coalition's single-pass "Tally Method" using extinction curve analyses found that although most litter was removed after one or two passes, sites dominated by smaller litter items required additional passes for complete removal (SFEI, 2021). Additionally, a recent plastic pollution study along the Pacific Crest Trail incorporated a "Resurveying Effort," in which eight single-pass surveys were repeated to evaluate underestimation in initial counts, and it was found that the first surveys

underestimated litter abundance by 44% (McGruer, 2025). To date, no studies have reproduced these evaluations or applied multiple-pass surveying paired with depletion modeling to quantify underestimation of plastic litter abundance by single-pass surveying. Consequently, the proportion of plastic litter missed by established single-pass surveys remains unknown. Moreover, existing survey and quality control methods generally lack standardized measures of abundance variability and effort, hindering cross-method comparison.

Estimating the abundance of hidden or cryptic populations has long challenged population ecologists (Seber, 1982). Like elusive wildlife species, plastics vary in size, color, and visibility, often going undetected during visual surveys in complex terrain. This shared challenge leads to systematic underestimation from single-pass efforts. K-pass depletion surveys, long used in fisheries to estimate population size, offer a solution. These surveys involve multiple sampling passes, each of which removes a portion of the population, with catch rates declining predictably as depletion occurs (McMahon & Brown 1989). By modeling this decline, researchers can estimate total abundance along with associated uncertainty (standard error or confidence interval). This approach, referred to as K-pass surveying with depletion modeling (or K-pass depletion), relies on three core assumptions: (1) each pass predictably depletes the population, (2) the population remains closed between passes, and (3) the probability of detection (or “catchability”) remains constant.

Here, the K-pass depletion method was adapted to quantify plastic litter abundance and uncertainty in terrestrial systems. This method builds on established ecological modeling principles and addresses a critical limitation in current plastic survey practices: the

systematic underestimation of total plastic count and mass when single-pass surveys are used. The approach was tested across nine sites representing high- and low-density plastic pollution to evaluate its robustness. The surveys were conducted within a coupled natural–human system in a section of the Owens River watershed, a headwater source for Los Angeles, California’s drinking water supply. Ultimately, this work aims to quantify the extent to which single-pass plastic surveys underestimate terrestrial plastic pollution and to establish a framework for estimating total litter abundance and associated uncertainty.

B. Methods

1. Study System

The study sites were located on the eastern side of the Sierra Nevada Mountains (California, USA), which extends approximately 700 km along the west coast of North America. While most of the range is protected as wilderness, lakes and watersheds are the center of human use and activity. Thus, this region provided the opportunity to survey plastic litter across a range of human activity, from protected areas with low plastic litter densities to hotspots for human use and recreation with relatively high densities.

Furthermore, via the Los Angeles Aqueduct, water is diverted from eastern Sierra Nevada watersheds approximately 250 miles south to support the city of Los Angeles’s 4 million residents. Today, approximately 65% of the city’s water comes from the eastern Sierra, drawing from the Owens River and Mono Lake Basin (LADWP, 2024). Locally, lakes are at the center of most human activity, which includes picnicking, hiking, camping, and fishing. Litter generated by these activities has become a concern in recent years. In 2023, an effort to collect litter from Lake George, located in the Mammoth Lakes Basin, generated a 410 kg

haul, which included 43 kg of plastic (Clean Up the Lake, 2024). Together, these observations suggest a growing risk to human and ecological health as these increasingly polluted watersheds drain into the downstream water supply.

Litter surveys associated with this study were conducted at two locations: The Sierra Nevada Aquatic Research Laboratory (SNARL) and Convict Lake (Figure 1). SNARL is a 55-acre field research station that is part of the University of California, Natural Reserve System (UCNRS) located in Mono County, on the eastern slope of the Sierra Nevada, and located 13 km east of the town of Mammoth Lakes, CA. Convict Creek, which drains the Convict Lake Basin, flows directly through the SNARL property. As part of the UCNRS, there is no public access to SNARL, however there are developed areas of the site near the parking lot and laboratory, where the reserve is more heavily trafficked. The SNARL property is leased from the Los Angeles Department of Water and Power (LADWP).

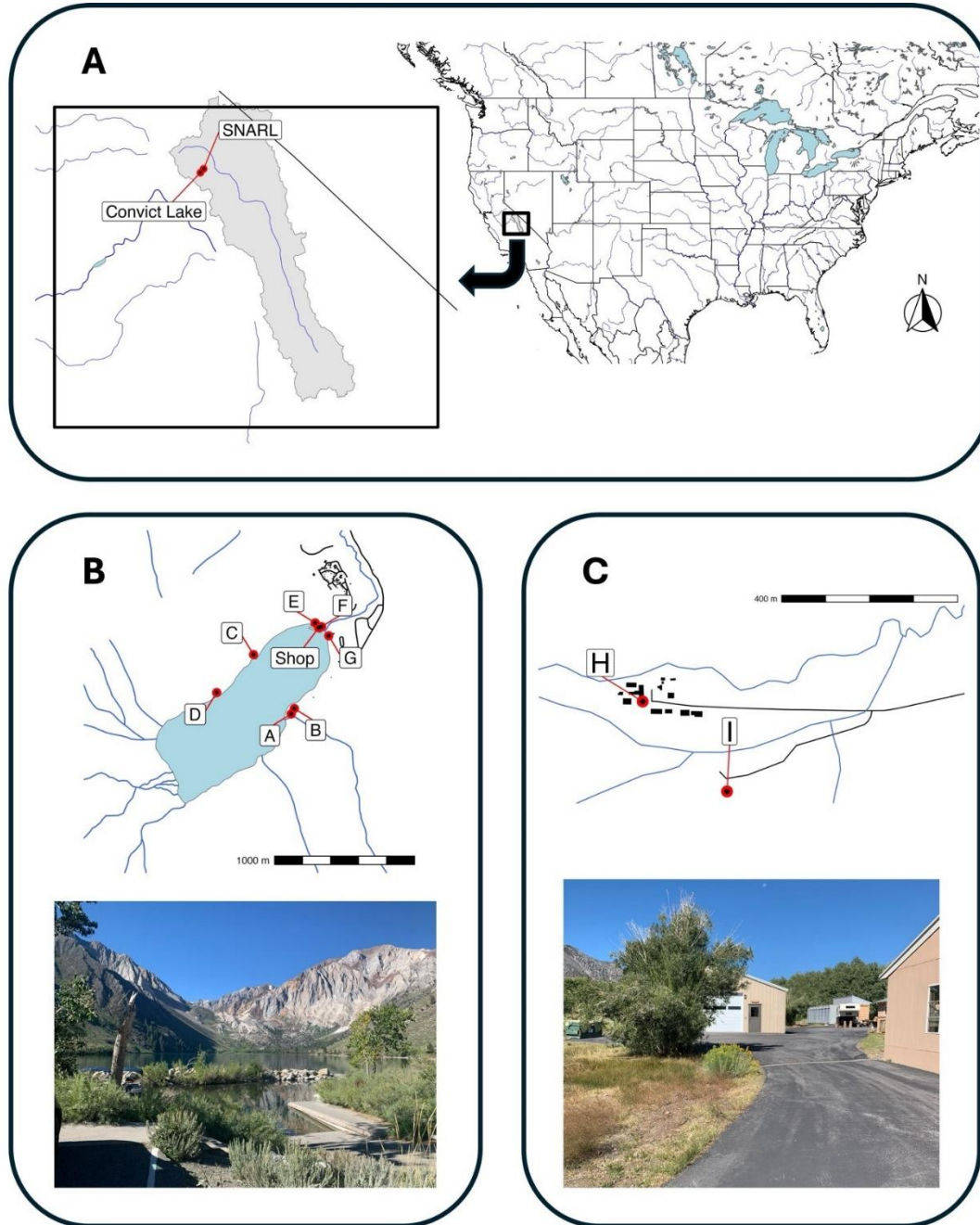


Figure 1. Sampling locations at the coupled natural and human systems interface. The eastern side of the Sierra Nevada Mountains of California, USA (Panel A) is home to the Sierra Nevada Aquatic Research Laboratory (SNARL) and nearby (<4 km) recreational access points, such as Convict Lake. The grey shading delimits the Owens River watershed. Convict Lake (Panel B) provides hiking access, fishing, and boating opportunities with infrastructure for ample parking, boat rentals, food, and a bait shop. In contrast, SNARL is an active field station, closed to public access, but with laboratory, storage, meeting, housing, and maintenance facilities. The red circles with black dot denote sites where depletion surveys were conducted. Blue lines indicate streams leading into

and out of Convict Lake. Black lines indicate access roads, and filled black shapes indicate structures. Photos are provided by coauthors.

Convict Lake is part of the Convict Creek Basin. The lake itself is located at 2,311 m in elevation, with a surface area of 0.68 km², and a maximum depth of 43 m (Reimers, 1955). Due to its easy public access, Convict Lake is a popular destination for outdoor recreational activities, such as picnicking, fishing, hiking, and camping. The surrounding area provides numerous visitor amenities, including campgrounds (28 campsites), rental cabins, a marina, a restaurant, and a general store. Convict Lake is well-stocked with trout twice each year, in spring and fall, prior to hosting two annual fishing derbies (Mono County, 2025). Convict Lake is known for producing large trout, due to its depth and water temperature, which although appealing to anglers raises concerns for bioaccumulation of environmental pollutants (Mono County, 2025).

2. K-Pass Studies

2.1 K-Pass Studies Applied to Plastic Litter

In this study, K-pass depletion surveys were used to estimate the true abundance of plastic litter with measures of variance in coupled natural and human systems. The study's K-pass plastic depletion approach followed the protocol of Reynolds et al. (2025). This protocol involves at least three individuals conducting three consecutive passes with consistent effort to remove all visible and removable litter from a closed population within a defined transect. After surveying is complete, captured litter is categorized as either plastic, metal, glass, paper, or a combination of the aforementioned materials. Figure 2 provides an illustration and brief explanation of our visual sorting and categorization approach.

Combined-material items included litter composed of plastic alongside another material,

such as cigarette butts (plastic filter and paper wrapper), fishing lures (metal and plastic), or lined aluminum cans. Items that appeared to be made solely of plastic were counted and weighed, resulting in observations of plastic litter count and mass, respectively. Notably, our observed plastic litter count and mass measurements exclude items made of plastic combined with another material, and are therefore a conservative observation of plastic litter in the environment. All other litter items made of metal, glass, paper, or combined materials were counted and weighed; these items were categorized as “other material”. All items were weighed using a laboratory benchtop balance. Due to their known toxicity to biota, including freshwater fish (Green, 2022; Slaughter, 2011), cigarette butts were counted separately from other materials. However, the mass of observed cigarette butts was not recorded, as researchers were unable to separate the plastic filter from the paper wrapper without compromising the integrity of the filter and potentially biasing mass measurements.

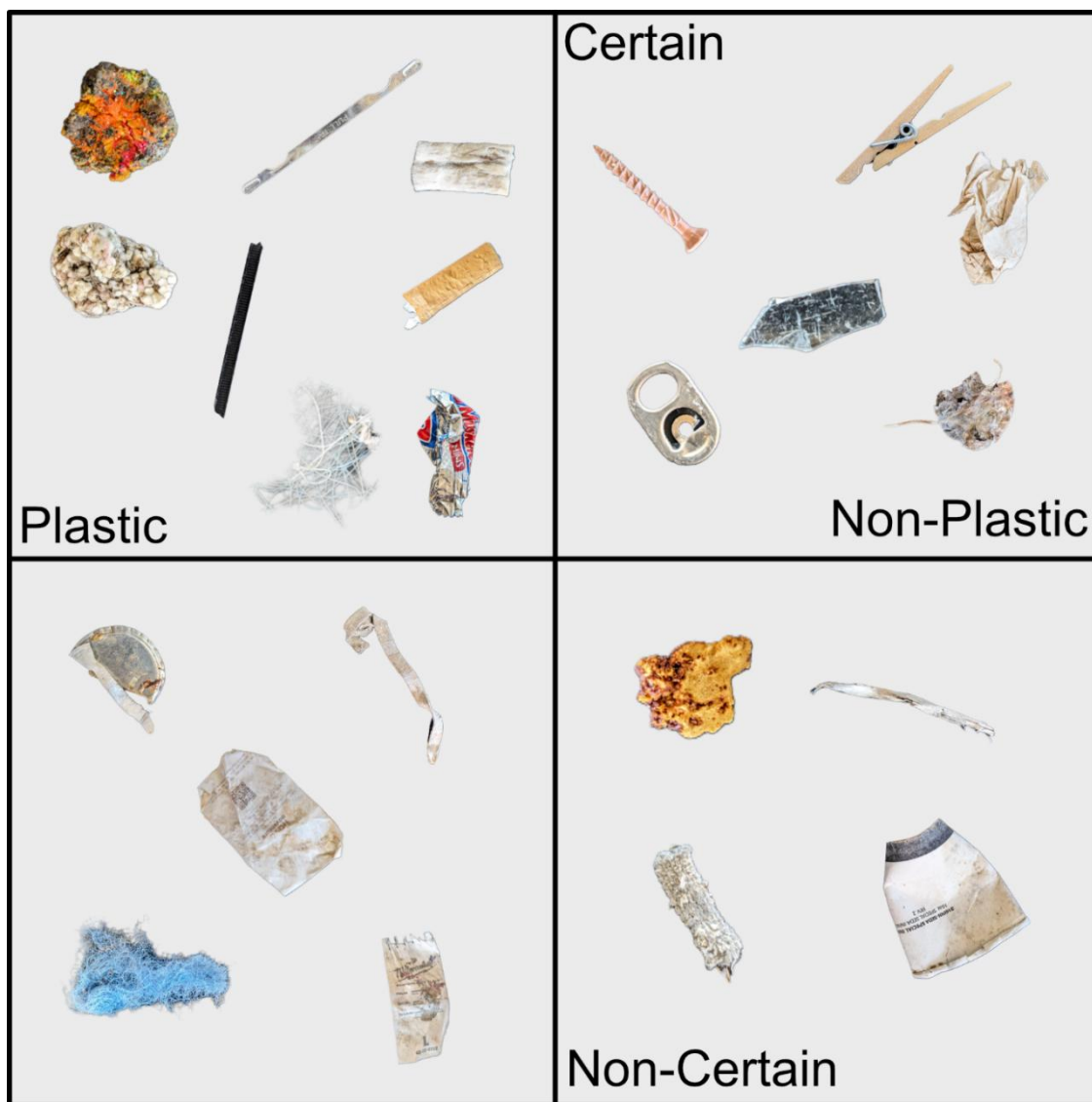


Figure 2. Litter sorting approach. Plastics are widely used in consumer products and packaging, but identifying them in the environment can be challenging. For example, surveyors may not realize that dough bait fishing lures are made from polyvinyl chloride (PVC) and often contain glitter composed of polyethylene terephthalate (PET), or that cigarette filters are typically composed of cellulose acetate. Environmental plastics may also resemble natural materials, particularly after accumulating dirt and debris or undergoing physical and chemical changes due to environmental exposure. Moreover, it is not always feasible to confirm the chemical identity of recovered litter using analytical instrumentation such as Attenuated Total Reflectance Fourier Transform Infrared Spectroscopy (ATR-FTIR), given time and cost constraints.

To illustrate our approach to categorizing litter items by material type, we present photographs of a representative subset of items collected across sites A–I. All photographs were taken by the authors. In the accompanying figure, the x-axis indicates whether an item appeared to be made of or contain plastic (non-plastics include metal, wood, glass, paper, or other natural materials), while the y-axis represents the surveyors' level of certainty associated with that categorization. By quadrant, from left to right and top to bottom:

- Q1 (Plastics, greater certainty): dough bait fishing lure, packaging seal, cigarette filter without paper wrapper, Styrofoam fragment, zip tie, cigarette filter with paper wrapper, fishing line, candy wrapper.
- Q2 (Non-plastics, greater certainty): metal screw, wood and metal clothespin, paper towel, metal pull tab, glass shard, leaf.
- Q3 (Plastics, lower certainty): packaging seal, rubber band, thermal paper receipt, fiber bundle, clothing tag.
- Q4 (Non-plastics, lower certainty): foam fragment, fibrous material, rope fragment, paper cup.

2.2 Training Surveyors

Surveyors consisted of eleven undergraduate students, two graduate students, and two senior scientists. Of these participants, one graduate student and one senior scientist were responsible for developing the Repeated Pass Removal Survey for Estimating Land-Based Trash Abundance protocol (Reynolds, 2025), and thus had previous experience conducting K-pass depletion surveys targeting plastic litter. This presented the opportunity to provide training to a group of individuals with no prior experience in plastics-focused K-pass depletion surveying, but with varied levels of experience (i.e., novice to expert) in general transect surveying methodologies. For this study, prior to surveying, participants were taught how to identify and safely capture litter, with an emphasis on the identification of commonly littered items known to contain or to be made of plastic material (i.e. single use packaging, cigarette butts, and nondescript synthetic fragments). In addition to reviewing the protocol by Reynolds et al. (2025), training included a review of the United States Environmental Protection Agency's (U.S. EPA) definition of litter, as well as a review of the definition and detailed description of plastics (Millican, 2021) to ensure that surveyors knew what to collect. Surveyors then observed a mock 3-pass plastic depletion survey. Immediately after training was complete, surveyors conducted an 11-pass depletion survey at a high litter density site (site H) at the Sierra Nevada Aquatic Research Laboratory (SNARL) under supervision of the two individuals with previous experience conducting K-

pass depletion surveys targeting plastic litter. The following day, after a brief methods review, four groups each led by either one senior scientist or one graduate student and otherwise consisting of two to three undergraduate students, conducted surveys at Convict Lake, CA (sites A – G). Finally, another 11-pass depletion survey was conducted at a low litter density remote site at the Sierra Nevada Aquatic Research Laboratory (site I) by undergraduate students under the supervision of one graduate student.

The undergraduate researchers who participated in this study were part of the Field-based Undergraduate Engagement through Research, Teaching, and Education (FUERTE) program at the University of California-Santa Barbara. This NSF-funded program was designed to introduce and prepare students for careers in environmental science and conservation. As a part of the program students take part in a summer field course at SNARL, where they live, conduct research, and recreate over the course of two weeks. During these two weeks, students learn about local ecosystems and issues targeting not only the natural environment but also the societal dimensions of environmental issues, including water rights and the increased prevalence of drought and wildfires. Thus, student participation in the current study provided the ideal opportunity for place-based learning, allowing students to link environmental concepts with societal issues.

2.3 K = 11 pass surveys at High- and Low- Density Litter Sites at SNARL

We selected two sites (H and I) at SNARL to evaluate the robustness of applying K-pass surveys with depletion models to plastic litter. Site H represented a high plastic litter density area due to its proximity to the reserve's dumpster and parking lot, while Site I represented a low plastic litter density area given its remote location and limited public access. Indeed, among all nine sites surveyed, Sites H and I were the highest- and lowest-density sites,

respectively. Surveying these contrasting sites provided an opportunity to examine the sensitivity of the depletion model to potential violations of key assumptions, including declining catch over successive passes, closed population, equal probability of capture among individuals, and constant effort.

The first of two 11-pass surveys conducted at SNARL was performed at site H, in the research station's parking lot, near a large dumpster which serves as the main trash receptacle for residential staff as well as visitors of the research station. The survey transect followed the boundary where the asphalt of the paved parking lot met the dirt ground of an adjacent undeveloped area that opens into the reserve. After communicating the transect boundaries to the team of surveyors, the first surveyor spent 15 minutes removing by hand all visible and removable litter from within the transect. Each additional surveyor then followed individually, spending approximately 15 minutes removing all visible and removable litter by hand within the transect boundaries, without passing the person ahead of them. In total, 11 surveyors passed through the transect capturing and removing litter. Notably, on the 10th pass of the 11-pass survey at site H, there was an anomalous increase in plastic litter count and mass, thereby violating the assumption that each pass depletes the plastic population predictably. Specifically, all surveyors picked up visible and removable plastics from the ground's surface, including surveyor 10. However, while removing plastics from the dirt area of the transect, surveyor 10 disturbed the dirt and noticed very small pieces of plastic buried just centimeters below the ground's surface. Surveyor 10 then removed these now visible pieces of plastic, violating the closure assumption.

The second 11-pass survey was conducted at SNARL at site I. This survey was performed in the same manner as the 11-pass survey at site H. The only differences being

the location of the survey site (i.e. site I is in a remote and undeveloped region of the reserve), and that all methodological assumptions were satisfied.

Litter collected at sites H and I was stored in labeled, sealed bags. Litter was sorted, counted, and weighed at SNARL immediately after surveying occurred.

2.4 K = 3 and 4 pass surveys at Convict Lake

Additional surveys consisting of either 3- or 4- passes were conducted at 7 sites (sites A, B, C, D, E, F, and G) at Convict Lake, CA following the protocol of Reynolds et al. (2025). Sites C and D were surveyed in 3 passes, while all other sites were surveyed in 4 passes, simply due to the total number of participants. Sites A and B were located along the southwest side of Convict Lake, sites C and D along the northwest, and sites E, F, and G on the north side of the lake near the marina shop. While sites A, B, E, F, and G are accessible by both vehicle and foot, sites C and D on the northwest side of the lake are accessible only by foot. Sites were selected based upon their accessibility to visitors and their approximate distance from the marina shop. This was to determine if plastic litter density is affected by the site's level of accessibility to the public and proximity to the most heavily trafficked location in the recreation area, while simultaneously exploring how the K-pass removal method performed across sites of varying plastic litter density and transect type. Litter collected during these surveys was stored in sealable bags and transported to SNARL where it was immediately sorted, counted, and weighed.

2.5 Depletion modeling using K-pass data

The depletion model can be implemented using the FSA package (Fisheries Stock Assessment) in the R programming language (Haddon 2011, R Core Team). The model

requires data on the number of plastic items captured in each pass, which is used to estimate the total count. The function estimates the total plastic count (N) by extrapolating from the observed depletion rate using statistical models that assume (1) Each pass depletes the plastic litter population predictably; (2) The abundance of plastic litter does not increase or decrease between passes (i.e., the transect is closed); (3) The probability of plastic capture is equal across survey passes, and; (4) surveying effort is constant. Standard errors are also provided for the estimate.

Plastic litter count and mass data were used to generate estimates of the true plastic abundance in each surveyed transect with standard errors. Plastic counts and standard errors were estimated using the *removal()* function and “*CarleStrub*” method with standard errors calculated using the *CS.se* “*alternative*” approach (Carle, 1978; Ogle 2023).

Mass estimates and standard errors were calculated from the standard deviation of plastic litter mass observed during three-pass surveys conducted in 2025 in the same transects, excluding sites C and F. For sites C and F, standard deviations from sites D and H were used, respectively, as these sites share similar characteristics. Future studies should measure the mass of each individual plastic litter item to allow direct calculation of mass standard errors from observed variability. Although samples are archived, the authors chose not to measure individual item masses retroactively because some items were fragile and could disintegrate with additional handling, potentially biasing average mass measurements.

Many plastics surveys focus on mass removal rather than counts. Fisheries research is no different in that it can be advantageous to estimate the total fish biomass rather than counts. In fisheries applications, the standard approach is to find the mean fish mass recorded from caught fish in the survey and then multiply this by the estimated fish

abundance. Thus, the total plastic mass (T_m) would be the estimated plastic count (N) from the depletion model times the average plastic mass for each plastic item collected, ($\bar{M}$) (Equation 1). The standard error ($SE\bar{M}$) of the total plastic mass can be estimated by dividing the standard deviation of the observed plastic mass (σ_m) by the square root of the estimated plastic count (N),

$$(Eq.1) T_m = N \times \bar{M}$$

$$(Eq.2) SE\bar{M} = \frac{\sigma_m}{\sqrt{N}}$$

When data are normally distributed, a confidence interval approach is generally used in fisheries research but is a known overestimate of the variance, and the development and testing of finite population correction methods applied to plastic pollution need to be further investigated (Shepard, 2013).

C. Results

Overall, single-pass surveys, on average, underestimated the observed count of plastic litter in a transect by 64% (SD $\pm 12\%$) and the observed mass by 38% (SD $\pm 22\%$) when compared to multiple-pass surveys (Figure 3). Further, single-pass surveys on average underestimated the true count and mass of plastic litter in a survey transect by 72% (SD $\pm 12\%$) and 53% (SD $\pm 17\%$), respectively, when compared to estimates from multiple-pass surveys with depletion modeling. Plastic litter removed during K-pass surveys ranged in size with the smallest litter items measuring 1 mm in their greatest dimension, and the largest item measuring 3,600 mm in its greatest dimension.

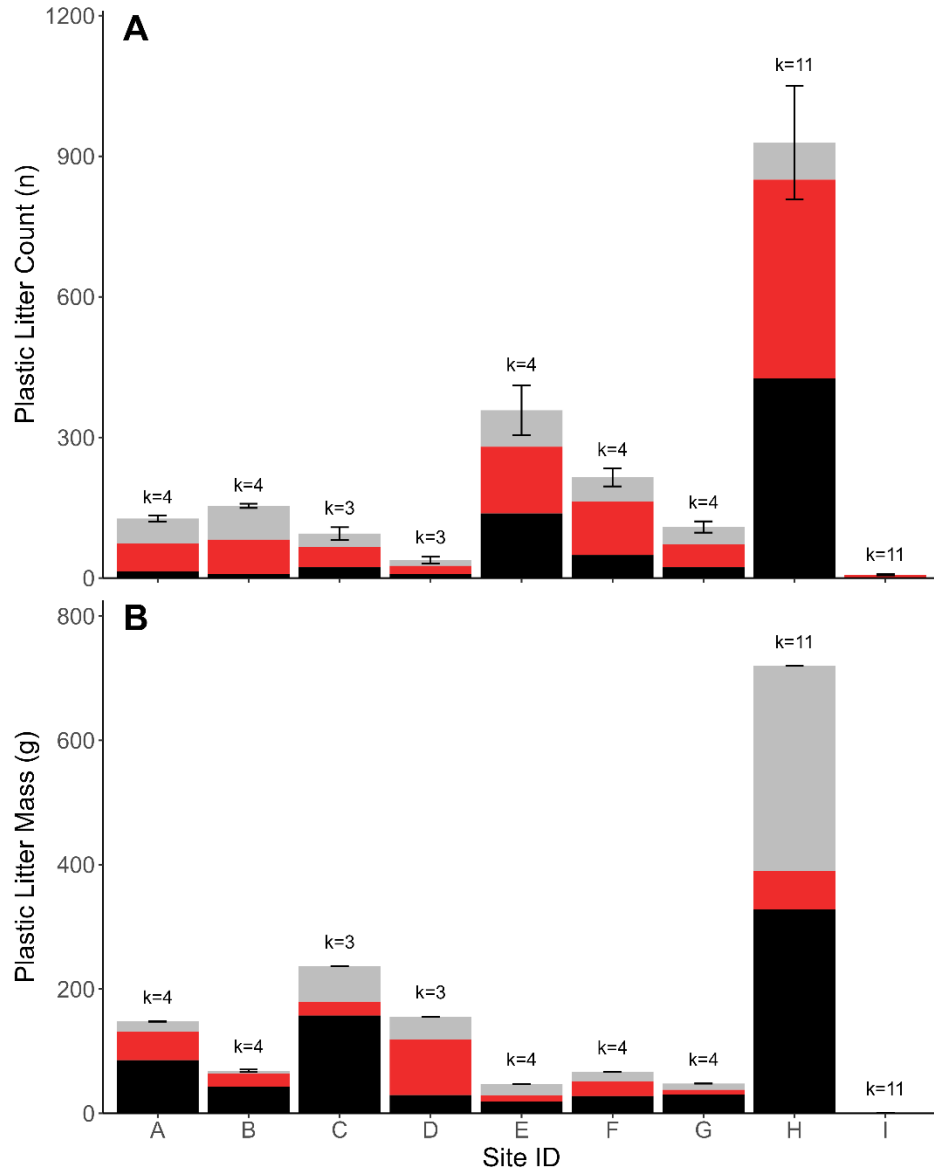


Figure 3. Plastic litter count (A) and plastic litter mass (g) (B) across all 9 sites surveyed in the Mammoth Lakes region in California. Litter recovered during pass one of each survey is represented by the black portion of each bar; the difference between total litter recovered by the final survey pass and litter recovered in pass one is indicated in red, and the estimation of the true abundance of litter is shown in grey, with standard errors. The number of passes (k) completed for each survey is reported for each site. Sites H and I were surveyed to validate the K-pass depletion method for plastic litter and indicate that the survey method is effective in cases where k is greater than or equal to three. Single-pass surveys, on average, underestimated the observed count of plastic litter in a survey site by 64% (SD $\pm 12\%$) and the observed mass by 38% (SD $\pm 22\%$) when compared to multiple-pass surveys. On average, single-pass surveys underestimate the true count and mass of plastic litter in a transect by 72% (SD 12%) and 53% (SD 17%), respectively.

Site H served as a high plastic density area based on its proximity to the reserve's dumpster and parking lot. Neither the observed nor the estimated plastic count at site H appear to plateau, even after 11 passes (Figure 4). The depletion model is sensitive to violations of assumed declining catch over successive pass. Surveyors observed relatively small, previously buried plastics being revealed as surveyor 10 disturbed the ground cover and dug for plastics undetectable to previous surveyors.

Plastic mass at site H appears to plateau by the fourth pass, and mass estimates appear less sensitive to violations than count estimates, despite additional plastic pieces being collected in later passes, emphasizing the abundance of small pieces of plastic litter in this area. In total, our 11-pass survey at SNARL, which occurred in the paved parking lot near a dumpster (site H), removed 503 pieces of plastic litter equivalent to 389.77 g, and estimated a total count of 929 ($SE \pm 127.61$) items weighing 719.87 g ($SE \pm 0.07$ g).

Site I was expected to have a low plastic litter density due to its remote location and limited public access. As with site H, neither the observed nor the estimated plastic count at site I appear to plateau, even after 11 passes (Figure 4). Passes 6, 7, 9, and 11 each yielded more items than the immediately preceding pass, violating the assumption of predictably declining catch. Unlike site H, where a specific mechanism (physical disturbance of buried plastic) explained the anomaly, the cause of non-monotonic catch at site I is less clear, likely reflecting the challenge of detecting sparse plastic items in complex shrub land terrain. However, there is only a small difference between the estimated plastic count and mass and the observed count and mass by the 9th pass. This both emphasizes the abundance of larger plastic items and demonstrates that multiple-pass surveying may deplete plastic pollution in

areas with low litter density, where inputs are minimal and disintegration is relatively slow due to fewer human-driven mechanical disturbances. Our 11-pass survey in the reserve remote Great Basin shrub land (site I) ultimately removed 6 pieces of plastic litter equivalent to 0.57 g from the transect, with an estimated plastic count of 7 ($SE \pm 4.22$), and plastic mass of 0.67 g ($SE \pm 0.05$ g).

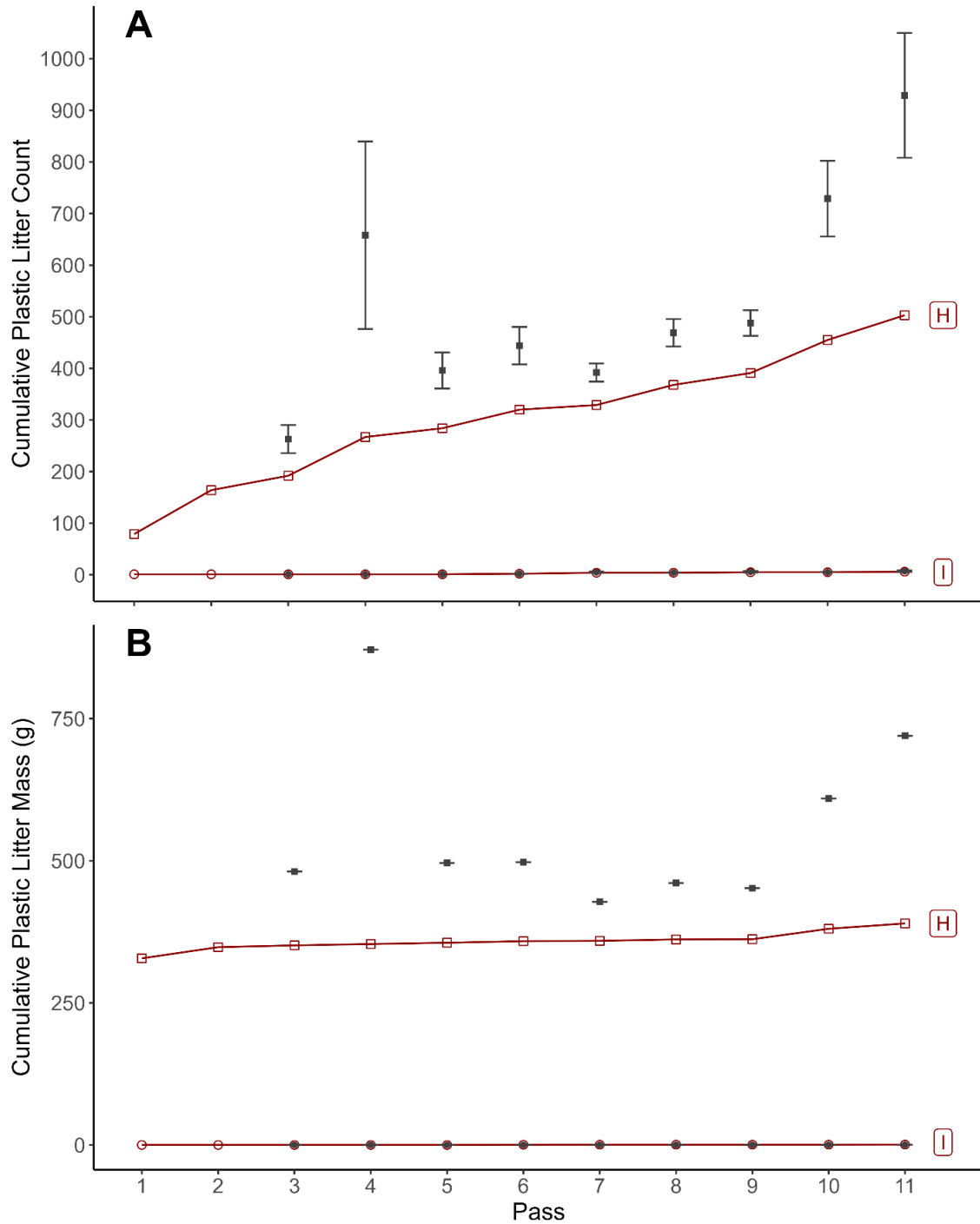


Figure 4. Count (A) and mass (g) (B) plastic litter accumulation curves for two, $k = 11$ pass surveys conducted at the SNARL. The x-axis indicates each pass completed at each survey site for sites H and I. In panel A, the y-axis represents the cumulative count of plastic litter captured per pass, while in panel B the y-axis represents the cumulative mass in grams (g) of plastic litter captured per pass. The observed cumulative mass of plastic litter captured during the survey at site H are represented by open dark red squares, while the estimation of the true cumulative mass with standard error is represented by closed grey squares. Site H was located in a parking lot near a dumpster adjacent to reserve housing. The observed cumulative count of litter captured during the

survey at site I are represented by open dark red circles, while the estimation of the true cumulative count with standard error is represented by closed grey circles. Site I was located in a remote region of Great Basin shrub land on the reserve. Consistently, the total estimated plastic litter count and mass are greater than what was observed by the 11th pass. K-pass depletion surveys allow for an estimation of the true abundance with a measure of uncertainty (i.e. a standard error). For sites H and I, total estimates and standard errors are greater than observed values indicating a need to better understand the abundance of plastic litter in the environment.

Surveys along the southwest side of the lake (sites A and B) used 4 passes. Site A is gravel shoreline popular with fishers and equipped with permanent picnic tables. Here, 113 pieces of plastic litter equivalent to 131.54 g were observed and removed. The estimated plastic count is 127 ($SE \pm 7.50$), and the estimated plastic mass is 147.84 g ($SE \pm 0.53$ g). Site B is a packed dirt walking path bordered on one side by a retaining wall separating the path from a road with parking spots and on the opposite side a steep densely vegetated bank to the lakeshore. 145 pieces of plastic litter equivalent to 64.34 g were observed and removed from site B. We estimate that site B had 154 ($SE \pm 4.83$) plastic items weighing 68.33 g ($SE \pm 2.07$ g).

Sites C and D were packed dirt walking paths along Convict Lake bordered by Great Basin shrub land, and were surveyed in 3 passes. At site C, 72 pieces of plastic litter equivalent to 179.56 g were observed and removed. Depletion modeling estimated 95 ($SE \pm 15.47$) pieces of plastic weighing 236.92 g ($SE \pm 0.02$ g). At site D, 29 pieces of plastic litter equivalent to 118.61 g were observed and removed, with an estimated plastic count of 38 ($SE \pm 10.04$), and an estimated plastic mass of 155.42 g ($SE \pm 0.03$ g). Sites A, B, C, and D are all located approximately 0.8 km from the bait shop, which we hypothesize is a hotspot of human activity and therefore a receptor of greater plastic litter inputs. As shown in Figure 5, estimated plastic litter counts at sites A, B, C, and D are lower than sites bookending the bait shop, but estimated plastic mass is higher.

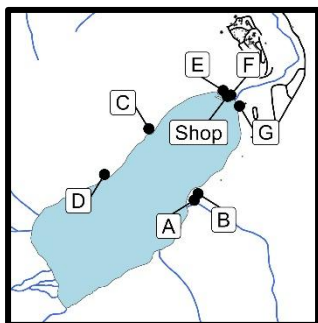
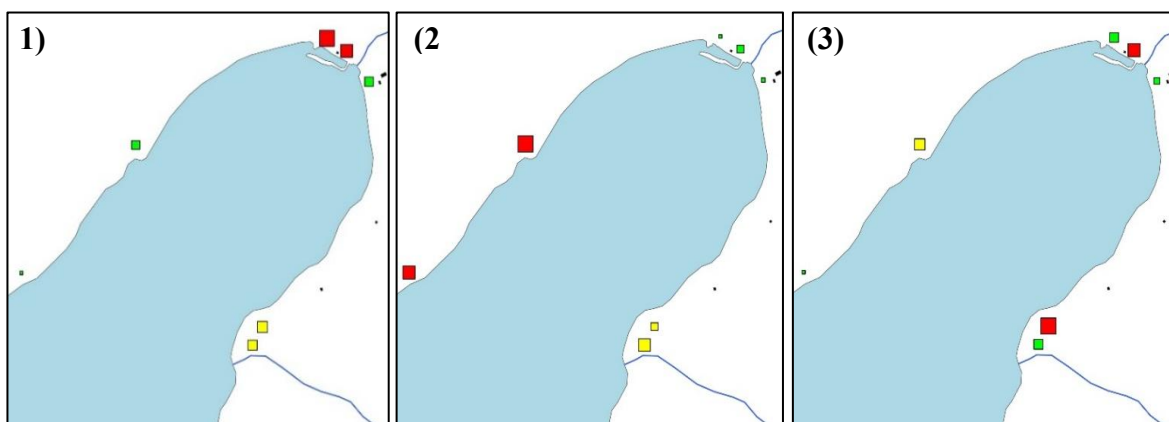


Figure 5. Maps of transects A–G at Convict Lake showing relative levels of (1) estimated plastic count, (2) estimated plastic mass, and (3) observed littered cigarette butt count. Count and mass estimates were divided into three equal-probability intervals (i.e., tertiles) based on the data’s empirical distribution to provide relative rankings. Points are color-coded by tertile, with low (0–33rd percentile) shown in green, medium (33rd–67th percentile) in yellow, and high (67th–100th percentile) in red. The size of the square is based on the count estimates at each site. Black squares represent buildings.

Sites A and B fall within the middle range for both estimated count and mass of plastics, indicating a mix of heavy and small items, whereas fewer but heavier items were removed from sites C and D. Sites E and F were dominated by many small pieces of plastic litter, while site G had the lowest count and mass of plastics. Notably, site G appears to receive custodial services, which may explain this anomaly. Most cigarette butts were observed near sites F and B, the two transects located closest to parking stalls.



Sites E, F, and G were surveyed in 4 passes. Site E is a packed dirt walking path along Convict Lake, bordered by Great Basin shrub land, and beginning at the Lake Loop trailhead which is bordered by the paved main parking lot. Here, 220 pieces of plastic litter equivalent to 28.94 g were observed and removed, while depletion modeling estimated 358 (SE $\pm$ 58.06) pieces of plastic weighing an estimated 47.09 g (SE $\pm$ 0.02 g). Site F is a paved parking lot, which we consider the main parking lot as it is the first parking lot visitors encounter when driving into the recreation area at Lake Convict. At site F, 166 pieces of plastic litter equivalent to 51.55 g were observed and removed. We estimate a plastic count

of 215 ($SE \pm 20.61$), and a plastic mass of 66.77 g ($SE \pm 0.15$ g). Finally, site G is a packed dirt bench seating area intersected by a walking trail and is located southwest of the main parking lot. Surveys at site G resulted in the observation and removal of 86 pieces of plastic litter equivalent to 37.77 g. Depletion models estimated 109 ($SE \pm 13.60$) pieces of plastic, equivalent to an estimated 47.87 g ($SE \pm 0.13$ g).

D. Discussion

The finding that first-pass surveys captured only 36% of total observed plastic litter and only 28% of the total estimated plastic litter underscores the substantial underestimation inherent in single-pass approaches. Underestimates of plastic litter mass were also appreciable, with first pass surveys removing on average 62% of the total observed plastic mass and only 47% of the total estimated mass. These results highlight a substantial underestimation of litter abundance when single-pass surveys are used to quantify plastic litter in terrestrial systems. This underestimation is especially noteworthy at high plastic density sites, which may not be depleted of litter even after 11 passes. We find that for medium and low plastic density sites, litter can approach depletion in 3 to 4 passes, indicated by relatively smaller differences between total observed litter after 3 or 4 passes and total estimated litter from depletion modeling (Table 2). Therefore, we recommend that multiple-pass surveys are used, when feasible, to measure, monitor, and remediate plastic litter loads in terrestrial systems, and that 3 or more passes are used to enable depletion modeling for more accurate estimations of litter abundance. The straightforward nature of K-pass depletion survey training and execution makes it accessible for non-specialists, offering managers a practical option to leverage community-science surveying when staffing is

constrained, and to collaborate with local non-government agencies and non-profits already working in the plastic litter space.

Results also show that standard errors around abundance estimates are narrow when plastic litter is predictably depleted, but they widen when this assumption is violated. Specifically, wider standard errors occurred when the closure assumption was violated, leading to variable detection probabilities across passes. In fisheries surveys, closure violations caused by emergent individuals have been shown to result in underestimation of population abundance (Seber, 1982; Ogle, 2013). Similarly, violations of the equal catchability assumption are common in K-pass removal surveys, and all K-pass removal methods are highly susceptible to this issue (Seber, 1986). Seber (1982) noted that when the average probability of capture decreases across passes, because the more catchable individuals are removed first, heterogeneity in catchability increases, resulting in underestimation of true abundance (Ogle, 2013).

Because violations of closure cannot be known a priori, it is important to report instances when this assumption may have been violated and to acknowledge that resulting estimates could be underestimated. At several sites (i.e., B, E, F, and H), plastic litter did not deplete predictably by pass. At site H, this appeared to result from small plastic items becoming detectable only in later passes after earlier passes disturbed the ground surface (i.e., a violation of closure). To mitigate this effect, we recommend that surveyors establish and maintain a defined transect boundary depth, and always record observed violations of closure, particularly when sampling in unpaved areas with loose substrates (e.g., dirt, sand, gravel, or plant debris). Additionally, during all K-pass surveys and particularly when working in loose substrates, all surveyors should apply a consistent level of effort. For

example, either all surveyors should carefully avoid disturbing the ground cover, or all should intentionally sample vertically through the ground cover down to the established depth boundary.

Sites B, E, and F exhibited relatively higher total observed counts but relatively lower total observed masses (Table 1), indicating that these transects were dominated by smaller plastic litter items. This may explain the wider standard errors on estimates from these sites, as smaller plastics are potentially more difficult for surveyors to detect and remove, leading to variable detection probability across passes. Although plastic items as small as 1 mm in their greatest dimension were removed during surveys, this method is limited in that it does not quantify microplastics less than 1 mm. Mechanical abrasion from vehicle traffic likely accelerated plastic litter fragmentation in these transects, which may explain why sites E and F which are within and adjacent to parking lots, respectively, exhibited high total plastic counts but low total masses (Ryan, 2020). Additionally, plastics and larger microplastics, though visible and theoretically catchable, may be challenging to distinguish from, or may even be obscured by, the surrounding environment, especially when small or cryptically colored (Malizia, 2019; Ryan 2020). In site B, which was bordered by dense vegetation on the north side of the transect, plastic litter along the transect's edge may have been more difficult to detect leading to variable detection probability per pass.

Altogether, these sources of detection variability highlight how violations of key model assumptions can influence abundance estimates and uncertainty in K-pass surveys. As is the case with fish surveys, as long as observed violations of closure are recorded and potential underestimation is acknowledged when reporting results, K-pass surveys with

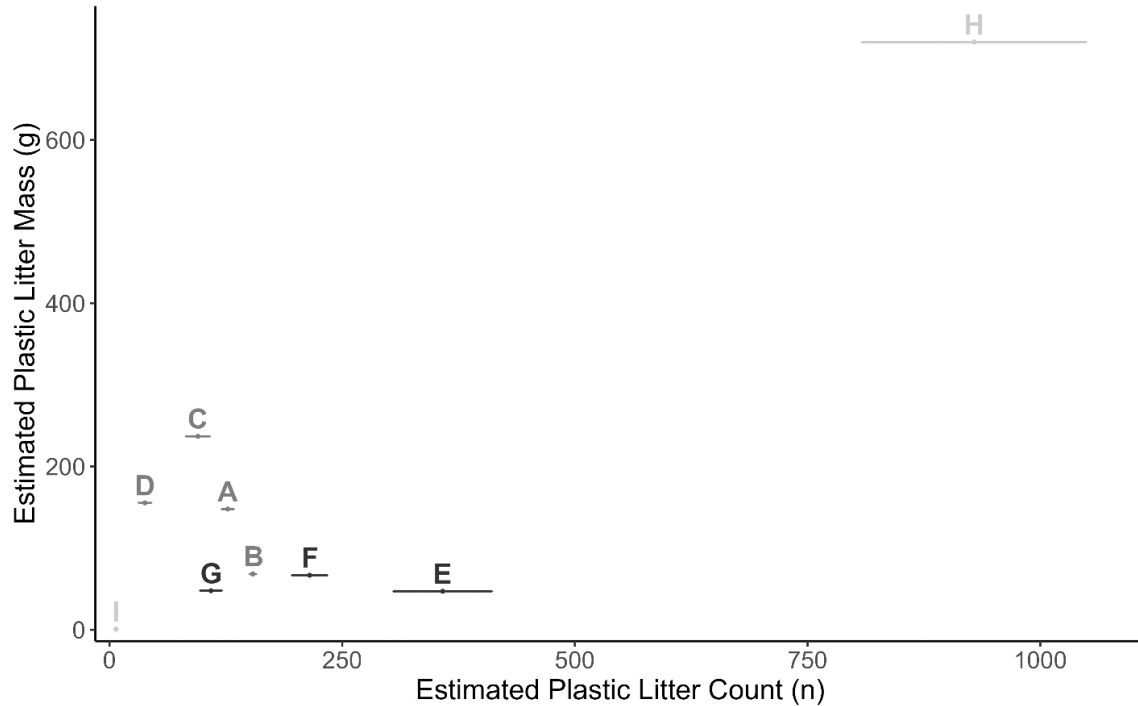
depletion modeling are a robust and accurate approach for estimating plastic litter abundance when compared to established single-pass methods. Future work will compare estimates and variance measures from K-pass depletion models to those derived from mark-recapture models to evaluate estimation bias arising from violations of equal catchability due to both closure violations and the physical characteristics of plastics.

Established methods for determining the abundance of plastic litter often rely on single-pass surveys, which sometimes include litter removal in addition to recording observed litter (Harris, 2018). However, data collected from single-pass surveys underestimate litter abundance, and lack associated measures of uncertainty. In contrast, K-pass surveys with depletion modeling offer a multi-benefit approach to quantifying terrestrial litter loading. When compared to a single-pass surveying approach, the K-pass depletion approach enhanced this study by yielding more accurate measures of litter abundance with quantifiable uncertainty (i.e., standard error), and resulting in the active removal of more litter from the environment. More accurate estimates with measures of variance allow for better comparisons with other litter datasets collected in the region using different approaches. Additionally, using K-pass surveys presented the opportunity to integrate practical fieldwork training with data science training for undergraduate students in environmental science. Students were trained in transect-based survey techniques that are transferable across disciplines, from fisheries research to plastic pollution monitoring. Students also learned how to process litter samples and record qualitative and quantitative data, and received training in data analysis and visualization using RStudio and the dataset they helped to collect. Ultimately, this effort resulted in the removal of 1.3 kg of litter, including items made from plastic, glass and metal, from the environment.

E. Conclusion

Performing multiple-pass removal surveys with depletion modeling revealed that plastic trash would have been substantially underestimated if only a single-pass survey method had been used. Single-pass surveys, here represented by the first pass of each removal survey, underestimated plastic litter counts by 64% (SD $\pm 12\%$) and mass by 38% (SD $\pm 22\%$) relative to multiple-pass surveys, and underestimated counts and mass by 72% (SD $\pm 12\%$) and 53% (SD $\pm 17\%$), respectively, relative to abundance estimates derived from depletion modeling. These findings underscore the substantial and systematic underestimation inherent in single-pass approaches, and highlight the urgent need for more accurate methods to monitor, manage, and remediate land-based plastic litter loads in terrestrial systems. multiple-pass surveys with depletion modeling offer a robust solution, providing accurate estimates of plastic litter abundance with quantifiable uncertainty. Critically, the data collection and analysis workflow is accessible to both experts and non-experts, making it a practical option for managers to leverage community-science surveying when staffing is constrained, and to collaborate with local non-governmental organizations and non-profits already working in the plastic litter space. Together, these attributes position multiple-pass surveys with depletion modeling as a broadly applicable and, when resources allow, immediately actionable tool for plastic litter monitoring and remediation.

F. Appendix



Supplemental Figure 1. Estimated plastic litter count versus estimated plastic litter mass (g) across all 9 sites surveyed in the Mammoth Lakes region in California. The x-axis indicates the estimation of the true count of plastic litter in each survey transect, while the y-axis represents the estimation of the true mass in grams (g) of plastic litter in each survey transect. Survey sites adjacent to a hotspot for recreation intensity at Convict Lake, CA are represented in dark grey (i.e. sites E, F, and G). Survey sites approximately 0.8 km away from the recreation hotspot, but still along the shoreline at Convict Lake, CA, are represented in medium grey (i.e. sites A, B, C, and D). Reference sites located at the Sierra Nevada Aquatic Research Laboratory (SNARL), which is within a Natural Reserve System, are represented in light grey (i.e. sites H and I). All estimations include standard errors. Estimated mass standard errors were calculated but are very small. Higher counts of lower-mass plastic litter were captured at sites near the recreation hotspot, while lower counts of higher-mass plastic litter were captured at sites located 0.8 km away. This pattern may be explained by increased plastic litter disintegration near the recreation hotspot, likely driven by mechanical abrasion from higher vehicle and foot traffic, compared to sites farther away that lack vehicle access and experience lower visitor use.

III. Fishing for plastics: Using fisheries population estimation models to assess environmental plastic load

A. Introduction

Plastic litter is now recognized as one of the most pervasive pollutants on Earth, with macroplastics present in virtually every ecosystem and serving as the ultimate source of micro- and nanoplastics (Alabi, 2019; Barnes, 2009). While these smaller fragments dominate concerns about long-term ecological and human health risks (Wright & Kelly, 2017), the accumulation of large, visible debris represents both a direct hazard and the starting point of plastic breakdown (Lechthaler, 2020). To quantify the extent of this issue, environmental litter surveys are frequently conducted, yet the majority rely on single-pass counts or mass-based collections (Cutter, 1991; Velander & Mocogni 1999). These single-pass surveys are highly valuable: they provide a baseline minimum estimate of plastic loads, enable comparisons across sites, and track relative changes in litter over time (Ostle, 2019). Importantly, they also serve the immediate function of removing large debris from the environment.

Despite their utility, single-pass surveys raise a critical question: how much plastic is left undetected? Visual surveys are inherently limited by observer variability, item visibility, and the physical complexity of the survey environment. Detection probability in visual surveys is known to vary with item characteristics such as size and color, as smaller or cryptically colored items are more likely to be overlooked (CSIRO, 2017). Whether accounting for these factors improves abundance estimates beyond single-pass surveys remains an open

question. As a result, single-pass counts likely represent a minimum estimate of true plastic abundance, and the magnitude of this underestimation remains poorly quantified.

Fisheries population models offer a valuable framework for addressing this limitation. Both fish and litter represent hidden populations that are difficult to fully count but can be sampled systematically. Just as removal and mark–recapture methods allow biologists to estimate fish abundance, these same approaches can be adapted to estimate total trash loads, persistence, and transport pathways across landscapes or waterways. Applying these well-established fisheries models to trash provides practical, quantitative tools for evaluating cleanup effectiveness, comparing sites, and guiding management strategies, transforming scattered counts of debris into rigorous estimates of environmental load and dynamics.

Removal and mark-recapture models are well-established in fisheries ecology for estimating population counts and biomass. Counts and masses of individuals physically removed from a closed transect over several sequential survey passes are used as data inputs for removal models, while counts and masses of individuals captured, marked, released, then recaptured over several sequential passes in a closed transect are used for mark-recapture models. Both models require individuals to be visible to and removable by surveyors under field conditions. The classic removal model is, in fact, a special case of capture-recapture models, in which the probability of initial capture varies from the probability of recapture, and in which capture probability becomes zero when an individual is removed (Rodriguez 2021). Capture probability is also size-dependent. For litter surveys, items below a minimum detectable size threshold (< 1 mm), are neither visible to nor removable by surveyors, representing a systematic lower bound on field-based litter estimates. Shepard and Taper (2013) note that count-based estimates emphasize smaller individuals, whereas biomass

estimates highlight larger ones. Similarly, plastic litter counts capture the prevalence of small items posing ecological and human health risks, while mass estimates reflect the contribution of larger items that, if not removed, will fragment into micro- and nanoplastics. A broad overview of the strengths and weaknesses of removal and mark-recapture sampling of plastics can be found in Table 1.

This study applied depletion and mark-recapture methods to terrestrial plastic litter to estimate plastic abundance on terrestrial landscapes. The effect of plastic size (length and mass) and color on detection probability was evaluated, and whether accounting for these factors improves abundance estimates beyond single-pass surveys was explored. By bridging tools from fisheries ecology with the study of plastic pollution, this work aimed to provide a new framework for quantifying litter loads while offering insight into the biases and limitations of existing survey methods.

B. Methods

1. Study Site

The study site is located within the Sierra Nevada Aquatic Research Laboratory (SNARL), a 55-acre field station in the University of California Natural Reserve System (UCNRS) situated along Convict Creek in Mono County, California. Nestled on the eastern slope of the Sierra Nevada Mountains, SNARL lies in a region where watersheds and lakes are central to both ecological processes and human activity. At SNARL, public access is restricted, but the developed area near the parking lot, laboratory, and dumpster site is a focal point of human activity on the property, increasing the potential for localized waste accumulation and wildlife interactions. The SNARL dumpster site represents both a

practical necessity for research operations and a microcosm of broader waste management challenges in the eastern Sierra Nevada.

2. Marking and Surveying Plastic Trash

Twenty plastic items were selected from the SNARL dumpster survey area to represent the range of plastics found at the site. Items were chosen to span a gradient of mass, length, and color, though not all possible combinations were included (see supplemental materials for photos provided by the authors). Each item was taken to the lab, weighed, measured, photographed, and marked with clear-drying black light-reactive paint. Once dry, the items were returned to their original locations before the repeated-pass survey. Surveyors were unaware that certain plastics had been marked.

Next, a six-pass removal survey was used to estimate true plastic litter abundance and associated variance in the SNARL dumpster survey area, following the protocol of Reynolds et al. (2025). Six surveyors conducted six consecutive passes with consistent effort, removing all visible and collectable litter from a closed population within a defined transect. The researcher who marked the plastics did not participate in surveying. Each surveyor placed collected items into plastic bags, and afterwards, litter was categorized as plastic, metal, glass, paper, or mixed materials (e.g., aluminum cans with plastic linings). Items identified as entirely plastic were counted and weighed to provide estimates of plastic litter abundance and mass. Because items containing mixed materials were excluded, all reported values are conservative estimates of plastic litter in the transect.

After the six-pass survey was completed and the samples processed, a black light revealed the number of plastic pieces recaptured in each pass. This was further confirmed

using the photos of marked items taken prior to the removal survey. Upon nightfall, after the survey's completion, a black light was used to recover any marked plastic not captured in the survey.

1. Estimation Approaches

Table 1. Overview of strengths and weaknesses of removal and mark-recapture sampling of plastic

Aspect	Removal Sampling	Mark–Recapture Sampling
Basic Idea	Permanently removes plastic from the environment; estimates plastic counts from decline in collections by survey/pass.	Collect, mark, replace, and recollect plastic items; estimates plastic counts from proportion of marked to unmarked plastic pieces.
Strengths	• Simple logistics (no marking needed) • No issues with mark loss or environmental interference (i.e., wind, rain, wildlife) • Removes litter from the environment • Works best in small transects or search areas	• Does not require multiple passes • Can identify differences in detection probabilities with different plastic characteristics (i.e., size, mass, color) • Can handle open populations (with models) • Works with larger transects and search areas
Weaknesses	• Assumes constant capture probability across passes • Inaccurate for heavy litter areas • Requires multiple, consistent removals (person power)	• Logistically complex • Potential bias from mark loss or detection issues • Requires assumptions about equal detection unless modeled • More resource-intensive (marking and replacing) • Potentially lost marked plastic in the environment (unrecovered)

The Carle-Strub removal function in the R package ‘FSA’ is designed to estimate population abundance from multiple-pass removal sampling, a method commonly used in fisheries to assess fish populations in streams and lakes (Carle & Strub 1978). For depletion sampling, when the proportion of the population taken in successive catches often does not

remain constant throughout sampling, the maximum weighted likelihood model of Carle & Strub (1978) is more robust compared to other models (i.e. Zippin, Seber) and has been found to be the only method which produces statistically reliable estimates (Cowx, 1983; Hedger, 2013). The function fits models to the decline in catch across successive sampling passes, assuming a closed population (i.e., no immigration, emigration, births, or deaths during sampling), equal catchability among individuals, and constant effort per pass. Its strengths lie in providing a straightforward, widely used framework for estimating abundance when mark–recapture is not feasible, and in offering diagnostics and flexibility for different model forms. However, its weaknesses include sensitivity to violations of assumptions, particularly if capture probability changes across passes due to gear avoidance, habitat heterogeneity, or operator fatigue. Overall, it is a powerful tool for small-scale, rapid assessments, but results should be interpreted cautiously in systems where assumptions are unlikely to hold.

The `mrClosed()` function in the R package FSA (Ogle, 2023) is used to estimate population size from closed-population mark-recapture studies, where individuals are captured, marked, released, and recaptured over one or more sampling occasions. It implements a variety of closed-population models, including the Chapman (1951) modification of the Petersen estimator, which was applied here as it produces an exactly unbiased estimate of true abundance (N) for finite populations and has been shown to exhibit lower bias and variance than the naive Petersen estimator across a range of sample sizes (Chapman, 1951; Ricker, 1975). This approach is well-established in fisheries ecology for closed-population abundance estimation (Peterson & Cederholm 1984; Gresswell, 1997) and was adapted here for estimation of true litter item abundance at surveyed transects. The

method's strengths are its flexibility in accommodating different capture scenarios, its ability to provide confidence intervals for abundance estimates, and its foundation in well-established mark-recapture theory. However, weaknesses arise when assumptions are violated, specifically that the population is closed to births, deaths, immigration, and emigration, and that marks are not lost or overlooked, which can lead to biased results. In the context of litter surveys, the closure assumption is reasonably satisfied as litter items are stationary and surveyed within a single session. In addition, small sample sizes or low recapture rates can reduce estimate precision, a limitation acknowledged given the sample sizes in the present study. Overall, `mrClosed` is a robust, versatile, and well-validated tool for abundance estimation, particularly well-suited for short-term studies where population closure can reasonably be assumed.

2. Analyses

The removal approach requires only the count of plastic items collected for each pass. In contrast, the mark-recapture method requires the number of marked plastic items recovered in each pass. For both approaches, the `FSA` package in R was used as described previously to estimate the total plastic count, with measures of standard error around the estimate.

Estimates of plastic count can be used to calculate estimates of plastic mass with standard error, as demonstrated in Chapter II. Additionally, standard errors can be calculated for observed plastic mass by dividing the standard deviation of observed masses by the square root of total observed count. Here, the estimated plastic mass was calculated by multiplying the estimated plastic count from each model by the average mass of each plastic item captured across all 6 survey passes. The standard error of the total estimated plastic

mass was calculated by dividing the standard deviation of the observed plastic masses by the square root of the estimated plastic count from each model. Because individual items were not weighed during these surveys, and only total mass per pass was recorded, the standard deviation of observed plastic masses was derived from per-item masses obtained in a six-pass removal survey conducted later in the same SNARL dumpster area (data not shown).

Each model makes assumptions regarding the probability of detecting individuals within a closed transect. In the removal model, capture probability is defined as the probability that an individual present is physically captured and removed during a survey pass (Zippin, 1956), and this probability is assumed to remain constant across passes. In the mark–recapture model, detection probability is defined as the probability that a marked individual present in the transect is detected and correctly identified (Otis, 1978; Lawson, 1992), with the assumption that detection probability is equal across individuals. Because mark–recapture data allow explicit modeling of detection probability, this approach provides an opportunity to evaluate the assumption of equal detection of plastics during surveys. In this study, it was assumed that all observed plastics were removed once detected, allowing us to examine assumptions around capture probability as well. It was hypothesized that plastics’ physical characteristics (e.g., color, mass, length) influence their probability of detection and, therefore, their probability of capture. To test this, trends in recapture by survey pass as a function of item color, log-transformed mass, and log-transformed length was visually explored (Figure 2).

As part of this data exploration, Principal Component Analysis (PCA) was used to convert observations of marked plastics’ dominant color (i.e., the color covering the largest surface area of the item) to continuous numeric variables for subsequent linear modeling.

Red, green, blue (RGB) values of all 20 marked plastics were determined using Adobe Illustrator 29.0.1 (see method in supplemental information), then were analyzed using PCA to determine what aspect of the items' colors (i.e., brightness, hue, saturation) accounted for the greatest variance between colors. Each item's Principal Component 1 value ($PC1_i$) was calculated using Equation 1, where L represents the PCA Loading for red (R), green (G), or blue (B), denoted by the subscript, and R_i represents the item's red value, G_i its green value, and B_i its blue value. To include the two dominant colors of the transect substrates (i.e., dirt and asphalt) in Figure 2, RGB values were extracted from a photograph of the transect taken during removal surveying and then converted using Equation 1.

$$(Eq. 1) PC1_i = L_R \cdot R_i + L_G \cdot G_i + L_B \cdot B_i$$

Then, the effects of plastic mass, maximum length, a proxy for density (i.e., mass $\times$ length), and color on detection were assessed using logistic regression of recaptured versus non-recaptured marked items. Logistic regression (binomial error, logit link) was performed in RStudio 2023.09.1+494 with the generalized linear model (GLM) function and Bayesian Information Criterion (BIC) for model selection (Table 2). Mass and length measurements were log-transformed only for visualization in Figure 2, and not for modeling.

C. Results

1. K-Pass Removal Results

The first pass collected 36 plastic items, the second pass 17 items, the third pass 48 items, the fourth pass 5 items, the fifth pass 46 items, and the sixth pass 9 items. At total, after 6 passes, 161 plastic items weighing 62.4 g (SE ± 0.17) were removed from the environment. The smallest item collected was 10 mm in its maximum length, and the largest

was 200 mm. The estimated true count of plastic items was 313 (SE ± 72.53), and the estimated true mass was 121.31 g (SE ± 0.12 g).

2. Marked Plastics' Characteristics

The 20 plastic items selected for marking covered a broad range of sizes, weights, and colors. Item weights ranged from 0.1 g to 18.2 g, with most items (16 out of 20) weighing < 1 g and four items exceeding 1 g (crayons, machine tag, rubber band, and red hard plastic). Lengths ranged from 12 mm to 103 mm. The colors were varied, including white (6 items), blue (3), metallic (3), gray (2), red (1), tan (1), black (1), clear (1), metallic gold (1), and multi-colored (1). Of the 20 marked plastic items, seven were recaptured and removed on the first pass, none were recaptured on the second pass, four were recaptured and removed on the third pass, one was recaptured and removed on the fourth pass, and none were recaptured on the fifth and sixth passes. This resulted in eight plastic items not being recaptured and therefore not being removed during the survey, three of which were later recaptured and removed, but excluded from mark-recapture analyses, during the post-survey evening search using a black light. Based on the number of recaptured and removed marked plastics, the estimated true abundance of plastic items was 268.33 (SE ± 74.5), and the estimated true mass was 103.10 g (SE ± 0.13 g).

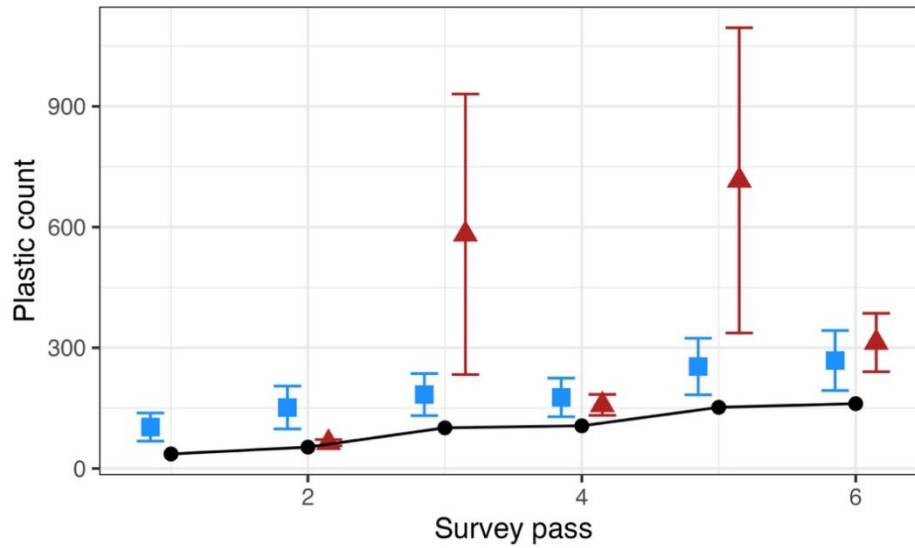


Figure 1. Observed (black) and estimated plastic counts as a function of the survey pass. Blue are mark recapture estimates and red are removal estimates. Observed plastic counts (black) substantially underestimate true litter abundance based on both mark recapture (blue) and removal (red) estimates.

3. Influence of Item's Characteristics on Recapture

The colors of marked plastics varied most in their brightness, which was determined by the PC1 proportion of variance (0.86), and by the PC1 loadings for red, green, and blue (i.e., 0.55, 0.62, and 0.55, respectively). Items with brightness levels higher or lower than mid-grey (i.e., mid-brightness) were detected in earlier passes, whereas items closer in brightness to mid-grey were detected in later passes or not at all (Figure 2A). The brightness levels of the survey area's two main substrates, dirt and asphalt, appear to bound most of the undetected items, suggesting that these items were undetected because they likely blended with the background (Figure 2A).

Further, a majority of the heavier items (items 1, 2, 4, 6 and 12) were detected during the removal survey (Figure 2B). Items 3, 8, and 9 were not recovered during the removal survey, but were recovered during the evening search using a black light providing certainty

that these items were in the transect during surveying, but were not removed. Item 3 was one of the heavier and larger items marked for recapture (Figure 2B), but was also the item most similar in brightness to mid-grey (Figure 2A). Item 18, which was not recovered during the survey or the post-survey evening search using a black light, was the smallest, lightest item (Figure 2B).

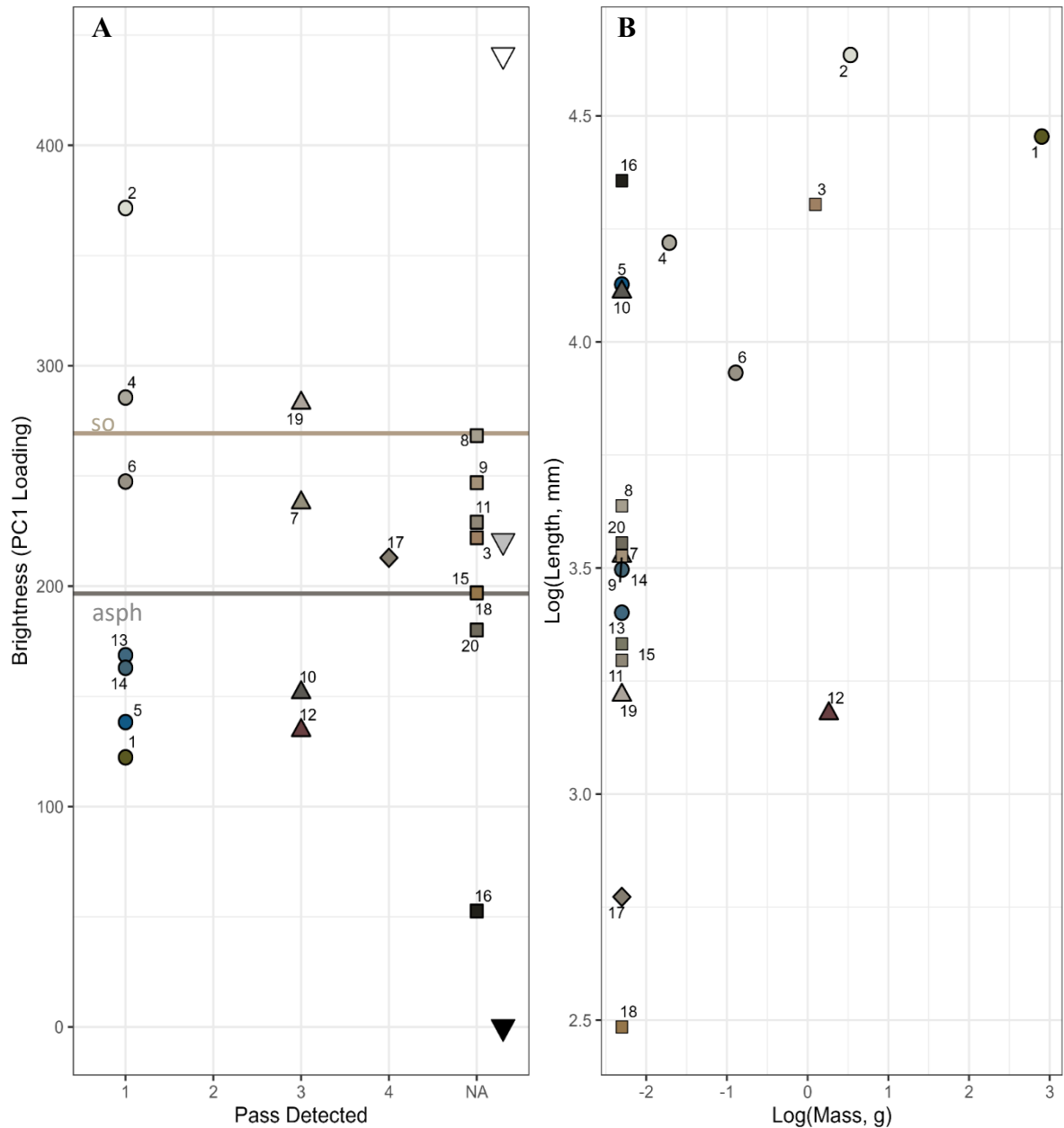


Figure 2. Physical characteristics of marked plastics. (A) Relative brightness of marked plastics recaptured during removal survey passes 1, 3, and 4, or not recaptured (NA). The horizontal lines represent the brightness and color of the soil (top) and asphalt (bottom) substrates in the transect. Circles indicate marked plastics recaptured in pass 1 ($n = 7$), triangles indicate marked plastics recaptured in pass 3 ($n = 4$), and the diamond indicates the marked plastic recaptured in pass 4 ($n = 1$). Squares represent marked plastics that were not recaptured ($n = 8$). Each point's color illustrates the plastic's dominant color. Upside-down triangles serve as reference points for white (bright), mid-grey (mid-bright), and black (dark) on the RGB brightness scale. (B) Log-normalized item mass (g) versus maximum item length (mm). Circles indicate plastics removed in pass 1, triangles indicate plastics removed in pass 3, and the diamond indicates item 17 recaptured in pass 4. Squares represent items that were not removed in the 6-pass removal survey.

A total of nine linear models, including a null hypothesis model, were tested to determine the effect of marked items' physical characteristics on probability of detection. These models did not detect any significant effect of plastics' characteristics on detection probability. The null model predicted a 60% probability of detection, which did not differ significantly from an expected equal detection probability of 50% ($p = 0.374$). There is weak evidence to select the null hypothesis model (model 0) over model 1 (Table 2). Model 1 provides evidence that heavier items are more likely to be detected (i.e., every 2.7-fold increase in an item's mass increases odds of its detection by approximately 70%), however the effect of mass on detection probability is not statistically significant ($p = 0.279$). Overall, current data does not allow for strong inferences regarding the effect of plastics' physical characteristics on probability of detection. However, ΔBIC values present weak to moderate evidence against models 1 through 6, and therefore these models should be retained for further consideration.

Table 2. Best-fit model selection using Bayesian Information Criteria (BIC), where BIC M_0 is the null hypothesis model BIC value, and BIC M_n represents the BIC values of Models $n = 1 - 8$.

Model	Hypothesis	BIC	ΔBIC (BIC $M_n - BIC$ M_0)	Evidence against model
0	Null Hypothesis, no predictors	29.9162	--	Best fit model
1	Item mass affects probability of detection	31.23997	1.32377	Weak
2	Item length affects probability of detection	32.30347	2.38727	Moderate

3	Item mass and length affect probability of detection	32.79848	2.88228	Moderate
4	Item density (mass * length) affects probability of detection	34.08614	4.16994	Moderate
5	Item color affects probability of detection	34.21632	4.30012	Moderate
6	Item color and length affect probability of detection	35.18281	5.26661	Moderate
7	Item color and mass affect probability of detection	37.049	7.1328	Strong
8	Item color and density (mass*length) affect probability of detection	39.54605	9.62985	Strong

D. Discussion

This work demonstrates that established ecological methods for estimating fish population abundance, namely removal and mark–recapture methods, translate effectively to estimating plastic litter abundance on terrestrial landscapes. This study found that the plastic load estimates from each model are similar, with almost equivalent standard errors (i.e., removal: count 313 (SE ± 72.53) and mass 121.31 g (SE ± 0.12 g), and mark-recapture: count 268.33 (SE ± 74.5) and mass 103.10 g (SE ± 0.13 g).

The removal model assumes that capture probability is constant across passes, while the mark-recapture approach assumes equal detection probability across individuals. This work presented an opportunity to explore detection probability of plastics based on their physical characteristics. Models did not detect a statistically significant effect of plastics’ physical characteristics (i.e., mass, length, density, color) on probability of detection. However, a model with a Δ BIC less than 2 exploring the effect of mass on detection probability suggests a potential positive relationship. This is important to consider in the context of plastic litter mobilization and transport, as heavier items, particularly those with relatively small surface areas, are less likely to be mobilized by wind from open, low-friction surfaces where they were deposited into adjacent vegetation or loose substrates where they may become

obscured (Mellink, 2022; Mellink, 2024). Other models with ΔBIC values between 2 and 6 provide evidence of characteristics' effects on detection probability, warranting further investigation using larger sample sizes.

When applying removal and mark–recapture models to plastics, researchers should recognize that transect type and plastic inputs can influence estimation accuracy in much the same way that habitat type and fish introductions affect fish population estimates (Hankin & Reeves 1988). In fisheries surveys, streams are stratified into riffles, pools, and glides because fish density and detection probability differ across habitat types; applying the same logic to plastic surveys suggests that transects should likewise be stratified into homogeneous units to avoid bias arising from variation in substrate, human activity, or litter accumulation patterns. Regarding plastic inputs, particularly in terrestrial systems with unpaved or loose substrates (e.g., gravel, leaf litter, soil, or sediment), items that were initially obscured may be revealed during later passes as surveyors disturb the ground cover violating the assumption of closure and biasing abundance estimates. Similarly, for mark–recapture models, closure may be violated by transport of plastics into or out of the transect between marking and recapture. In this study, surveys were conducted early in the day, before strong afternoon winds developed, to minimize such transport; however, it remains possible that some marked items that were never recaptured, even after the evening black-light survey, were carried out of the transect by winds (maximum speed 11.15 m/s, UC Natural Reserve System Dendra Science), as the black-light survey had to be conducted after nightfall.

Together, the results from the removal and mark–recapture models were consistent with the assumption of equal detection probability, though the trends observed suggest this

assumption could be violated with a larger sample size. Thus, additional exploration of detection probability of plastic litter is warranted. Importantly, this work demonstrates that, at minimum, plastics should be surveyed in no fewer than three passes, and potentially many more, to produce accurate estimates (Figure 1), and that, as with fish surveys, removal surveys require a decreasing trend in the number of plastics recovered to provide unbiased results. As seen in this study, this assumption is not guaranteed; when it is violated, as occurred in removal survey passes 3 and 5 (Figure 1), estimates can be biased (here, resulting in overestimates, though underestimates are also possible in other scenarios) and standard errors increase. Removal surveys are particularly sensitive to violations of the predictable depletion assumption, whereas this work shows that the mark–recapture approach was more robust to heterogeneity in detectability of plastic litter, as is also the case in fisheries studies (Zippin, 1956; Seber, 1982; White, 1982; Hankin & Reeves, 1988). Therefore, when resources allow, surveyors should either perform additional passes if they observe that plastic litter is not decreasing predictably per pass or clearly note biased estimates when reporting results. It is worth noting that conducting many passes for removal surveys can be labor intensive. Similarly, mark–recapture approaches require either introducing additional litter or invisibly marking items (the latter approach used in this study), which also demands considerable effort.

Ultimately, this study shows that both removal and mark–recapture methods yield comparable estimates of plastic litter abundance and mass in terrestrial systems, with nearly identical measures of standard error. By validating results across these two established approaches, we provide robust estimates of plastic abundance and mass that would otherwise be missed or underestimated in conventional single-pass surveys, confirm that the

per-pass probability of detection was approximately equal in these surveys, and demonstrate that at least three passes should be used when surveying plastic litter. These findings highlight the importance of applying multiple-pass approaches to plastic litter surveying and underscore the sensitivity of removal surveys to deviations from predictable depletion, guiding future efforts to improve accuracy and reliability in terrestrial plastic litter monitoring.

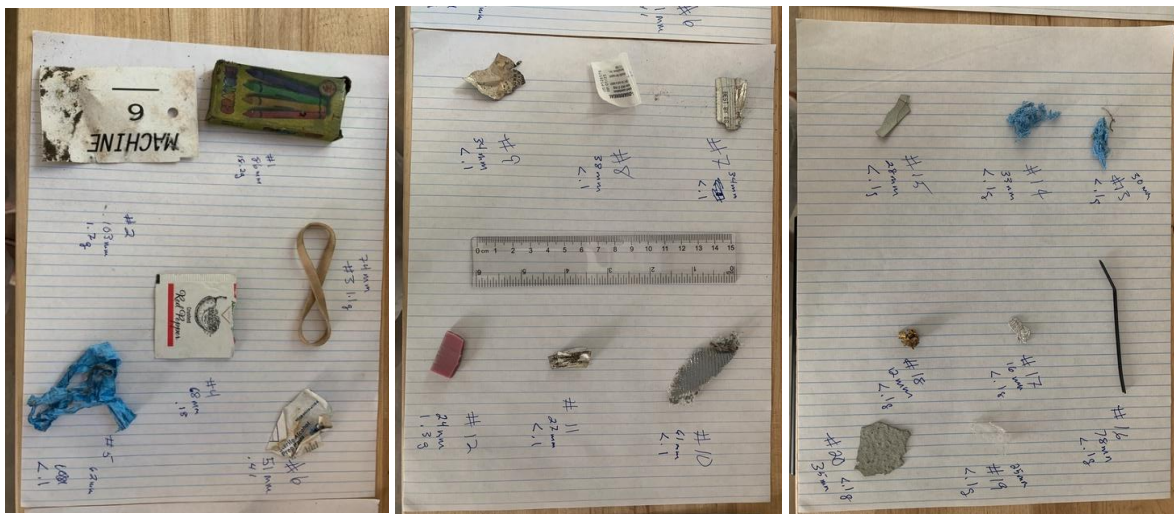
E. Conclusion

This study demonstrates that removal and mark-recapture methods, long established in fisheries ecology, translate effectively to estimating plastic litter abundance and mass on terrestrial landscapes, yielding comparable estimates with nearly identical standard errors across both approaches. By validating results across two independent methods, we provide robust estimates of plastic litter abundance that would otherwise be missed or underestimated by conventional single-pass surveys. Both models were broadly consistent with the assumption of equal detection probability across individual items, though trends suggesting a positive relationship between item mass and detectability warrant further investigation with larger sample sizes. Critically, this work demonstrates that a minimum of three survey passes is required for accurate litter estimation, and that removal surveys are particularly sensitive to violations of the predictable depletion assumption, which has direct practical implications for the design of future terrestrial plastic litter monitoring programs. As plastic pollution research increasingly demands quantitative rigor, these findings provide a methodological foundation for applying ecologically grounded, multi-pass survey approaches to terrestrial litter monitoring at broader scales.

F. Appendix

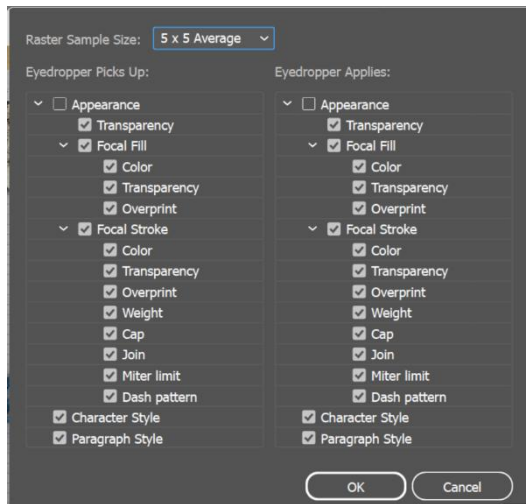
Image 1. Photographs of 20 plastic items collected from the survey transect, prior to being marked with black light paint and returned to their original positions in the transect. Ruler included for scale.

Method for determining RGB values using Adobe Illustrator:



Adobe Illustrator version 29.0.1 was used to determine the RGB values of the 20 plastic items designated for the mark recapture survey. Photographs of items were uploaded into Adobe Illustrator, and the eye dropper was set to sample from a 5x5 average pixel area; the eye dropper settings were otherwise set to default (Image 2). The eye dropper was then used to determine the red, green, blue (RGB) value of the color covering the greatest surface area of the item.

Image 2. Eyedropper settings from Adobe Illustrator



Additional Modeling

Discrete time survival models were also used to explore the effect of plastics' physical characteristics on capture probability by pass as part of the study's multimodel inference approach. Because these models are also generalized linear models (GLM), their BIC values were compared against the BIC values of the GLMs used to explore the effect of plastics' characteristics on probability of detection. However, there was strong evidence ($\Delta\text{BIC} > 45$) against selecting these models' over the best fit GLM (model 0).

IV. Spatially Explicit Quantification of Trash Mass by Priority Land Use using Depletion Modeling and Empirical Bayesian Kriging Regression Prediction

A. Introduction

Trash is defined under the California Clean Water Act Trash Provisions as "all improperly discarded solid material from any production, manufacturing, or processing operation including, but not limited to, products, product packaging, or containers constructed of plastic, steel, aluminum, glass, paper, or other synthetic or natural materials." Plastic trash threatens both ecosystem and human health through the generation of microplastics (plastic particles ≤ 5 mm) and the release of associated toxins such as per- and polyfluoroalkyl substances (PFAS), Bisphenol A (BPA), phthalates, and heavy metals (Abahussain, 2025; Corbett, 2026; Kumar, 2025). Paper, glass and metal trash also warrants concern. Paper may contain Bisphenol A (Garcia, 2023) and paper, glass and metal packaging have been shown to leach heavy metals (Kourkopoulos, 2025; Turner, 2019; Seref, 2025; Verma, 2025).

Trash that has accumulated in terrestrial environments can be transported via stormwater runoff into nearby natural and engineered waterways, ultimately reaching aquatic and marine sinks including lakes and oceans (Jambeck, 2015; Lin, 2026; McLaughlin, 2023; Werbowski, 2021). Freshwater systems serve as critical habitat for aquatic wildlife as well as drinking water sources for humans. Drinking water represents a major exposure pathway for consuming microplastics, plastic-associated contaminants like PFAS and phthalates, and other well-characterized as well as emerging contaminants

associated with commonly littered items (Haleem, 2024; Dehghani, 2025; Varatharajan, 2025). Microplastics and associated chemical contaminants have been widely detected in both source waters and treated drinking water (Eerkes-Medrano, 2019), yet conventional drinking water treatment systems were not designed for their removal and often exhibit variable or incomplete removal efficiencies (Cai, 2025; Alimi, 2018). Monitoring and analytical methods for these contaminants remain under development and lack standardization (Cai, 2025). Because contaminants enter source waters via pathways including but not limited to untreated stormwater runoff (Cai, 2025; Hoellein 2021), reducing terrestrial litter inputs to freshwater systems represents a critical upstream strategy for limiting human and wildlife exposure. The need to manage urban litter is especially pressing under changing climatic conditions in which trash may accumulate during longer-than-usual dry periods, then mobilize even more readily during intense first-flush storm events (Shwenk, 2025; Kelly, 2025). Reducing terrestrial litter inputs therefore requires not only upstream source reduction but also a regulatory framework capable of incentivizing and measuring progress toward that goal.

Under the Clean Water Act, the United States Environmental Protection Agency (US EPA) regulates trash discharges from point sources into navigable waters via National Pollutant Discharge Elimination System (NPDES) permits (Clean Water Act Trash free Waters Program). The US EPA Trash Free Waters Program provides regulatory tools (i.e., Total Maximum Daily Loads and Municipal Separate Storm Sewer Systems (MS4) permits) and Best Management Practices for states and municipalities to address trash discharges, however, it does not mandate specific monitoring methods or numeric reduction targets for trash at the national level. In 2015, the California State Water Resources Control Board

adopted the Trash Amendments to the State's Water Quality Control Plans, establishing statewide requirements for the elimination of trash discharges from MS4 permit stormwater systems by 2030. Compliance is achieved either through installation of certified full-capture systems on stormwater infrastructure in Priority Land Use areas, or through an equivalent programmatic combination of institutional controls such as street sweeping and partial capture devices that achieves equivalent load reduction. Statewide, progress toward compliance is monitored primarily using the On-Land Visual Trash Assessment (OVTA) (Conley 2022), a standardized visual survey approach that assigns survey areas to categorical trash condition levels based on observed litter density. While alternative methods may be used, they must demonstrate equivalency to OVTA-derived estimates of trash generation and reduction. However, OVTA generates categorical rather than quantitative estimates of litter abundance, and the relationships between OVTA ranks and true litter mass have not been rigorously established, a gap this study directly addresses.

In 2016, the Tracking California's Trash project evaluated relationships between OVTA ranks and measured trash volumes on streets and sidewalks and found that while OVTA ranks were in reasonably good agreement with trash volumes overall, sidewalk measurements did not consistently demonstrate a relationship with OVTA ranks, attributed to trash obscured by vegetation in street tree wells and adjacent landscaped areas (EOA Inc., 2016). This inconsistency highlights a fundamental limitation of visual assessment methods: they are subject to detectability biases that systematically vary with the physical environment. Reynolds et al. (2025) proposed a repeated-pass removal survey protocol to address this limitation by estimating true litter abundance through sequential depletion of the transect coupled with depletion modeling, analogous to removal sampling methods used in

fisheries ecology, to provide measures of uncertainty regarding true litter abundance that are not available from single-pass methods. Applying this novel method for trash surveying allowed this study to address the knowledge gap regarding the relationships between OVTA ranks and true litter mass.

Determining the true abundance of litter with associated measures of variance through field-based observations presents a novel opportunity to characterize the spatial distribution of litter mass across the study area using a probabilistic interpolation framework. In this study, Empirical Bayesian Kriging Regression Prediction (EBKR) was selected for this purpose because it explicitly propagates measurement uncertainty from input observations into the prediction surface, accommodates spatially continuous covariates, and is specifically designed to produce reliable predictions and uncertainty estimates for small datasets (Krivoruchko & Gribov, 2019), making it well-suited to the inherently variable and spatially structured nature of urban litter accumulation.

While previous studies have modeled litter accumulation at the watershed scale using landscape, land use, and hydrologic predictors, these approaches have predominantly focused on litter in and near rivers and streams (Cowger, 2019; McLaughlin, 2023) or relied on modeled parameters such as urban debris buildup rates rather than field measurements (Bagheri, 2024; Palmer, 2025). Jambeck et al. (2015) used a Bayesian hierarchical mixed model to predict litter counts along roadways within river basins across the United States, and Conley et al. (2019) applied vehicle-based visual trash assessments on city streets and sidewalks following the OVTA protocol to characterize litter conditions at the parcel level. Notably, Conley et al. (2019) considered Empirical Bayesian Kriging (EBK) for spatial interpolation of litter but ultimately selected a Nearest Neighbors approach due to its

simplicity of application and interpretation, while acknowledging that EBK provides greater spatial coverage and the advantage of explicitly accounting for uncertainty in semivariogram parameters. Critically, litter data used as inputs across all of these studies were derived from single-pass surveys, which are subject to systematic underestimation and provide no measures of uncertainty regarding true litter abundance. To the authors' knowledge, no study has explicitly quantified spatial variation in terrestrial litter accumulation on sidewalks at fine spatial scales, specifically by Priority Land Use category within watersheds, using depletion-estimated true abundances of litter mass with associated measures of variance derived from field measurements.

In this study, four litter surveying approaches were applied within each of 29 sites along the sidewalk network across the City of Santa Barbara, California, enabling direct comparison across methods. These approaches were: (1) a single-pass On-Land Visual Trash Assessment; (2) a single-pass trash removal survey; (3) a three-pass sequential removal survey; and (4) depletion modeling using data from the three-pass surveys to estimate true litter abundance with associated uncertainty. This experimental design allowed for direct comparison of litter counts and masses across approaches and evaluation of agreement between quantitative estimates and OVTA ranks across sites stratified by Priority Land Use type. Additionally, Empirical Bayesian Kriging Regression Prediction (EBKR) was used to interpolate litter mass with measures of uncertainty across Priority Land Use-designated sidewalks in three watersheds within the city. The objectives of this study were to: (1) evaluate the agreement between depletion-modeled litter abundance and OVTA rankings across Priority Land Use types; (2) identify site-level urban covariates of litter mass accumulation, including commercial activity, transit infrastructure, and waste

management infrastructure; and (3) produce spatially explicit estimates of total litter mass loading on sidewalks by land use type and watershed with quantified uncertainty, providing actionable spatial information for stormwater managers working toward California Clean Water Act Trash Amendment compliance.

B. Methods

1. Study Region

The City of Santa Barbara (109 km²; population approximately 87,000) is located along California's Central Coast (Figure 1). The city occupies a series of uplifted marine terraces extending approximately 4 km inland and is bounded by the Santa Ynez Mountains to the north and the Pacific Ocean to the south. The region has a Mediterranean climate characterized by warm, dry summers (16–24 °C) and mild, wetter winters. Precipitation is highly seasonal, with more than 80% of annual rainfall occurring between November and May (Paulinski, 2018).

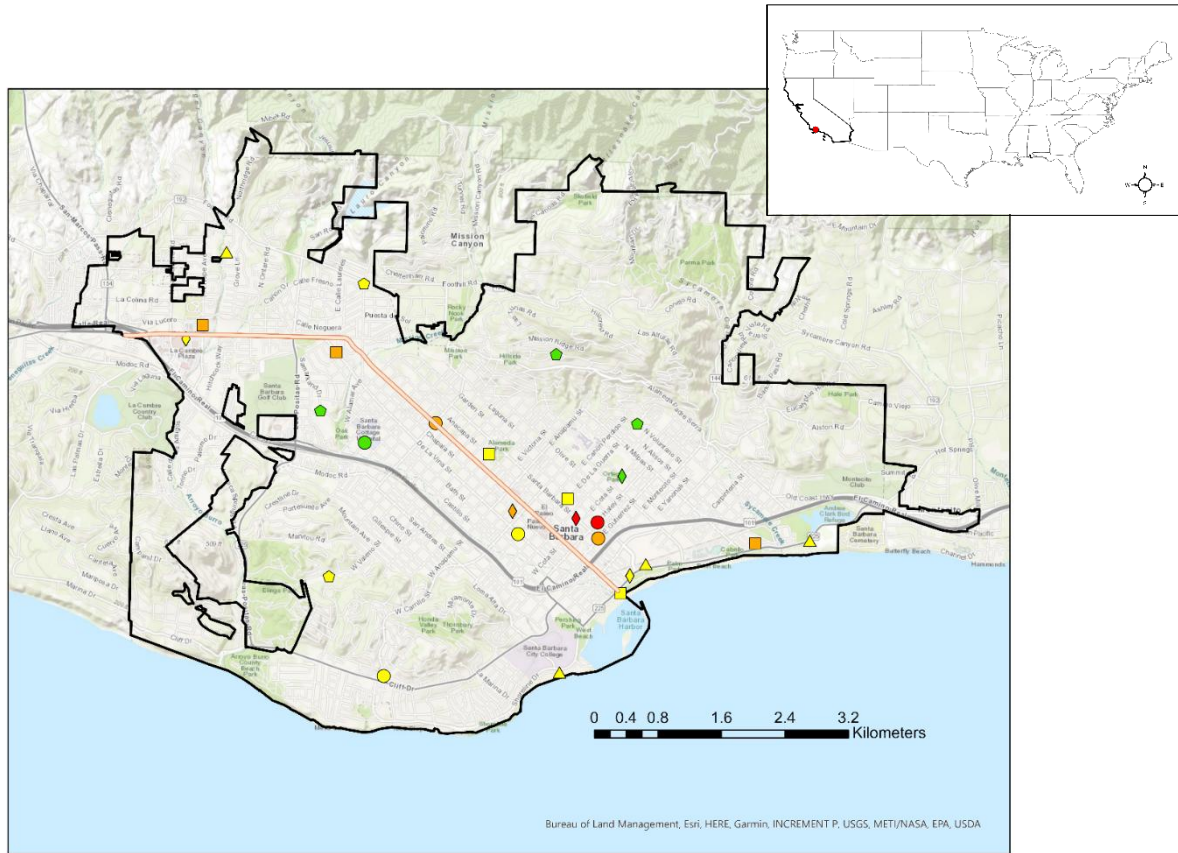


Figure 1. On-Land Visual Trash Assessment Levels at Survey Sites across Santa Barbara, California A map of the 29 survey sites within the City of Santa Barbara, CA, outlined in black, showing the sites' On-Land Visual Trash Assessment Level (Trash Level), and land use designation. Sites that were categorized as “not littered” are green, “slightly littered” sites are yellow, “Littered” sites are orange, and “Very Littered” sites are red. Circles represent commercial sites, squares are mixed urban, triangles are park, diamonds are transportation, and pentagons are residential. A majority of sites ($n = 13$) were “Slightly Littered”, while “Littered” and “Very Littered” sites are those which track nearest to State St. (orange line), the city’s main boulevard. Only two of the 29 sites were ranked “Very Littered”.

Four primary watersheds drain the city: Arroyo Burro, Mission Creek, Laguna Channel, and Sycamore Creek (Water Quality, 2019). Each watershed includes large undeveloped, natural headwaters within the Santa Ynez Mountains and Los Padres National Forest, transitioning to developed, urbanized reaches within city limits. Land use within the study area is predominantly residential and commercial (Paulinski, 2018). Mission Creek and

Arroyo Burro discharge into small tidal estuaries (~8,000 m²) along the Santa Barbara coastline.

Under the Federal Clean Water Act, the Central Coast Regional Water Quality Control Board has designated multiple beneficial uses for these four creeks, reflecting their importance for local water supply, groundwater recharge, and habitat for rare, threatened, and endangered species (Water Quality, 2019).

Trash surveys were conducted citywide and spatial analyses were performed over the areal extent of the city; however, both surveying and analyses excluded the Santa Barbara Airport, which is technically within city limits but is in Goleta, California approximately 5 km northwest of downtown Santa Barbara. Geospatial interpolation outputs were ultimately clipped to the developed and urbanized lower Mission Creek watershed, as well as the Laguna Channel Drain and Laguna Tidal Drain watershed boundaries to calculate litter abundance on sidewalks within these areas. Arroyo Burro and Sycamore Creek watersheds were excluded from spatial interpolation due to insufficient survey coverage at the edges of the study area. All watershed boundary shapefiles were provided by the City of Santa Barbara Sustainability and Resilience Department.

2. Surveying Protocols

Two published protocols, the On-land Visual Trash Assessment (OVTA) Protocol for Stormwater (EOA Inc.) and the Repeated Pass Removal (RPR) Survey for Estimating Land-Based Trash Abundance (Reynolds, 2025), were applied within each survey transect to assess trash abundance and allow direct comparison between methods.

The OVTA protocol is designed to establish qualitative baseline levels of trash and to assess changes in trash accumulation over time. The OVTA protocol is “intended to assess

the level of trash greater than 5 mm in length that is observed on-land and can reasonably be transported to the stormwater conveyance system” (EOA Inc., 2016). It was developed as part of the Bay Area Stormwater Management Agencies Association’s *Tracking California’s Trash* project, sponsored by the California State Water Resources Control Board (SWRCB), and is currently used by City of Santa Barbara managers to meet Municipal Separate Storm Sewer System (MS4) Permittee Track 2 compliance under the California Clean Water Act Trash Amendments. This study used OVTA Protocol Version 1.3 as it was the most updated version of the protocol for the types of transects to be surveyed. Because the OVTA protocol does not involve removal or intentional disturbance of trash within the survey transect, OVTA surveys were conducted prior to RPR surveys at each site.

Repeated Pass Removal (RPR) Surveys for Estimating Land-Based Trash Abundance (Reynolds, 2025) adapt an established method from fisheries ecology, used to estimate fish populations and biomass, to instead estimate the quantity and mass of trash in terrestrial systems (Reynolds 2025). RPR surveys have been previously used to quantify the underestimation of single-pass trash surveys in coupled natural and human systems. The biases and limitations of the RPR survey approach for terrestrial trash assessment have been explored, and the method has been found to translate effectively to quantify trash abundance for pieces of trash greater than 1 mm in size. As implied by its name, the Repeated Pass Removal survey removes trash from the transect over 3 or more sequential surveying passes and therefore was conducted after OVTA surveys.

For both surveying protocols, trash was defined following the OVTA protocol as “all improperly discarded waste material, including, but not limited to, convenience food,

beverage, and other product packages or containers constructed of steel, aluminum, glass, paper, plastic, and other natural and synthetic materials, thrown or deposited on the lands and waters of the state, but not including the properly discarded waste of the primary processing of agriculture, mining, logging, sawmilling, or manufacturing” (California Code Section 68055.1(g), EOA Inc., 2016).

2.1 On-Land Visual Trash Assessment

Trash levels were assigned to survey sites based on visual observations of the magnitude and spatial extent of trash within each transect. The four trash condition categories from the OVTA protocol were used to rank sites: (1) A (“Not Littered”), (2) B (“Slightly Littered”), (3) C (“Littered”), and (4) D (“Very Littered”) (SI, Table 2). Following OVTA protocol guidance, sites where effectively no trash was observed were categorized as “Not Littered.” Sites that were predominantly free of trash except for a few littered areas were categorized as “Slightly Littered.” “Littered” sites were those predominantly covered by trash with only a few clean areas, while “Very Littered” sites exhibited continuous trash throughout the assessment area.

Upon arrival at a survey site, one surveyor walked through the transect at a normal pace for 15 minutes, carefully observing trash within the defined boundaries and assigning an initial OVTA rank. This approach standardized effort by time across the OVTA and RPR surveys, but slightly modified the standard OVTA protocol, which requires two surveyors to walk the transect together. To account for this modification, although the initial rank was assigned by a single OVTA surveyor, all three surveyors collectively discussed and agreed upon the final OVTA rank after completion of the three removal passes. To assess whether the modification of the OVTA protocol used in this study introduced systematic bias, a

Cohen's kappa analysis was performed in RStudio comparing the ranks assigned by the first OVTA surveyor to the final consensus ranking across all 29 sites.

2.2 Repeated Pass Removal Survey

Following the OVTA assessment, the RPR survey was conducted within the same closed transect. Three surveyors performed sequential, independent passes, each removing all visible and removable trash. Effort was standardized at 15 minutes per surveyor per pass, resulting in three consecutive removal passes per site.

3. Surveyor Training

Seventeen volunteers were recruited to conduct OVTA and RPR surveys, six of whom had prior experience with RPR surveys. All surveyors attended a one-hour virtual training session prior to the field campaign. On the morning of the surveying event, and before departing to assigned survey sites, participants met at a public park and observed a mock OVTA survey followed by a mock RPR survey followed by a question-and-answer session. Written protocols were provided to each team for field reference.

3. Survey Site Selection and Descriptions

Survey sites were randomly selected and stratified across five land-use types: Commercial, Transportation, Mixed Urban, Residential, and Parks. These land-use categories represent equivalent alternative land areas to the Trash Amendment Priority Land Use (PLU) classifications and fall within areas designated as PLUs by City of Santa Barbara managers. The existing land use dataset was provided by the City.

Using RStudio 2023.09.1+494 "Desert Sunflower" Release (2023-10-16), a 450 m² grid was overlaid on the study area, bounded by the City of Santa Barbara and excluding the

Santa Barbara Airport. Because surveying effort is standardized by time, transect areas cannot be known *a priori*. Therefore, the grid size was selected based on the mean area plus one standard deviation covered in pilot 15-minute effort-based transects of similar land use types ($n = 17$; data not shown), ensuring that each survey transect would approximately fit within a single grid cell.

Each grid cell was assigned a unique identifier, and six cells were randomly selected within each land-use type. Surveyors were provided with precise sidewalk starting coordinates and required survey direction using Google Street View and My Maps to ensure consistent coverage of the designated land-use type within each randomly selected transect.

A total of 29 sites were surveyed. Although 30 sites were initially targeted, only five Transportation land-use sites were deemed safe for volunteer surveys. As a result, survey findings are representative of accessible pedestrian areas and may not reflect trash accumulation in non-walkable or inaccessible areas of the city. The selected sites are described and images of the selected sites obtained prior to surveying via Google Street View are provided in the Supplemental Information.

6. Conducting Surveys

All 29 surveys were conducted in a single day on November 18th, 2023, between 08:00 and 14:00, at the end of the dry season and prior to the first-flush rainfall event. The first 2.54 mm rain event of the wet season began shortly after surveying ended, totaling 2.8 mm, and the first-flush storm event occurred on December 13th, totaling 26.7 mm. The date of surveying also accounted for recurring trash control activities (e.g., street sweeping) at each transect to ensure that the transect had not been cleaned prior to surveying.

Teams consisted of three surveyors, with at least one experienced RPR surveyor per team. OVTA assessments were always conducted by the team member with the highest level of transect survey experience. At each site, the OVTA assessment was conducted first, followed by the RPR survey. The surveyor order of the first two RPR passes was randomized, and the OVTA surveyor always completed the third pass of the RPR for efficiency and to reduce potential bias from the OVTA surveyor having already made a pass through the transect. After completion of all three removal passes, surveyors discussed the ranking assigned by the OVTA surveyor and agreed to a finalized ranking.

7. Characterizing Trash

Removed trash was stored and transported to a nearby laboratory in 1-gallon re-sealable bags. A separate bag was used to store removed trash for each pass at each transect. Samples were stored in a dark, temperature-controlled room (4 °C), and trash was characterized in a chemical fume hood. For each item, mass (g), longest dimension (mm), dominant color (defined as the color covering the greatest surface area), apparent functional use, and apparent material type were recorded. Any visible brand name and recycling identification number was also documented.

Rather than binning items into predefined use categories during sorting, each item was described in writing when its function was apparent, and items were later grouped into broader functional use categories. When an item's function was not obvious, it was described and subsequently categorized as undeterminable. A table listing specific items within each functional use category is provided in the Supplemental Information.

Items made of only one material were categorized as either plastic, cardboard, cardstock, cellulose, chalk, cork, glass, gum, metal, paper, rubber, silicone, or wood. Items that

appeared to be made of multiple materials were categorized as cardstock/plastic, cotton/paper, cotton/plastic, metal/plastic, metal/wood, paper/metal, paper/metal/plastic, paper/plastic, rubber/plastic, wood/plastic, or wood/plastic/metal. If an item appeared to be human-made, but the material was unidentifiable and the functional use was undeterminable, it was described as anthropogenic; items that appeared to be human-made and the material appeared to be unnatural were described as synthetic and were mostly categorized under the textiles functional use.

8. Analyses

8.1 Basic Descriptive Statistics

The material type and functional use composition of all trash collected across the 29 survey sites was summarized using descriptive statistics, including counts and proportions of items by each category (Figure 2). The brand names observed on trash items were summarized using descriptive statistics and their relative observed frequencies was visualized using a word cloud (Figure 3). The distributions per RPR survey pass of removed trash mass (g) and size (mm) were determined and visualized in Figures 4 and 5. The cumulating proportions of trash removed per pass relative to the total quantity of trash in a transect was visualized using minimum convex polygons (Figure 7). Because each trash condition category contained fewer than ten observations ($n \approx 7-8$ per group), minimum convex polygons (100% MCPs) were used to visualize group extent and overlap without imposing distributional or smoothing assumptions. All descriptive statistical analyses were conducted in RStudio, "Apple Blossom" Release (0e924abb, 2026-02-04).

8.2 Depletion Modeling

The number of trash items removed per pass was used to estimate the total count of trash with standard errors. Estimates of total count were extrapolated using the *removal()* function and “*CarleStrub*” method with standard errors calculated using the *CS.se* “*alternative*” approach (Carle 1978, Ogle 2023) in the FSA package (Fisheries Stock Assessment) in the R (Haddon 2011, R Core Team). Depletion modeling assumes that (1) Each pass depletes total trash predictably; (2) The abundance of trash does not change between passes (i.e., the transect is closed); (3) The probability of trash removal is equal across survey passes, and; (4) surveying effort is constant. The Carle & Strub method for depletion sampling is well-established in fisheries ecology for estimating population abundance, and when the proportion of the population taken in successive catches does not remain constant throughout sampling, the maximum weighted likelihood model of Carle & Strub (1978) is more robust compared to other models (i.e. Zippin, Seber) and has been found to be the only method which produces statistically reliable estimates (Cowx, 1983, Hedger, 2013). Standard errors are also provided for the estimate.

Mass estimates and standard errors were calculated from measurements of the mass of each individual trash item. The mean trash mass recorded from removed trash was multiplied by the estimated trash abundance. Thus, the total trash mass (T_m) was the estimated trash count (N) from the depletion model times the average trash mass for each trash item collected, ($\bar{M}$) (Equation 1). The standard error ($SE\bar{M}$) of the total trash mass was estimated by dividing the standard deviation of the observed trash mass (σ_m) by the square root of the estimated trash count (N).

$$1. \text{ (Eq.1) } T_m = N \times \bar{M}$$

$$2. \text{ (Eq.2) } SEM = \frac{\sigma_m}{\sqrt{N}}$$

8.3 Analysis of Variance

To test whether observed and estimated trash counts and masses differed significantly across OVTA ranks, one-way ANOVAs were conducted using the `aov()` function in base R. Six models were fit using log-transformed response variables: first-pass trash count, first-pass trash mass, total observed trash count, total observed trash mass, depletion-modeled estimated trash count, and depletion-modeled estimated trash mass. The 'Very Littered' rank was excluded from all analyses as only two sites fell into this category, which was insufficient for reliable group-level estimation. All ANOVAs were followed by Tukey's Honestly Significant Difference (HSD) post-hoc tests to identify significant pairwise differences between rank groups. Levene's test was then used to determine to what extent residual standard errors differed across OVTA ranks, testing the assumption that the depletion model captures true abundance more accurately than first pass and cumulative survey observations as opposed to the case that the depletion model has more variance at high densities and therefore less power to detect differences between different OVTA ranks.

8.4 Random Forest Modeling

To identify which trash and site-level variables best predicted trash condition categories, a Random Forest (RF) classification was performed. Predictor variables included log-transformed trash counts and mass (first pass, total observed, and estimated), measures of trash size (mean and standard deviation), transect land use type, and the dominant and largest trash colors observed in the first pass. For each site, additional summary statistics were calculated, including the mean and standard deviation of trash mass and size, the most

frequently observed trash color, and the color of the largest item. All predictors were numeric or categorical as appropriate, and the response variable was the site's trash condition category.

The RF model was run using 1,000 trees with the randomForest package in R (Liaw & Wiener, 2002), and variable importance was assessed via the Mean Decrease in Gini index, which quantifies how much each predictor improves classification accuracy. To evaluate stability, the analysis was repeated one hundred times, and the mean and standard deviation of each variable's Mean Decrease in Gini were calculated.

8.5 Multi-Model Inference Exploring Litter Mass Co-Variates

Previous studies show that cigarette butt waste is highly concentrated around businesses where cigarettes are sold or consumed (Marah, 2011), and that there is a positive and statistically significant relationship between the number of food and drink related businesses in an area and the number of food and drink related litter generated in that area (Rossi, 2023). Based upon the apparent intended use of the litter items removed during surveying, businesses where these littered items are sold or used were considered as a possible covariate for estimated litter mass. A georeferenced dataset containing the description of all businesses holding a 2023 Santa Barbara Business License were obtained from the City Administrator's Office. The data were filtered to include retailers of tobacco and alcohol products, products commonly in single-use plastic packaging (both food and non-food), clothing, and pharmaceutical products; additionally, businesses where tobacco products and alcohol are commonly used were also included. This was performed through manual identification based on business type descriptions in the dataset. Additionally, litter density has been positively correlated to transit locations (i.e. bus stops) and waste containers. Data

of georeferenced bus stops were provided by UC Santa Barbara's Center for Spatial Studies and Data Science, and data of georeferenced public waste containers was provided by the City of Santa Barbara Sustainability Department.

A 152 m (500 ft) buffer was generated around each of the 29 survey sites in ArcGIS Pro version 2.9.5 using the Buffer tool, and a spatial join was used to count the number of qualifying businesses, bus stops, and public waste containers falling within each buffer, producing a continuous count variable representing commercial activity, transit, and waste management in the immediate vicinity of each survey site.

Three linear regression models were fit using the $\text{lm}()$ function in base R to examine the correlation between log-transformed depletion-modeled estimated litter mass (g) and commercial activity, bus stops, or public waste containers. In these equations, $\hat{y}$ is the estimated trash mass in grams, and β_0 is the intercept. Coefficients are defined below for each model tested:

The first model tested whether the number of businesses within 152 m of a survey site ($\beta_{n_businesses}$) predicted natural log-transformed litter mass across all sites.

$$(1) \ln(\hat{y}) = \beta_0 + \beta_{n_businesses}x + \varepsilon$$

The second model tested whether the number of bus stops within 152 m of a survey site ($\beta_{n_bus_stops}$) predicted natural log-transformed litter mass across all sites.

$$(2) \ln(\hat{y}) = \beta_0 + \beta_{n_bus_stops}x + \varepsilon$$

The third model tested whether the number of public waste containers within 152 m of a survey site ($\beta_{n_containers}$) predicted natural log-transformed litter mass across all sites.

$$(3) \ln(\hat{y}) = \beta_0 + \beta_{n_containers}x + \varepsilon$$

The fourth model tested whether the number of businesses, bus stops, and public waste containers within 152 m of a survey site ($\beta_{n_containers}$) predicted natural log-transformed litter mass across all sites.

$$(4) \ln(\hat{y}) = \beta_0 + \beta_{n_businesses}x + \beta_{n_bus_stops}x + \beta_{n_containers}x + \varepsilon$$

Based on the results of the first four models, a fifth model exploring a binary presence/absence variable for businesses was additionally derived. The fifth model tested whether the presence of any business within 152 m ($\beta_{p_businesses}$), regardless of count, predicted natural log-transformed litter mass across all sites.

$$(5) \ln(\hat{y}) = \beta_0 + \beta_{p_businesses}x + \varepsilon$$

Models 1 – 5 were compared to a sixth intercept-only (null) model, which was fit as a baseline for model comparison, and represented the absence of explanatory effects. Inclusion of a null model allows evaluation of whether candidate models with predictors provide improved explanatory power relative to a constant-mean model, as assessed by information-theoretic criteria (e.g., Bayesian Information Criterion (BIC)).

The linear model with the lowest Bayesian Information Criterion (BIC) value was selected as the best-fit model. The ΔBIC , defined as the between-model difference of the

best-fit model and each of the other models tested, was used to determine if any models other than the best-fit model should be retained for consideration. Otherwise, models with ΔBIC values greater than 7 were disregarded as a ΔBIC of 7 or greater indicates positive to very strong evidence for selecting the best-fit model over the other model being considered (Raftery, 1995). Additional analyses were only performed using the best-fit model.

Prior to interpreting model results, the normality of residuals was assessed using the Shapiro-Wilk test (`shapiro.test()` in base R), with $p > 0.05$ indicating residuals consistent with a normal distribution. Additionally, homoscedasticity was assessed using the Breusch-Pagan test (`bptest()` in the `lmtest` package), with $p > 0.05$ indicating no significant evidence of heteroscedasticity. Finally, influential observations were assessed using Cook's distance (`cooks.distance()` in base R), with values above 0.5 flagged as moderately influential and values above 1.0 flagged as highly influential.

8.6 Spatial Statistics

8.6.1 Empirical Bayesian Kriging Regression Prediction

Empirical Bayesian Kriging Regression Prediction (EBKR) is a geostatistical interpolation method that generates a spatially continuous prediction surface with associated standard errors from discrete sample measurements, using neighboring sample points weighted by proximity to each prediction location (Krivoruchko, 2012; Krivoruchko & Gribov, 2019; Gribov & Krivoruchko, 2020). Spatial structure is modeled via semivariogram models that describe how similarity between observations decays with distance. Unlike standard kriging methods, which treat semivariogram parameters as fixed once estimated, EBKR treats them as random variables and accounts for their uncertainty

through repeated resampling, generating a distribution of plausible semivariogram models. EBKR also accepts a spatially continuous covariate alongside the measured values, and critically, explicitly incorporates measurement uncertainty as a model input, allowing the standard errors of the depletion-modeled litter mass estimates to be propagated directly into the interpolation process rather than treating point estimates as if they were observed without error. EBKR was selected for this study for three reasons: (1) it explicitly propagates input measurement uncertainty into the prediction surface, allowing the standard errors of depletion-modeled litter mass estimates to be incorporated directly into the interpolation process rather than treating observations as error-free; (2) it accommodates spatially continuous covariates, enabling the incorporation of urban covariates identified through multi-model inference; and (3) it is specifically designed to produce accurate predictions and standard errors for small datasets (Krivoruchko, 2012; Krivoruchko & Gribov, 2019; Gribov & Krivoruchko, 2020), making it well-suited to this study's calibration dataset of $n = 29$ survey sites.

EBKR makes several key assumptions: (1) input data are normally distributed; (2) the phenomenon being modeled is spatially continuous; (3) local stationarity holds within each prediction neighborhood, meaning the mean and variance are approximately constant locally though not necessarily across the full study area, which is an assumption EBKR is robust to moderate violations of; (4) the data exhibit spatial autocorrelation such that nearby observations are more similar than distant ones; and (5) sample locations were not preferentially selected. Each of these assumptions was evaluated prior to model fitting, as described in the following section.

8.6.2 Testing Empirical Bayesian Kriging Regression Prediction Assumptions

Prior to fitting EBKR models, data was explored to determine that there were no violations of EBKR assumptions, and that 29 samples comprised an adequate sample size for the planned analysis.

First, Average Nearest Neighbors analysis was performed in ArcGIS Pro version 2.9.5 to assess the spatial dispersion of the 29 survey sites. Normality and spatial autocorrelation of the log-transformed estimated and observed trash counts and masses (g) was tested via Shapiro-Wilks and Global Moran's I, respectively. Global Moran's I was performed using Inverse Distance Weighting in which nearby neighboring features have a larger influence on the computations for the target feature than other features that are farther away. This decision was based upon visual trends observed in the data (SI). Euclidean distance was used, and no standardization of spatial weights was applied since sites were randomly selected.

Ultimately, log-transformed estimates of trash mass (g) with standard error, derived from depletion modeling at 29 survey sites, were used as inputs for EBKR dependent variable because the data fit all EBKR modeling assumptions and was determined to have strong positive spatial autocorrelation. Log-transformation of estimated trash mass was performed using the natural logarithm function $\log()$ in R. Standard errors of the trash mass estimates were propagated onto the log scale using the Delta Method, whereby each standard error was divided by its corresponding untransformed estimate ($SE_{\log} = SE / \text{estimate}$). The suitability of the Delta Method approximation was confirmed by calculating the coefficient of variation ($CV = SE / \text{estimate}$) for all 29 observations, with all values falling well below

the 0.20 reliability threshold (mean CV = 0.006, max CV = 0.031). No additional data transformations were applied prior to interpolation.

A bootstrapping analysis was then conducted on log-transformed estimated trash masses to identify the sample size at which the variance of the bootstrapped means stabilizes, suggesting that additional samples would not substantially change the estimated mean log-transformed litter mass. Subsets of the log-transformed trash mass estimates were resampled with replacement across a range of sample sizes ($n = 5-29$, iterations = 10,000) to identify the sample size at which the mean variance in log-transformed litter mass stabilizes, indicating adequate representation of the population.

8.6.3 Incorporating Litter Mass Co-Variates into the Empirical Bayesian Kriging Regression Prediction Model

A kernel density surface created using the presence or absence of businesses where the most frequently observed trash items are sold or used was generated at a 21.7 m resolution to serve as a spatially continuous covariate, or explanatory variable raster, for EBKR. This covariate was selected based on the results of the multi-model inference approach explained previously. A search radius of 152 m was selected for kernel density estimation, consistent with the 152 m buffer distance used to quantify business influence on litter mass in regression analysis and representative of a radius of accessibility of pedestrians to the survey site, and a 21.7 m resolution was selected to match the cell size of the EBKR which is the default selected by ArcGIS Pro and calculated as the shortest extent dimension (i.e., either width or height) divided by 250.

8.6.4 Leave-One-Out Cross Validation of Empirical Bayesian Kriging Regression

Predictions

Model fit was assessed using leave-one-out cross-validation, in which each observation is temporarily withheld from the dataset and predicted from the remaining points; the predicted value is then compared to the observed value. Model performance was evaluated using the following diagnostics: Average Continuous Ranked Probability Score (CRPS), percentage of predictions falling within the 90% and 95% prediction intervals, Mean Standardized Error, Root Mean Square Standardized Error, Average Standard Error, Root Mean Square Error, and Mean Error. All EBKR interpolation and cross-validation were performed in ArcGIS Pro version 2.9.5.

8.6.5 Calibrating Empirical Bayesian Kriging Regression Predictions Using a Bland-Altman-Like Analysis

Bias in EBKR model predictions was quantified using a modification of the Bland-Altman method, which is a statistical method for assessing agreement between two methods of measurement as opposed to using a correlation coefficient which may falsely indicate agreement if, for example, the range of measured values is wide (Bland & Altman, 1986). In contrast to correlation, agreement is described by Bland and Altman as the amount by which a new method's measurements are likely to differ from the old and is demonstrated if this difference is acceptable for the desired application to use the two methods interchangeably. Where $\hat{d}$ is the mean of the differences between the Predicted and Measured values, and s is the standard deviation of the differences, Bland and Altman define the limits of agreement between two methods as differences within $\hat{d} \pm 2s$. Ideally, an acceptable disagreement should be decided in advance of Bland-Altman analysis, however, as this work represents

early exploratory application of EBKR for trash mass prediction at the watershed scale, limits of agreement will instead be reported here for consideration. Here, the two methods to be compared are the depletion model estimates of litter mass based upon observations made during 3-pass removal surveys, and the EBKR predicted litter mass interpolated using depletion model estimates.

Estimated litter mass is represented by M , denoting measured values, and EBKR model predictions from the best-fit model determined via leave-one-out cross validation were used, represented by P , for predicted values. For the best-fit and next-best-fit models, the difference between predicted and measured values was plotted against measured values, and were compared to the mean of the difference between Predicted and Measured values as well as the limits of agreement. Because the data are normally distributed, 95% of differences will lie between the limits of agreement which were calculated for each model using the equation:

$$(7) \hat{d} \pm 1.96s$$

In this way, Bland and Altman summarize the lack of agreement by calculating the bias, which is estimated by the mean difference ($\hat{d}$) and the standard deviation of the differences (s). A consistent bias can be adjusted for it by subtracting it from the new method (Bland & Altman, 1986).

To quantify bias across predicted values, a series of regressions were fit to the data (i.e. differences plotted against measurements), using `glm()` in base R, and the best fit model was selected using Bayesian Information Criteria (BIC). Regressions included linear, quadratic, cubic and quartic, as well as a null hypothesis model where $y = 1$. The intersect as well as the slope of the best fit regression line were used to determine the under- or over- estimation

of predicted values across the range of EBKR predictions, and the value at which predictions were most accurate.

9. Calculating Total Trash Mass and Density Across the Sidewalk Network by Priority Land Use Types

Kriging produces a surface of predicted values based on observed measurements. However, surveys only observed trash mass in accessible pedestrian areas. As such, the entire predicted surface is an unrealistic estimate of trash loading in the system that was actually surveyed as it covers areas that were not surveyed and are either unlikely to accumulate trash (i.e. building rooftops) or that may differ in trash accumulation from observed measurements (i.e. in the case of private properties or areas inaccessible to pedestrians). Priority land uses were assigned to sidewalk segments based on the land use designation of the nearest parcel, and this modified prediction layer was used to calculate trash mass loading and density across sidewalks both by land use and by watershed. For this reason, a layer of the city's sidewalk system buffered to have an area equivalent to the average transect width of 3.6 m was used to constrain the layer of predicted trash mass; this ultimately resulted in a 3,606,229 m² sidewalk network. A shapefile of the City of Santa Barbara's sidewalk inventory from 2020 was provided by UC Santa Barbara's Center for Spatial Studies and Data Science. The linear sidewalk network in this shapefile was first segmented at 5 m intervals, then these segments were converted to points which each represent a 5 m length of sidewalk. This created a total of 292,190 points. Then, sidewalk points were intersected using a 5 m buffer around parcels with assigned land uses contained in a shapefile of Existing Land Uses by parcel from 2023 which was provided by the City of Santa Barbara. Sidewalk points excluded from this intersect approach were assigned land

uses via Voronoi polygons. Quality control was performed throughout this workflow to ensure that no point was excluded from land use assignment and that no point received more than one land use assignment. Ultimately, 100% of the sidewalk point system was assigned to the land use of the nearest parcel.

Next, the sidewalk points with assigned land uses were used to extract EBKR log-transformed trash mass predictions and delta-transformed prediction standard errors in ArcGIS Pro version 2.9.5. Points were assigned to one of the three watersheds they fell within, and the attribute table was exported from ArcGIS Pro and used to perform all remaining analyses in R. EBKR predictions of log-transformed litter mass were back-transformed to gram scale using the exponential function prior to area weighting and summation. Point-level 95% confidence intervals were constructed on the log scale using delta-method standard errors before back-transformation, then summed across points within each watershed and land use combination to produce total mass estimates with conservative confidence bounds.

Initially, when calculating trash mass across watersheds and land uses, points were taken as 18 m² areas (5m segments $\times$ 3.6m width), but this resulted in a 45.8% over-count due to points clustering at intersections and curves. Therefore, a proportional approach was instead used to distribute the total sidewalk area evenly across all points regardless of land use, by dividing the total sidewalk area (3,606,229 m²) by the total number of points (292,190) points. Ultimately, each sidewalk point represented a 12.34 m² area. A total over-counting bias of 0.56% still occurred due to curved segments of sidewalk where the curve caused segments to overlap. A bias analysis revealed that the total potential over-count across all

land use types was 0.56% of total sidewalk area and affected no single land use by more than approximately 3%, which was considered negligible and no correction was applied.

C. Results

1. Description of Removed Trash

A total of 3,098 pieces of trash were removed during repeated pass surveys, equivalent to 2.6 kg (SI Table: Raw Data). Trash items ranged in mass from less than 0.01 g to 77.07 g (SI Table: Raw Data). The median mass was 0.17 g and the average mass was 0.85 g (SD $\pm$ 3.79). The length of each item's longest dimension was measured, and the smallest items were 2 mm with the largest item being 770 mm (SI Table: Raw Data). The median size was 31 mm, and the mean was 46.8 mm (SD $\pm$ 53.3 mm). Only 49 pieces of trash were 5 mm or less in size, and were therefore considered microplastics. Most ($n = 889$) plastic items removed during surveying were mesoplastics (i.e. 5 mm – 25 mm), while 485 plastic trash items were macroplastics (i.e. 25 mm – 1 m)

Forty percent of items ($n = 1230$) could not be assigned to a functional use category due to their level of degradation or lack of distinguishable features; these items ranged in size from 2 mm to 620 mm, with masses ranging from less than 0.01 g to 23.49 g. Fifty percent of the items with an undeterminable functional use appeared to be made of plastic (Figure 2). Many plastic items within the undeterminable functional use category were described as films, fragments, and foams.

Approximately 20% of items were identified as tobacco cigarettes ($n = 611$), 10% as single-use food packaging ($n = 303$), and 8% as single-use packaging ($n = 263$). Of all

collected items, 1,404 (45%) appeared to be composed solely of plastic, 573 (18%) of paper–plastic composites, and 541 (17%) of paper.

Tobacco cigarette butts were the second most frequently observed trash item ($n = 611$) (Figure 2). Most were composed of both paper and plastic, indicating that the paper wrapper was still partially or fully intact at the time of removal surveying. Cigarette butts without a paper wrapper were categorized as plastic, as these consisted of filters, which are most commonly made of cellulose acetate, a type of plastic derived from wood pulp (Novotny, 2024). Alternatively, cigarette butts consisting only of paper wrappers without filters were categorized as paper.

Other items appeared to be made of combinations of materials, or materials other than plastic, paper, metal, or glass. This includes items made of metal/plastic ($n = 56$), paper/metal ($n=46$), rubber ($n=26$), gum ($n=18$), wood ($n=12$), paper/metal/plastic ($n=8$), cardboard ($n=4$), cellulose ($n=4$), cotton/plastic ($n=4$), cardstock/plastic ($n=3$), rubber/plastic ($n=3$), wood/plastic ($n=3$), cardstock ($n=2$), chalk ($n=2$), silicone ($n=2$), cork ($n=1$), cotton/paper ($n=1$), metal/wood ($n=1$), wood/plastic/metal ($n=1$). Forty-six items appeared to be human-made, but their material composition was unidentifiable, so they were

categorized as “anthropogenic”. Thirty-seven items appeared to be human-made and the material appeared to be unnatural, and these were categorized as “synthetic”.

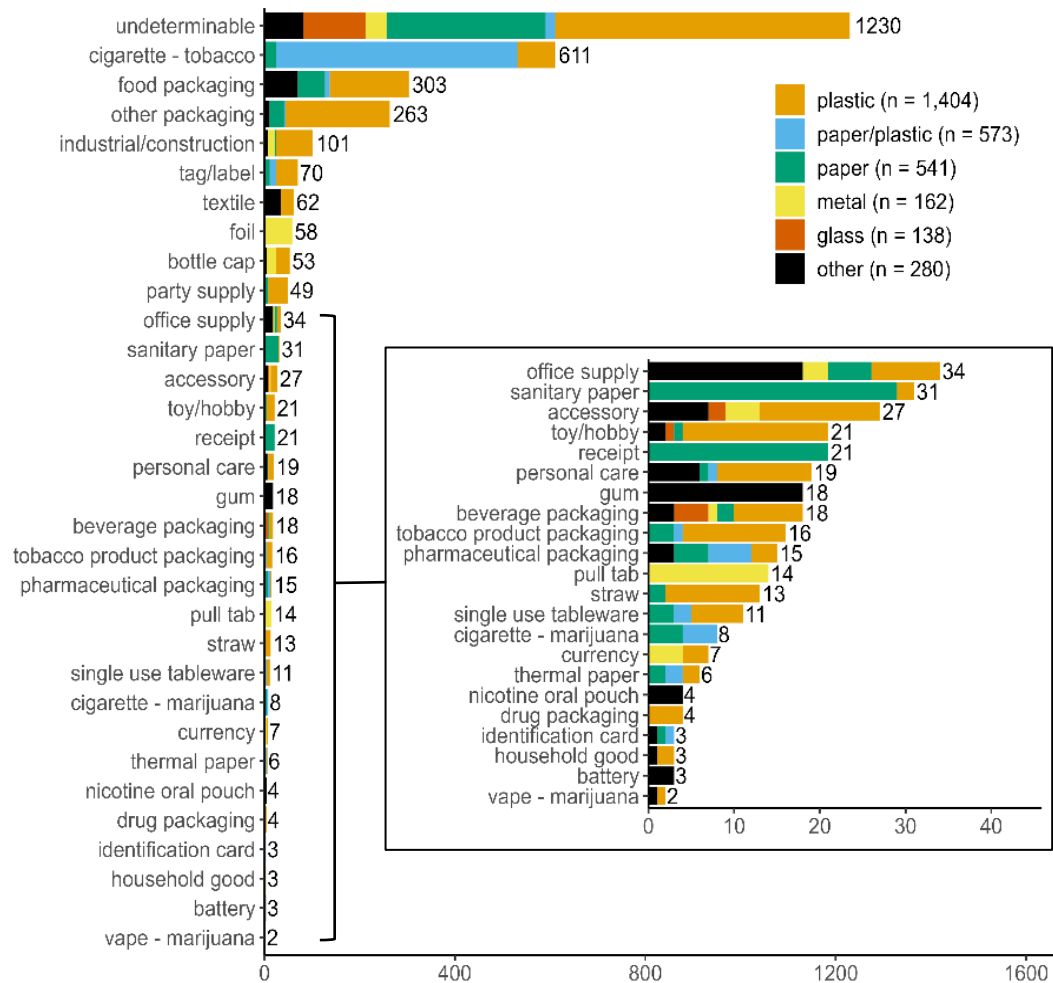


Figure 2: Observed trash abundance and material composition by functional use category. Each item collected during repeated-pass surveys was counted and classified according to its inferred functional use (i.e., intended use) and suspected material. Functional use categories are shown on the y axis, and count is shown on the x axis. The total number of items within each functional use category is shown to the right of each stacked bar. Colored segments within each bar indicate the material composition of items in that category, with colors corresponding to the legend, which also reports the total count of each material across all categories.

Although over 196 unique brand names were associated with trash removed during repeated pass surveys, the three most frequently observed brands were tobacco companies Marlboro (n = 75), Camel (n = 29), and Seneca (n = 19) (Figure 3).

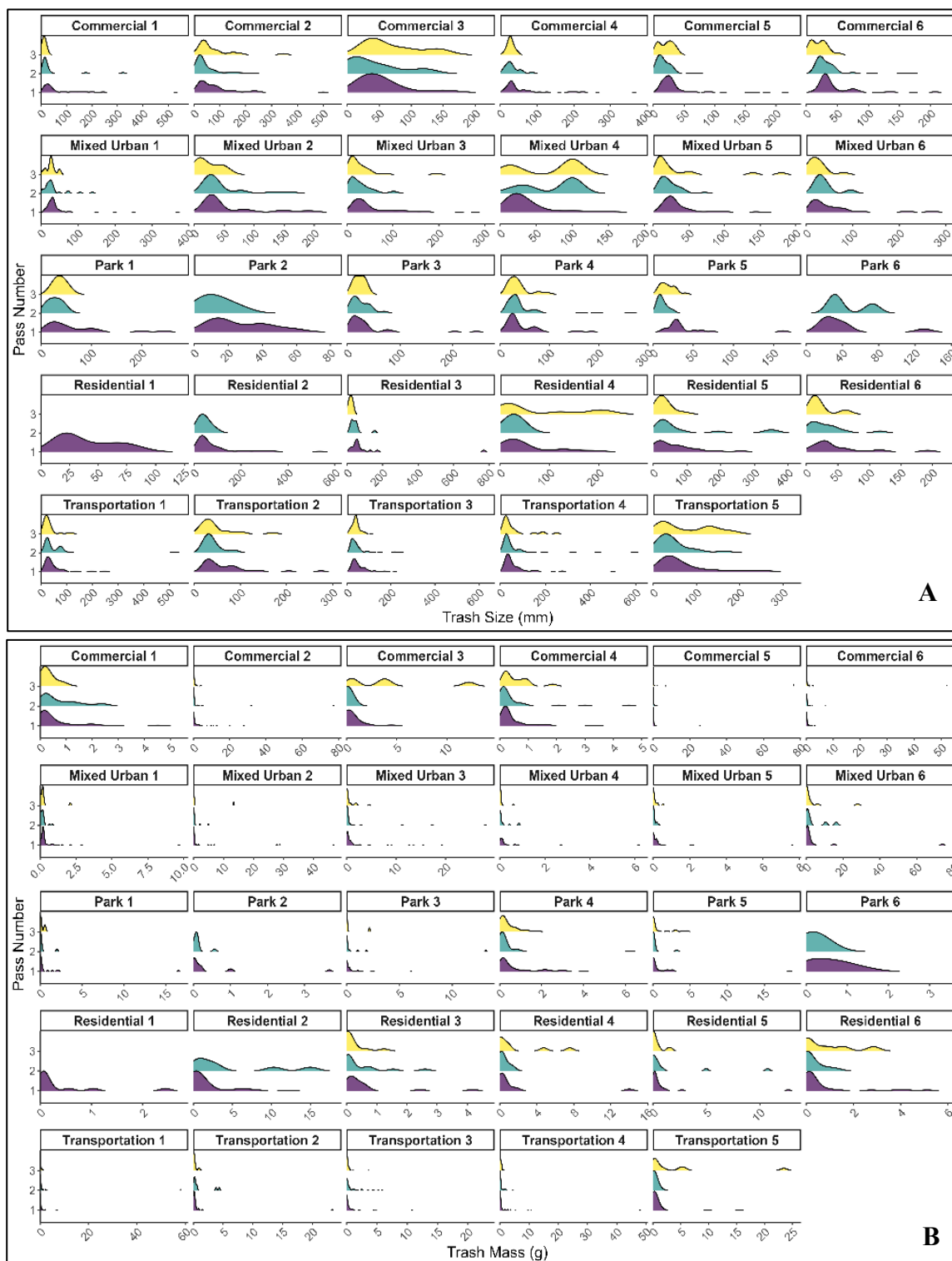


Figure 4. Distributions of Removed Trash Size and Mass Across 3-Pass Removal Surveys For each of the 29 survey sites, the distribution of size (mm) (A) or mass (g) (B) of removed trash is visualized per survey pass. First pass distributions are purple, second pass are teal, and third pass are yellow.

2. Agreement Between On-Land Visual Trash Assessment Ranks and Depletion-Modeled Trash Estimates

First pass trash counts and masses (g) were underestimated by 48% ($\pm 18\%$) and 46% ($\pm 16\%$), respectively, when compared to total trash abundance estimations derived from depletion modeling (Figure 5).

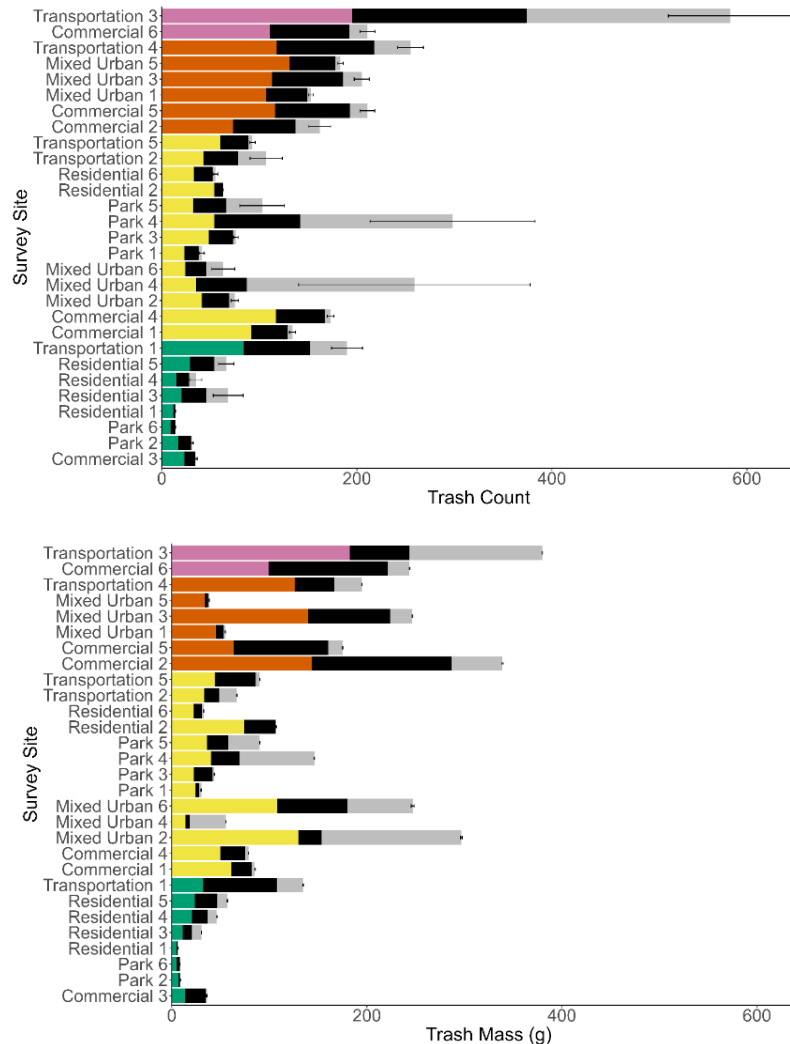


Figure 5. Litter count (top) and litter mass (g) (bottom) across all 29 sites surveyed in Santa Barbara, California. Litter recovered during pass one of each survey is represented by either the green, yellow, orange, or pink portion of each bar, where each color represents one of four OVTA ranks (i.e., green: Not Littered, yellow: Slightly Littered, orange: Littered, and pink: Very Littered); the difference between total litter recovered by the final survey pass and litter recovered in pass one is indicated in black, and the estimation of the true abundance of litter is shown in grey, with standard errors.

To assess whether the single-surveyor modification of the OVTA method introduced systematic bias, initial OVTA ranks assigned by the lead surveyor were compared to final consensus ranks across all 29 sites. Initial and consensus ranks agreed at 24 of 29 sites (82.8%), with five sites receiving a revised rank following post-hoc group discussion. Cohen's kappa indicated substantial inter-rater agreement ($\kappa = 0.75$; Landis & Koch, 1977). Of the five rank-revised sites, four were downgraded by one rank level and one was upgraded by one rank level, spanning three Priority Land Use types with no clustering in any single category. All disagreements occurred between adjacent trash ranks only. The absence of consistent directional bias, the distribution of changes across priority land use types, and the substantial kappa value together suggest that the single-surveyor modification to the OVTA method did not introduce systematic bias into rank assignments. Furthermore, because OVTA ranks are used in this study for agreement assessment rather than as a primary analytical input, any residual inter-rater variability would affect only the methods agreement analysis and would not propagate into litter mass estimates or spatial predictions.

The cumulating proportions of trash count and mass removed per pass were visualized using minimum convex polygons, with group separation quantified using normalized centroid distances and convex hull intersection areas (Figure 6). For both count and mass measurements, a positive linear trend was observed between first-pass removal and total trash removed across all OVTA ranks, with the highest ranks (i.e. not littered and very littered) showing the greatest centroid separation (normalized distances: 2.07–2.51), while adjacent ranks were substantially less distinct, particularly not littered vs. slightly littered (0.67–0.92) and slightly littered vs. littered (1.16–1.30). Hull intersection analysis confirmed substantial overlap between adjacent ranks, with 35–81% of littered hull area overlapping

with slightly littered hulls, indicating that depletion proportions become increasingly indistinguishable between neighboring trash condition categories.

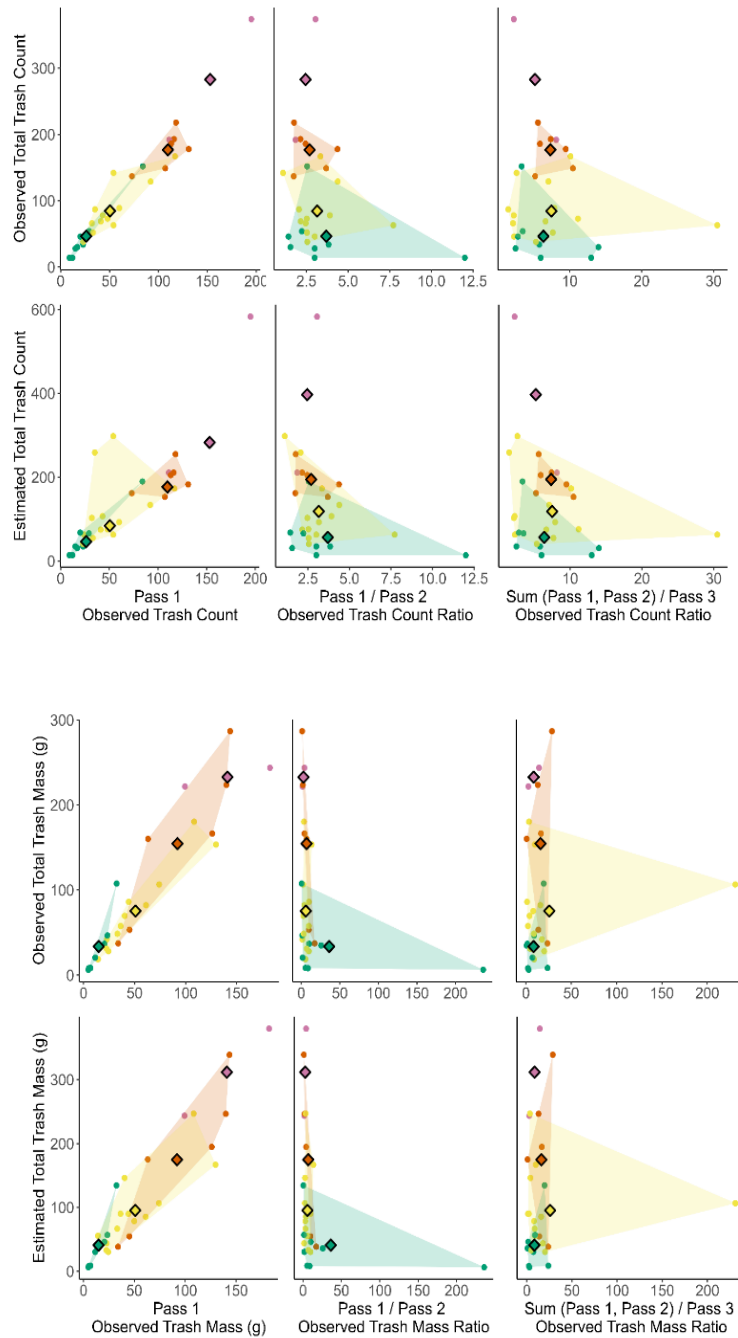


Figure 6. Cumulating proportions of trash removed per pass relative to total observed and estimated trash by OVTA rank. Points represent observations at each survey site (n=29), diamonds represent centroids (mean) of points within each rank and are shown to aid visual comparison of central tendency among trash condition categories. Contours are minimum convex polygons which visualize group extent and overlap. Green represents “not littered” sites, yellow represents “slightly littered”, “littered” sites are shown in orange, and “very littered” in pink.

To measure agreement between trash count and mass measurements and OVTA visual assessment ranks, one-way ANOVAs were conducted comparing three measures of log-transformed trash counts and three measures of log-transformed trash masses across OVTA categories (not littered, slightly littered, and littered). The Very Littered rank was excluded from all analyses as only two sites fell into this category, which was insufficient for reliable group-level estimation.

First-pass log-transformed trash counts differed significantly across OVTA ranks ($F(2, 24) = 18.62, p < 0.001$), with all pairwise comparisons significant (Not Littered vs. Slightly Littered: $p = 0.005$; Not Littered vs. Littered: $p < 0.001$; Slightly Littered vs. Littered: $p = 0.005$). Log-transformed total observed trash count also differed significantly across OVTA ranks ($F(2, 24) = 16.43, p < 0.001$), with all ranks differing from each other (Not Littered vs. Slightly Littered: $p = 0.006$; Not Littered vs. Littered: $p < 0.001$; Slightly Littered vs. Littered: $p = 0.012$). Depletion-modeled estimated trash count varied significantly by OVTA rank ($F(2, 24) = 11.0, p < 0.001$), with significant differences between Not Littered and Slightly Littered ($p = 0.010$) and Not Littered and Littered ($p < 0.001$), but not between Slightly Littered and Littered ($p = 0.112$).

OVTA rank significantly predicted log-transformed litter mass across all three mass metrics (first-pass mass: $F(2, 24) = 15.39, p < 0.001$; total cumulative mass: $F(2, 24) = 8.17, p = 0.002$; depletion-estimated mass: $F(2, 24) = 7.78, p = 0.002$), confirming that objectively measured litter mass is consistent with independent visual assessments across all measurement approaches. However, Tukey's HSD post-hoc tests revealed that Slightly

Littered and Littered sites were not significantly different in any mass-based metric (first-pass mass: $p = 0.150$; total mass: $p = 0.225$; estimated mass: $p = 0.429$), and no significant difference was detected between Slightly Littered and Littered sites in the depletion-estimated count model either ($p = 0.112$). In contrast, all three count-based models and all three mass-based models identified significant differences between Not Littered sites and both Slightly Littered and Littered sites ($p \leq 0.023$ across all comparisons). These results are visualized in Figure 7.

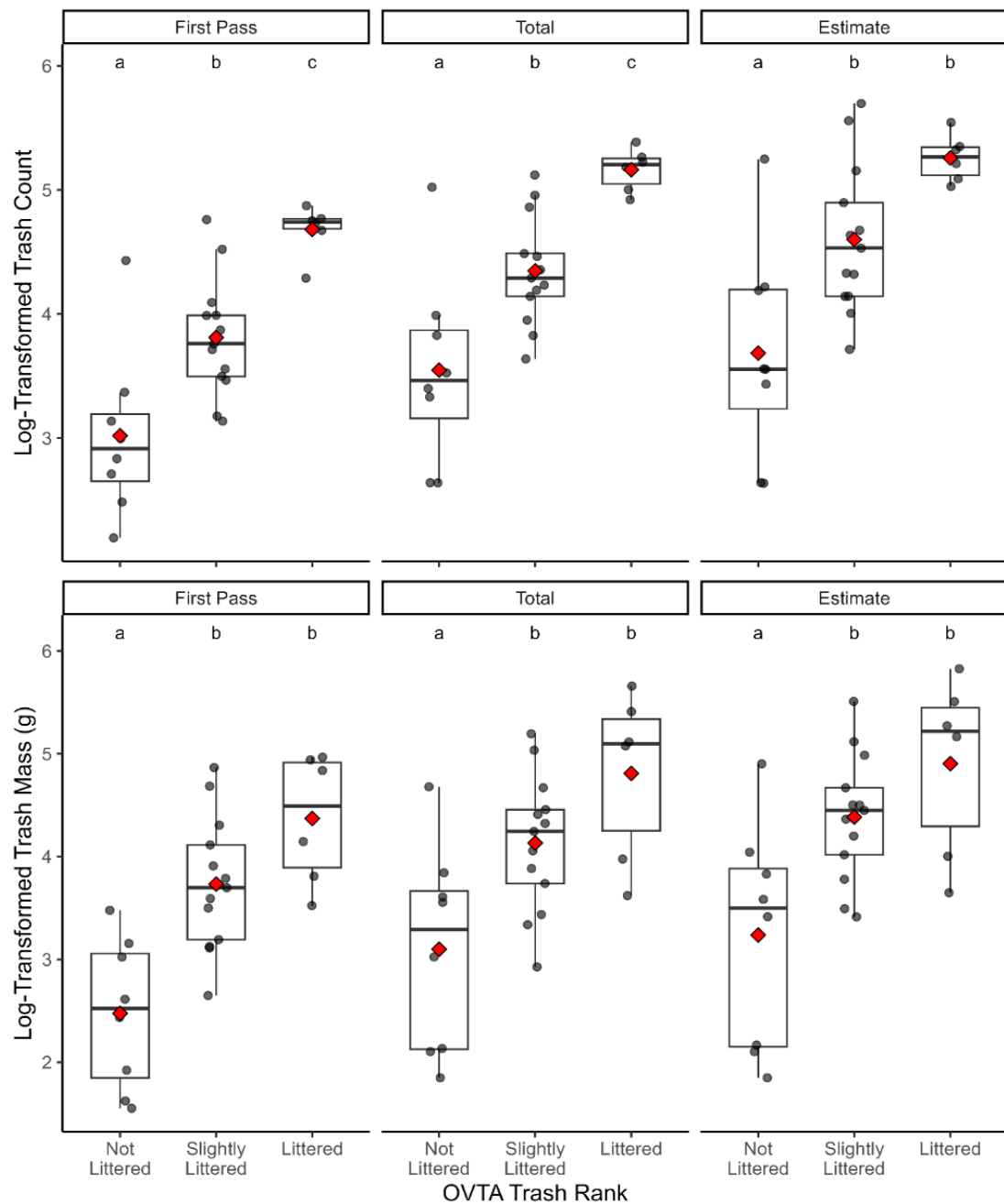


Figure 7. Log-transformed trash count and mass by OVTA rank across 27 survey sites. Grey points represent individual site observations and red diamonds represent group means. Shared letters above boxplots indicate no statistically significant difference between groups (Tukey's HSD, $\alpha = 0.05$).

Levene's tests confirmed homogeneity of residual variance across ranks for all six models (for count models, log-transformed total: $F(2, 24) = 2.56$, $p = 0.098$; log-transformed estimate: $F(2, 24) = 2.34$, $p = 0.118$; log-transformed first-pass: $F(2, 24) = 1.82$, $p = 0.184$; and for mass models, first-pass mass: $F(2, 24) = 0.17$, $p = 0.842$; total mass: $F(2, 24) = 1.01$, $p = 0.380$; estimated mass: $F(2, 24) = 1.33$, $p = 0.284$), ruling out differential variance as an explanation for the non-significant Slightly Littered vs. Littered comparisons. Notably, residual variance decreased monotonically with rank across all count-based models, suggesting that littered sites were measured most consistently regardless of method, while “Not Littered” sites showed the greatest measurement variability.

Mass-based models showed no such consistent variance reduction across ranks (Littered residual SD: 0.63–0.83 vs. Not Littered: 0.72–1.09), in contrast to the monotonically decreasing variance observed in count-based models. This suggests that while litter item counts are reliably and consistently measured at high-density sites, litter mass remains highly variable regardless of OVTA rank. This likely reflects site-to-site differences in litter composition rather than true abundance. The convergence of all mass-based models on a non-significant Slightly Littered vs. Littered comparison, combined with the homogeneity of variance confirmed by Levene's tests, indicates that genuine compositional variability, and not differential measurement error, is the source of mass uncertainty at higher litter densities, and that litter mass is a less sensitive visual discriminator of litter density than item count.

3. Variables Predicting OVTA Trash Condition Categories

To identify which trash and site-level predictor variables best predicted trash condition categories, a Random Forest (RF) classification was performed in which the response variable was the site's trash condition category. Variable importance was assessed via the Mean Decrease in Gini index, which quantifies how much each predictor improves classification accuracy.

Although a variety of characteristics related to trash items and transect type were used as predictors, pass 1 observed trash count was the most important predictor in separating survey sites by OVTA rank, followed by total observed trash count after 3 survey passes, then pass 1 observed trash mass (Figure 8).

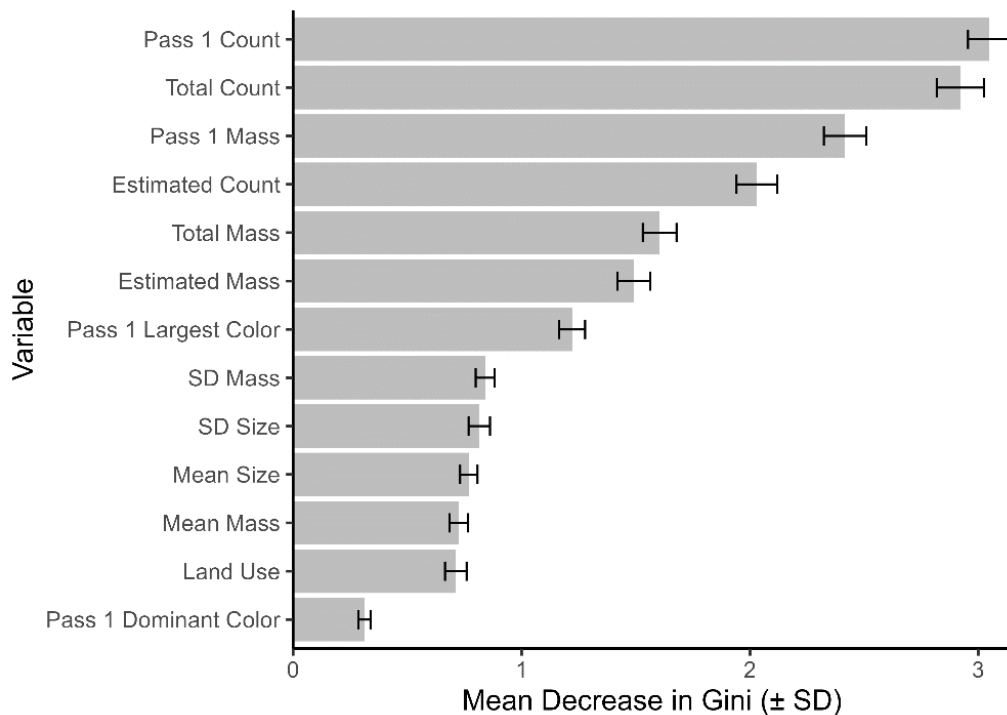


Figure 8. Mean Decrease in Gini of Trash and Site-level Predictor Variables. Grey bars show the mean decrease in Gini, and error bars (black) show standard deviation, for random forest analysis repeated 100 times.

4. Trash Mass and Density Across the Sidewalk Network

4.1 Litter Mass Co-Variates

Multi-model inference identified business presence/absence as the best-supported predictor of log-transformed depletion-estimated litter mass ($\text{BIC} = 81.08$, $R^2 = 0.388$, Adj. $R^2 = 0.365$, $p < 0.001$), with strong to very strong evidence against all alternative models ($\Delta\text{BIC} \geq 7.09$) (Table 1). Sites with at least one qualifying business within 152 m had significantly higher estimated litter mass than sites without ($\beta = 1.317$, $p < 0.001$). Business count was the only other significant single-predictor model ($R^2 = 0.219$, $p = 0.011$, $\text{BIC} = 88.17$), but was strongly outperformed by the binary model ($\Delta\text{BIC} = 7.09$) (Figure 9). Bus stop count ($R^2 = 0.077$, $p = 0.144$, $\text{BIC} = 92.98$), public waste container count ($R^2 = 0.039$, $p = 0.305$, $\text{BIC} = 94.16$), and the full model including all three predictors ($R^2 = 0.251$, $p = 0.061$, $\text{BIC} = 93.68$) all performed no better than the null model ($\text{BIC} = 91.95$), with ΔBIC values of 11.90, 13.08, and 12.60 respectively (Table 1) indicating very strong evidence against each relative to the binary presence/absence model.

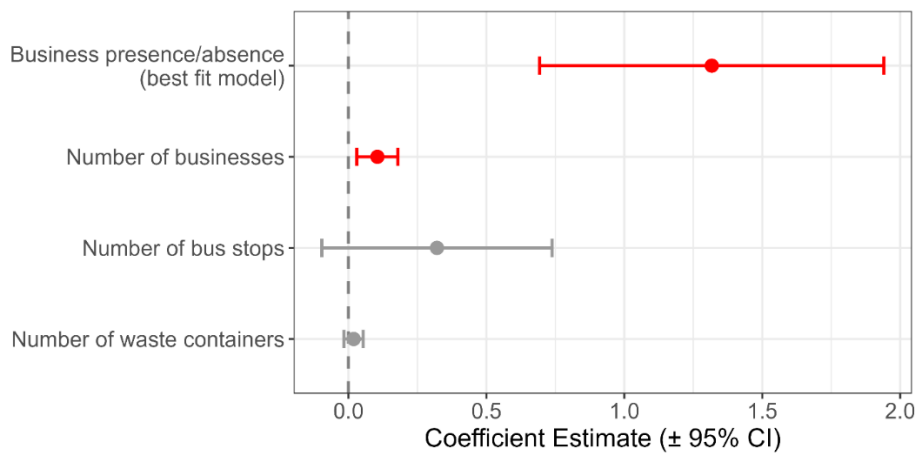


Figure 9. Multi-Model Inference Coefficient Plot. Coefficient estimates ($\pm 95\%$ CI) from single-predictor linear models of log-transformed depletion-estimated litter mass (g) at 29 survey sites in Santa Barbara, CA. Red points indicate significant predictors ($p < 0.05$); grey points indicate non-significant predictors. Business presence/absence was the best supported predictor based on BIC model selection ($\Delta\text{BIC} \geq 7.09$ vs all alternatives).

Table 1. Results of multi-model inference

Model	Predictor	n	R ²	Adj. R ²	p-value	BIC	Δ BIC	Evidence
Business presence/absence (best fit)	p_businesses	29	0.388	0.365	<0.001	81.08	0	Best supported
Business count	n_businesses	29	0.219	0.190	0.011	88.17	7.09	Strong evidence against
Null (intercept only)	—	29	—	—	—	91.95	10.87	Very strong evidence against
Bus stops	n_bus_stops	29	0.077	0.043	0.144	92.98	11.90	Very strong evidence against
Full model (all predictors)	n_businesses + n_bus_stops + n_containers	29	0.251	0.161	0.061	93.68	12.60	Very strong evidence against
Trash containers	n_containers	29	0.039	0.003	0.305	94.16	13.08	Very strong evidence against

Diagnostic tests confirmed that the business presence/absence best-fit model, as well as all other models, met Ordinary Least Squares assumptions. Residuals of the best-fit model were normally distributed (Shapiro-Wilk: $W = 0.976$, $p = 0.720$) and homoscedastic (Breusch-Pagan: $BP = 2.192$, $df = 1$, $p = 0.139$). No observations for the best-fit model exceeded Cook's distance thresholds for moderate ($D > 0.5$) or high influence ($D > 1.0$), with the maximum Cook's distance of 0.17, indicating no unduly influential observations.

4.2 Satisfying Assumptions of Empirical Bayesian Kriging Regression Prediction

Average nearest neighbor analysis indicated that the 29 survey sites were slightly dispersed relative to complete spatial randomness ($R = 1.16$), but this pattern was not statistically significant ($z = 1.61$, $p = 0.11$).

Of all potential dependent variables tested, log-transformed estimated litter mass exhibited the strongest and most distance-magnitude dependent spatial autocorrelation, making it the most appropriate input variable for EBKR, which models spatial structure through a semivariogram and uses that model to predict values at unsampled locations. Global Moran's I analysis, performed using inverse distance weighting with Euclidean distance and no spatial weight standardization, indicated significant positive spatial autocorrelation in log-transformed estimated litter mass among the 29 sampling sites (Moran's Index = 0.488, $z = 4.13$, $p < 0.001$). This result confirms that nearby sites tend to have more similar estimated litter mass measurements than distant sites, validating the assumption of spatial autocorrelation required for geostatistical interpolation and supporting the use of EBKR to predict litter mass at unsampled locations across the study area. Although the number of sampling sites ($n = 29$) falls just below ArcGIS Pro's recommended minimum of 30 for Global Moran's I analysis, the observed clustering pattern is statistically unambiguous and spatially consistent with known land use and street network structure in Santa Barbara.

Log-transformed cumulative observed mass and log-transformed estimated count and cumulative observed exhibited relatively weaker spatial autocorrelation (SI) and therefore were not used for EBKR modeling.

Raw litter mass estimates were significantly non-normal (Shapiro-Wilk: $W = 0.858$, $p = 0.001$), exhibiting a right-skewed distribution consistent with the stochastic nature of litter accumulation. Log-transformation successfully normalized the data ($W = 0.950$, $p = 0.185$), justifying the use of log-transformed estimated litter mass as the input variable for EBKR modeling.

A bootstrapping analysis was conducted on estimated trash masses to identify the sample size at which the variance of the bootstrapped means stabilizes, suggesting that additional samples would not substantially change the estimated mean log-transformed litter mass. Bootstrapping analysis confirmed sample adequacy for mean estimation at $n=25$ (Figure 10), supporting the stability of EBKR predictions despite a small sample size.

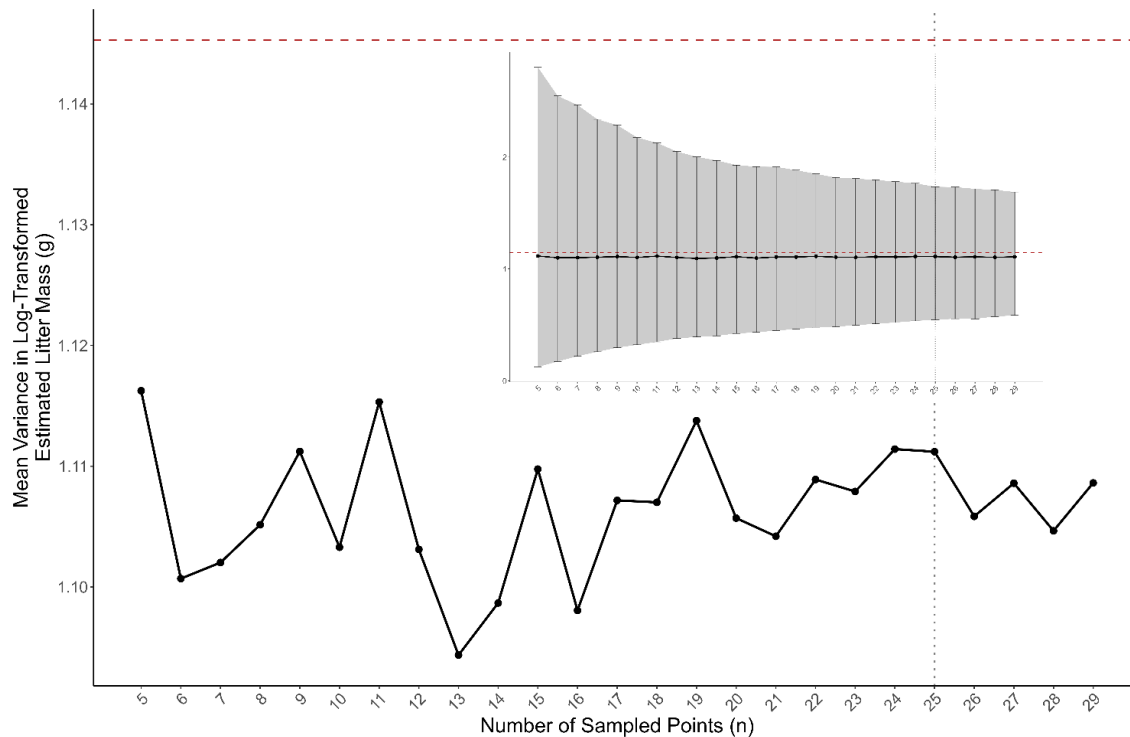


Figure 10. Bootstrap-based estimates of variances for log-transformed estimated litter mass (g) across sample sizes ($n = 5–29$). Black points represent the mean variance estimated via nonparametric bootstrapping with replacement (10,000 replicates per sample size). The horizontal red dashed line indicates the variance of the full dataset ($n = 29$). The vertical gray dotted line at $n = 25$ marks the sample size at which the mean variance begins to stabilize. The inset displays the same results and includes 95% bootstrap percentile confidence intervals.

4.3 Empirical Bayesian Kriging Regression Prediction Validation

EBKR using log-transformed estimated litter mass with delta-transformed standard errors of the litter mass estimate and a whittle semivariogram model incorporating a binary kernel density surface of business presence/absence as a covariate outperformed all other semivariogram models (i.e. exponential and K-Bessel) across all cross-validation metrics. The cross-validation metric results for the best-fit EBKR model are included in Table 2.

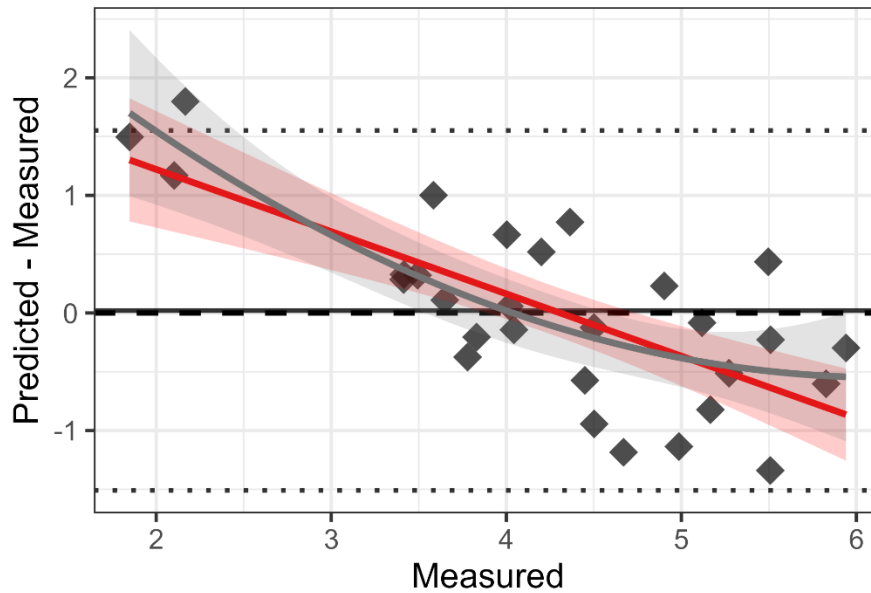
Table 2. Leave-One-Out Cross-Validation Metrics for Best-Fit EBKR Model

EBKR Cross-Validation Metric	Value	Justification
<i>Average Continuous Ranked Probability Score</i>	0.43	Lowest of all models fit
<i>Inside 90 Percent Interval</i>	89.66	Close to 90
<i>Inside 95 Percent Interval</i>	100	Close to 95
<i>Mean Error</i>	0.02	Close to 0
<i>Root-Mean-Square Error</i>	0.77	Lowest of all models fit
<i>Mean Standardized Error</i>	0.02	Close to 0
<i>Root-Mean-Square Standardized (RMSE)</i>	1.03	Close to 1
<i>Average Standard Error</i>	0.77	Small and similar to RMSE

4.4 Bland-Altman-Like Calibration of Best-Fit Empirical Bayesian Kriging Regression Prediction Model

Bias of the best-fit EBKR model was assessed using a Bland-Altman-like approach. Multi-model inference using Δ BIC identified a linear relationship as the best supported description of bias between EBKR predictions and depletion-modeled litter mass estimates (BIC = 55.35; Δ BIC = 0.41 vs quadratic, Δ BIC = 18.31 vs null). The linear model revealed statistically significant proportional bias (slope = -0.529, $p < 0.001$), whereby the model

over-predicted litter mass at low-mass sites and under-predicted at high-mass sites, with the transition from over- to under-prediction occurring at approximately 74g estimated litter mass (equivalent to 4.31 g when log-transformed) (Figure 11). The quadratic model had marginally lower AIC but was not preferred by the Δ BIC approach due to the non-



significant quadratic term ($p = 0.107$), suggesting the bias pattern is adequately described by a linear relationship across the observed range of litter mass.

Figure 11. Bland-Altman-like plot for Best-Fit EBKR Model. Agreement between predicted and measured log-transformed litter mass (g) across 29 survey sites shown as grey diamonds. The dashed horizontal line indicates perfect agreement (bias = 0); the solid horizontal line indicates mean bias (0.021 log g); dotted horizontal lines indicate 95% limits of agreement (-1.509 to +1.551 log g). The red line and shading show the best supported linear trend (BIC-selected); the grey line and shading show the next-best quadratic trend for comparison. Both fits include 95% confidence intervals.

4.5 Predicted Litter Mass Across the Sidewalk Network

Total estimated litter mass across Priority Land Use-designated sidewalks in all three watersheds was 106,013 kg (95% CI: 37,987–345,596 kg), based on EBKR-predicted litter mass extracted at 260,970 PLU-designated sidewalk points, each representing 12.4 m² of

sidewalk, for a total PLU sidewalk area of 1,231,952 m² across the Mission Creek watershed, Laguna Channel Drain, and Laguna Tidal Drain.

4.6 Predicted Litter Mass at the Watershed-Level and Priority Land Use-Level

Mission Creek had the highest total estimated litter mass at 69,912 kg (95% CI: 23,046–246,079 kg), consistent with it having the largest PLU sidewalk network of the three watersheds (1,038,599 m², 83,758 points). Laguna Channel Drain had an intermediate total mass of 21,114 kg (95% CI: 7,578–66,435 kg; 134,565 m²), and Laguna Tidal Drain had the lowest total mass at 14,987 kg (95% CI: 7,363–33,082 kg; 58,788 m²). Figure 12 visualizes the total estimated litter mass in megagrams (Mg) across all Priority Land Uses for each watershed.

Across all three watersheds, sidewalks assigned to residential land use had the highest total estimated litter mass at 56,363 kg (95% CI: 16,910–214,025 kg), reflecting their dominant areal representation in the sidewalk network (856,642 m², 69,084 points). Commercial sidewalks had the second highest total mass at 34,951 kg (95% CI: 14,744–91,546 kg), followed by Transportation (6,064 kg; 95% CI: 2,581–16,430 kg), Mixed Urban (5,189 kg; 95% CI: 2,399–12,613 kg), and Parks (3,446 kg; 95% CI: 1,353–10,981 kg).

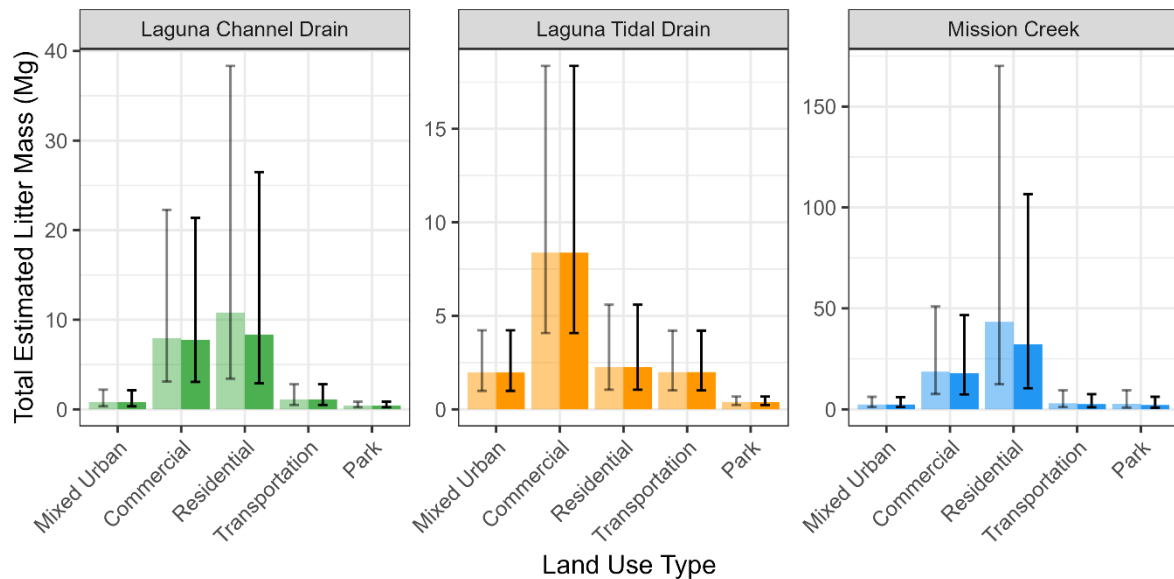


Figure 12. Total estimated litter mass (Mg) on Priority Land Use-designated sidewalks by watershed and land use type. Transparent bars represent estimates derived from all EBKCR predictions with 95% confidence intervals (grey error bars). Solid bars represent estimates derived from the precision-filtered subset of EBKCR predictions retained within the Bland-Altman-like limits of agreement with 95% confidence intervals (black error bars). Confidence intervals reflect the conservative summation of point-level prediction uncertainty and should be interpreted as upper bounds on total uncertainty. Note that y-axis scales differ across panels; bar heights are not directly comparable between watersheds.

However, when accounting for differences in watershed size by expressing litter load as mass per unit sidewalk area, the watershed-level ranking reversed. Laguna Tidal Drain had the highest litter density at 255 g/m², approximately 3.8 times higher than Mission Creek (67.3 g/m²) and 1.6 times higher than Laguna Channel Drain (157 g/m²). This suggests that while Mission Creek receives the greatest total litter load due to its larger PLU sidewalk network, Laguna Tidal Drain sidewalks accumulate disproportionately more litter per unit area, indicating a spatially concentrated litter problem in the Laguna Tidal Drain watershed independent of network size.

Expressing litter load as mass per unit sidewalk area also revealed that Mixed Urban sidewalks had the highest total litter density at 177 g/m², closely followed by Commercial at

146 g/m², which are both substantially higher than Residential sidewalks (65.8 g/m²).

Transportation sidewalks had an intermediate density of 111 g/m², while Residential (65.8 g/m²) and Parks (65.1 g/m²) had the lowest and nearly identical densities. This pattern is consistent with California Trash Amendment Priority Land Use designations, which identify commercial and Mixed Urban land uses as disproportionate contributors to litter generation, and provides local empirical support for those designations in the context of the City of Santa Barbara. Figure 13 visualizes litter density in grams per square meter of sidewalk (g/m²) across all Priority Land Uses for each watershed.

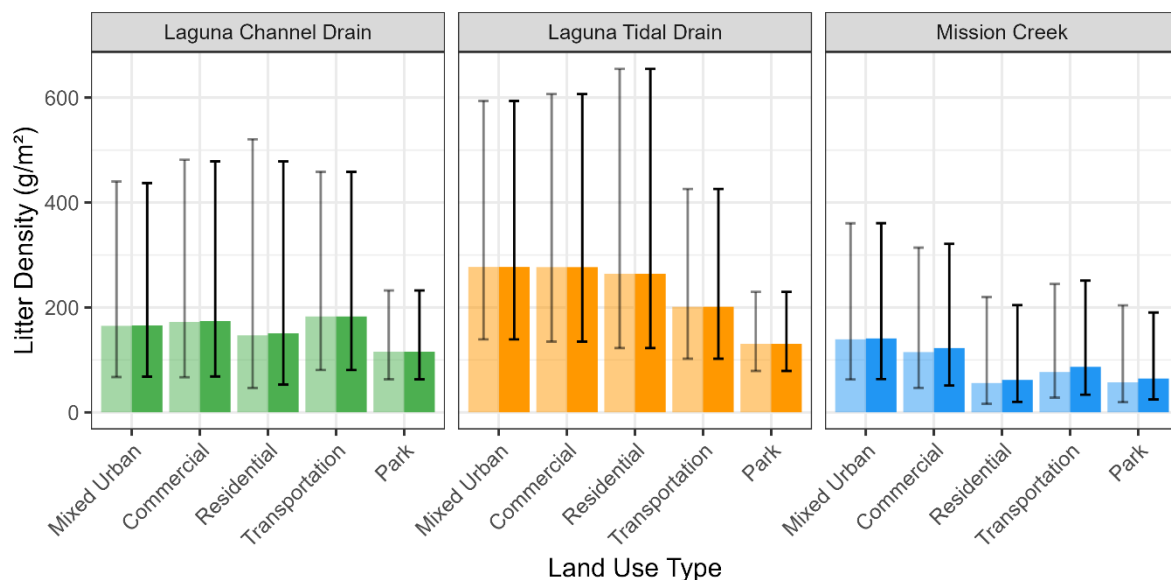


Figure 13. Litter density (g/m²) on Priority Land Use-designated sidewalks by watershed and land use type. Transparent bars represent estimates derived from all EBKR predictions with 95% confidence intervals (grey error bars). Solid bars represent estimates derived from the precision-filtered subset of EBKR predictions retained within the Bland-Altman-like limits of agreement with 95% confidence intervals (black error bars). Confidence intervals reflect the conservative summation of point-level prediction uncertainty and should be interpreted as upper bounds on total uncertainty. Note that y-axes are scaled equally across panels; bar heights are directly comparable between watersheds.

Litter density patterns varied across watersheds when examined at the land use level, revealing important spatial heterogeneity beyond the watershed-level findings. In Mission Creek, the clearest Priority Land Use signal was observed, with Mixed Urban (139 g/m²)

and Commercial (115 g/m²) sidewalks having the highest litter density, approximately 2.5 times and 2.1 times higher than Residential (55.9 g/m²) and Parks (56.9 g/m²) sidewalks, respectively. Laguna Channel Drain showed a similar but attenuated pattern, with Transportation (183 g/m²) and Commercial (172 g/m²) sidewalks having the highest density, followed by Mixed Urban (165 g/m²), while Parks (116 g/m²) had the lowest.

Laguna Tidal Drain exhibited a markedly different pattern: litter density was uniformly elevated across all land use types, with even Residential sidewalks (264 g/m²) exceeding Commercial sidewalk density in Mission Creek (115 g/m²). Commercial and Mixed Urban sidewalks both reached 277 g/m² in Laguna Tidal Drain, which were the highest densities observed across any land use and watershed combination in this study. The uniformly elevated litter density across all land use types in Laguna Tidal Drain suggests a location-specific effect beyond land use designation alone, warranting targeted area-wide intervention regardless of land use type.

When the analysis was restricted to predictions meeting the Bland-Altman-like limits of agreement precision threshold ($SE \leq 0.781$; 48.4% spatial coverage overall), total mass estimates were modestly reduced across all watersheds and land use types, while density rankings and relative magnitudes were preserved in all cases. Laguna Tidal Drain retained 100% of its sidewalk points under the precision filter, providing the highest confidence in its estimates. Mission Creek and Laguna Channel Drain retained 71.9% and 85.2% of their sidewalk points, respectively.

Under the precision filter, watershed-level density estimates remained the same for Laguna Tidal Drain 255 g/m² but increased in both the Laguna Channel Drain and Mission

Creek watershed to 161 g/m² and 76.5 g/m², respectively. Land use density rankings were generally preserved, with Mixed Urban (179 g/m²) and Commercial (154 g/m²) land uses remaining the highest density land use types, and Residential (73.1 g/m²), Parks (74.2 g/m²), and Transportation (124 g/m²) following the same relative ordering as in the full dataset. The consistency of findings between full and precision-filtered analyses supports the robustness of the reported patterns.

The precision filter retained the highest proportion of Mixed Urban (82.4%) and Commercial (66.5%) points, and the lowest proportion of Parks (44.1%) and Residential (44.2%) points, suggesting that EBKR predictions are relatively most precise in high-density commercial areas and relatively least precise in lower-density residential and parks-adjacent sidewalks which is consistent with the spatial distribution of the survey sites, which, although not clustered, were more densely concentrated in commercial areas of the study region due to the land use stratification approach to surveying and the spatial pattern of Priority Land Uses across the City.

D. Discussion

This study evaluated agreement between single-pass, multiple-pass, and depletion-modeled litter abundance (i.e., counts and masses) and OVTA rankings from sidewalk surveys across Priority Land Use types in three watersheds in the City of Santa Barbara, California. Site-level urban covariates of litter mass accumulation were identified via multi-model inference, with business presence/absence emerging as the strongest predictor and serving as a spatially continuous covariate for Empirical Bayesian Kriging Regression Prediction (EBKR) of litter mass across the sidewalk network. To the authors' knowledge,

this is the first study to evaluate the relationship between OVTA condition levels and estimated true litter mass, and to produce spatially explicit, mass-based litter density estimates with quantified uncertainty for a sidewalk network partitioned by Priority Land Use category across urban watersheds in California. These contributions address a critical gap in California's Trash Amendment compliance framework: OVTA generates categorical rather than quantitative estimates of litter abundance, and spatially explicit mass-based estimates by land use and watershed have not previously been available to managers designing regionally informed institutional controls for pre-first-flush litter load reduction.

OVTA rank significantly predicted log-transformed litter mass across first-pass, total cumulative, and depletion-modeled mass estimates; however, Slightly Littered and Littered sites were not significantly different from one another across any metric. This suggests that OVTA surveys may systematically fail to distinguish between higher litter load sites, which are of greatest concern from a pollutant loading perspective based on their potential to discharge greater masses of litter into nearby waters via runoff. Additionally, first-pass trash counts and masses (g) were underestimated by 48% ($\pm 18\%$) and 46% ($\pm 16\%$), respectively, when compared to total trash abundance estimations derived from depletion modeling. This suggests that “Not Littered” sites may still harbor meaningful litter loads undetected by a single-pass OVTA survey. This interpretation is further supported by the random forest variable importance assessment, which revealed that first-pass count was the most important predictor of OVTA rank, followed by total observed count after three passes, then first-pass mass. Together with the methods agreement results, random forest analysis supports the interpretation that OVTA surveys function largely as a proxy for first-pass count rather than true litter abundance. Currently, the On-Land Visual Trash Assessment protocol does not

require additional management actions at sites ranked as “Not Littered”. More broadly, the California Trash Amendments require MS4 permittees to eliminate trash discharges from Priority Land Use areas entirely, either through installation of full capture systems on all storm drains or through a combination of controls demonstrated to achieve equivalent load reduction. All littered sites, regardless of litter level, are subject to this standard. The underestimation of trash by OVTA surveys presents a potential concern for true regulatory compliance.

While count-based agreement analyses showed monotonically decreasing residual variance across ranks, mass-based models showed no consistent variance reduction, indicating that litter item counts are measured reliably and consistently at high-density sites whereas litter mass remains highly variable regardless of OVTA rank. This likely reflects site-to-site differences in litter composition rather than true abundance. The convergence of all mass-based models on a non-significant Slightly Littered vs. Littered comparison, combined with homogeneity of variance confirmed by Levene's tests, indicates that genuine compositional variability, not differential measurement error, is the source of mass uncertainty at higher litter densities, and that litter mass is a less sensitive discriminator of litter density than item count.

Items composed solely of plastic were the most frequently recovered material type (45%), while paper–plastic composites and paper accounted for 18% and 17% of recovered items, respectively. Although paper may appear less environmentally concerning than plastic, many of the paper–plastic composite items recovered in this study were cigarette butts and many of the paper items were cigarette filter wrappers. Discarded cigarette butts, which include both the filter and any remaining paper wrapper, are a well-documented

source of environmental contamination, releasing nicotine, heavy metals including cadmium and lead, polycyclic aromatic hydrocarbons, and organochlorine pesticides into soil and water with documented toxic effects on aquatic organisms (Novotny et al. 2014; Dobaradaran et al. 2021; Slaughter 2011; Roselli 2021). Consistent with this, tobacco brand names were the most identified brands in the dataset. Where feasible, incorporating brand composition into litter assessments may provide a compelling basis for extended producer responsibility policies (SB 54), in which the financial burden of Trash Amendment compliance is shifted to manufacturers of the most frequently littered items. This may be particularly relevant in regions such as the City of Santa Barbara, where substantial regulatory efforts have already been made to address cigarette litter at the end-of-use stage, including a 2017 citywide ordinance prohibiting smoking on all public sidewalks, parks, beaches, and open spaces that explicitly cited cigarette butt litter as a primary motivation (City of Santa Barbara Ordinance 5801, 2017). Yet, tobacco brands still dominated the brand composition of recovered litter in this study, suggesting that even robust end-of-use regulatory infrastructure may be insufficient without complementary producer responsibility measures targeting the production and packaging stage.

Surveys were conducted as a single time-point snapshot at the end of the dry season, a design choice that precludes characterization of seasonal dynamics in litter accumulation but that captures cumulative litter inputs over an extended dry period, including both ongoing deposition and the effects of routine management activities such as street sweeping and pressure washing. The high proportion of items categorized as undeterminable, predominantly films, fragments, and foams, suggests the presence of highly degraded materials consistent with extended dry season residence times, providing indirect evidence

of litter transport and breakdown processes over the accumulation period. Most recovered items were greater than 5 mm in size, consistent with the OVTA monitoring threshold of items greater than 5 mm that can reasonably be transported to stormwater conveyance systems, supporting the applicability of these findings within the OVTA regulatory framework.

Taken together, these results demonstrate that OVTA surveys reliably distinguish Not Littered from higher-litter-density environments but have limited sensitivity within the higher ranks, systematically underestimate true litter abundance, and are poorly suited to characterizing litter mass. This is consistent with findings from the 2016 Tracking California's Trash project, which found that OVTA sidewalk measurements did not consistently relate to measured trash volumes (EOA Inc., 2016). Where feasible, depletion-based surveying methods should be considered for Track 2 compliance verification, particularly in the context where distinguishing between sites that are and are not littered to demonstrate meaningful progress toward load reduction targets.

Multi-model inference revealed that the binary presence or absence of businesses where the most commonly littered items are sold or consumed was the best-supported predictor of sidewalk litter mass. Sites with at least one qualifying business within 152 m had approximately 3.73 times more estimated litter mass than sites without. This threshold effect, in which the presence of any commercial activity, rather than the number of businesses, predicted litter mass suggests a mechanistic explanation rooted in littering behavior: cigarette butts, food packaging, and other single-use items are littered near the commercial sites where they are purchased and consumed. Commercial zones in combination with the sidewalk network thus serve as a proxy for pedestrian urban mobility

and consumption activity, a relationship with a growing body of empirical support (Marah, 2011; Rossi, 2023; Cowger, 2022).

These findings may provide additional evidence for extended producer responsibility policies. The significant association between commercial presence and litter mass suggests that packaging reduction at points of sale, which shifts product end-of-life waste management responsibility upstream to manufacturers rather than downstream to municipalities and taxpayers, may be an effective complement to, or substitute for, expanding waste management infrastructure. This interpretation is supported by the non-significant results for public waste container count and the full model including all three urban predictors: neither waste containers nor transit infrastructure added explanatory power beyond business presence alone. The non-significance of waste containers is consistent with a reactive placement hypothesis, in which containers are installed in response to existing litter problems rather than as a preventative measure, potentially confounding any protective effect. Taken together, these results suggest that container placement alone may be insufficient to meaningfully reduce litter mass at the site level, and that source reduction near commercial areas warrants greater prioritization.

Global Moran's I analysis confirmed that estimated litter mass exhibited the strongest spatial autocorrelation of all variables tested, demonstrating that litter mass is not randomly distributed across the urban landscape but instead clusters near commercial areas and along pedestrian corridors (i.e., the City's main boulevard). This spatial pattern is consistent with the business presence finding and supports the interpretation that litter accumulation in Santa Barbara is driven by spatially structured processes rather than random littering events.

The spatial structure of litter mass accumulation and the statistically significant business presence covariate together justify the use of EBKR for interpolating litter mass across the watershed sidewalk network. The Whittle semivariogram model incorporating the binary business kernel density surface as a covariate outperformed all alternative semivariogram models across cross-validation metrics, indicating adequate model fit for a calibration dataset of $n = 29$. Predictions falling outside the 90% prediction interval were limited to the three sites with the lowest estimated litter mass and one site with higher estimated mass near the edge of the study area, which is a pattern consistent with expected edge effects and regression to the mean, both of which are common behaviors for geostatistical interpolation methods at the limits of their calibration extent. To address this, calibration was further refined using a Bland-Altman-like approach.

Conley et al. (2019) considered EBK for mapping OVTA trash condition categories with calculated certainty levels (95% credible intervals), but ultimately chose a different method, Nearest Neighbors (NN), for its relative simplicity, explicitly acknowledging EBK's advantages in accounting for semivariogram uncertainty. However, the authors noted that EBK does not constrain predictions to road networks as effectively as NN, which is an important consideration given that roads channel pedestrian activity, car traffic, and stormwater flows that influence trash distribution. This study takes the step Conley et al. 2019 identified as advantageous, addresses sidewalk network connectivity by constraining EBKR predictions to the sidewalk area, and adds a further advance: depletion-estimated true abundances with propagated standard errors and businesses as a covariate as inputs, rather than single-pass OVTA observations. This approach rigorously quantifies uncertainty by propagating measurement standard errors directly into the interpolation process. However, it

faces limitations in its own right, one of which is that the 29 survey transects collectively covered 8,741 m², equivalent to 0.24% of the total 3,606,229 m² sidewalk network modeled, underscoring the degree of spatial extrapolation involved in producing citywide litter mass estimates from this dataset and highlighting the importance of the uncertainty quantification framework applied in this study. Bootstrapping confirmed $n = 29$ is an adequate sample size globally, finding that variance of the bootstrapped mean stabilized at $n = 25$ survey sites. However, while bootstrapping addresses global sample adequacy, it does not resolve spatial heterogeneity in prediction uncertainty, which is a limitation addressed through the Bland-Altman-like limits of agreement precision filter, which identified spatially variable prediction uncertainty at the point level rather than globally. The mean bias was near zero ($\hat{d} = 0.021 \log g$; equivalent to a multiplicative factor of 1.02 on the gram scale), indicating that EBKR predictions were on average only 2% higher than depletion-modeled measurements across the 29 calibration sites. However, the Bland-Altman-like analysis also revealed statistically significant proportional bias (slope = -0.529 , $p < 0.001$), whereby the model over-predicted at low-mass sites and under-predicted at high-mass sites. This is a common pattern in kriging models that exhibit regression to the mean. Point-level 95% confidence intervals were summed across sidewalk points to produce aggregate uncertainty bounds, an approach that assumes all prediction errors are simultaneously in the same direction and therefore represents a conservative upper bound on total uncertainty. Because kriging prediction errors are spatially correlated but not perfectly so, meaning errors at distant locations are partially independent and tend to cancel when aggregated, true aggregate uncertainty likely lies between this conservative upper bound and the narrower bounds that would result from assuming full independence among prediction errors (Cressie, 1993).

Taken together, these results highlight two distinct dimensions of the litter problem across Santa Barbara's Mission Creek watershed, Laguna Channel Drain, and Laguna Tidal Drain. First, total litter load is dominated by the large Residential land use extent and the large Mission Creek watershed. Second, litter density is highest in Commercial and Mixed Urban areas and in Laguna Tidal Drain, regardless of land use type. These two dimensions have different management implications: reducing total litter load requires addressing Residential areas given their large spatial extent; while reducing litter density requires prioritizing commercial corridors and the Laguna Tidal Drain, where litter had accumulated most intensively per unit sidewalk area during the dry season. The confidence intervals reported throughout are wide, reflecting the conservative summation of point-level prediction uncertainty across tens of thousands of sidewalk points and the inherent challenge of extrapolating from 29 calibration sites across a 109 km² urban area. Wide uncertainties are common in litter modeling and have been seen in predicted litter counts from other spatially explicit litter studies (Jambeck, 2024). Despite the uncertainty in EBKR predictions, the consistency of density rankings and relative magnitudes across both the full and Bland-Altman-like adjusted analyses, and across all three watersheds, supports the robustness of the reported spatial patterns.

Mixed Urban and Commercial sidewalks had substantially higher litter densities than Residential and Parks sidewalks across all three watersheds, providing local empirical validation of California's Priority Land Use framework, which designates Commercial and Mixed Urban areas as disproportionate contributors to stormwater litter loading. Mission Creek showed the clearest PLU signal, with density highest in Mixed Urban, Commercial, and Transportation land uses. In contrast, Laguna Tidal Drain exhibited uniformly elevated

litter density across all land use types, indicating a location-specific effect that overwhelms the PLU signal. Laguna Tidal Drain retained 100% of its sidewalk points under the Bland-Altman-like adjustment, making it the highest-confidence result in this study and a clear priority for area-wide intervention regardless of land use type. To the author's knowledge, these results provide the first spatially explicit, mass-based empirical support for California's PLU framework at the local watershed scale and identify Laguna Tidal Drain and Commercial corridors as priority targets for local litter management under the California Clean Water Act Trash Amendments.

E. Conclusion

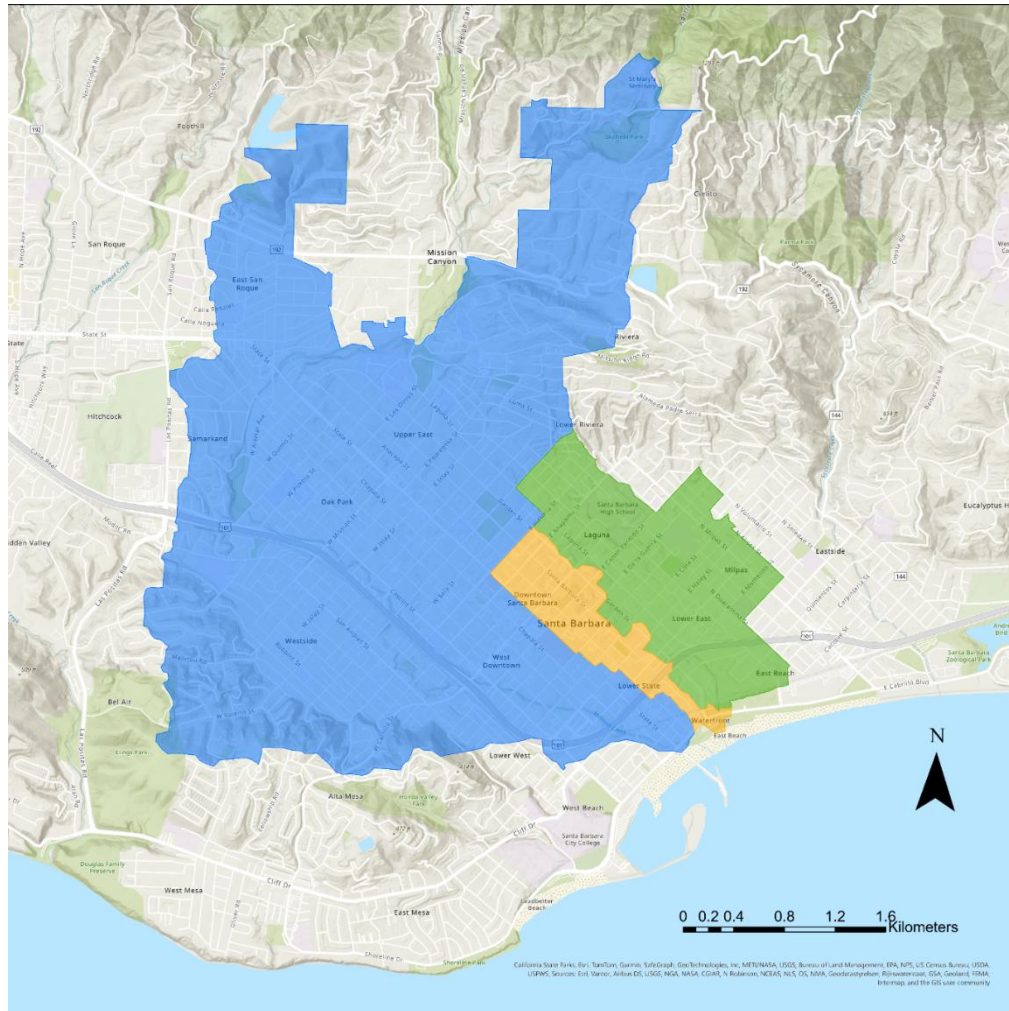
This study demonstrates that while the OVTA method reliably distinguishes between sites ranked as “Not Littered” and those with higher litter loads, it fails to differentiate between higher litter condition categories when mass is the measured variable. This is a critical limitation given that higher-density sites represent the greatest pollution risk under California's Trash Amendments. This insensitivity at higher ranks reflects genuine compositional variability in litter mass rather than measurement error, and is compounded by the fact that OVTA functions primarily as a proxy for first-pass item count, which itself underestimates true litter abundance by 48% for count and 46% for mass relative to depletion-modeled estimates derived from multiple-pass removal survey data. These findings provide empirical evidence that single-pass OVTA surveys have limited capacity to meaningfully distinguish between littered sites, where reductions matter most, and likely underestimate litter abundance even at sites ranked as “Not Littered”, where litter was nonetheless recovered during repeated-pass surveys. This suggests that repeated-pass removal surveys with depletion modeling should be explored further as a complement or

alternative to OVTA, both to assess whether “Not Littered” sites are systematically under-ranked and to determine whether OVTA consistently fails to distinguish between medium and high litter density sites.

The presence of businesses where commonly littered items are sold or consumed was the strongest predictor of sidewalk litter mass, indicating an effect consistent with littering behavior concentrated near points of purchase and consumption and corridors assumed to have relatively higher rates of urban mobility. This finding, combined with the dominance of tobacco brands in the recovered litter composition, provides empirical support for extended producer responsibility policies that shift the financial burden of Trash Amendment compliance upstream to manufacturers of the most frequently littered items. Spatially, litter density was highest on Mixed Urban and Commercial sidewalks across all three watersheds, providing local empirical validation of California's Priority Land Use framework. However, Laguna Tidal Drain exhibited uniformly elevated litter density across all land use types, indicating a location-specific effect that supersedes land use as a driver of accumulation and warrants area-wide intervention independent of priority land use designation. Together, these findings provide both a methodological framework and spatially explicit, mass-based litter density estimates with quantified uncertainty to support California Clean Water Act Trash Amendment compliance in the City of Santa Barbara and similar areas.

F. Appendix

Map of Mission Creek (blue), Laguna Tidal Drain (orange), and Laguna Channel Drain (green) watersheds in Santa Barbara, California.



Trash Level Definitions from EOA Inc. Version 1.3 April 2015

Trash level	Definition
A Not Littered	• Effectively no trash is observed in the assessment area. • Approximately less than one piece per two car lengths on average • There may be some trash in the area, but it is not obvious at first glance. • One individual could easily clean up all the trash observed while walking at a normal pace.
B Slightly Littered	• Predominantly free of trash, except for a few littered areas. • On average, one piece per two car lengths • Some trash is noticeable at first glance. • The trash observed could be collected by one or two individuals in a short period of time.
C Littered	• Predominantly littered, except for a few clean areas. • Trash is widely/evenly distributed and/or small accumulations are noticeable on the streets and sidewalks. • At least 2 or 3 pieces per car length, on average. • It would take a more organized effort to remove all trash from the area.
D Very Littered	• Trash is continuously seen throughout the assessment area. • Large piles and there is a strong impression of lack of concern for litter. • There is often significant litter along gutters • It would take a large number of people during an organized effort to remove all trash from the area.

Additional analysis of population density as a potential co-variate of litter mass:

Population density (WorldPop 100 m resolution) was evaluated as a potential second EBKR covariate. Pearson correlation indicated negligible collinearity with the business KDE covariate ($r = -0.189$, $p = 0.327$). However, regression analysis demonstrated that population

density explained essentially no variance in log-transformed litter mass independently (adjusted $R^2 = 0.005$), and its inclusion reduced model performance relative to the single-covariate model (adjusted $R^2 = 0.246$ vs 0.263 ; AIC = 82.9 vs 81.3). Population density was therefore excluded from the final EBKR model.

Global Moran's I Results for Log-Transformed Estimated Litter Mass

Moran's Index	0.487546
Expected Index	-0.035714
Variance	0.016048
z-score	4.130519
p-value	0.000036

V. Microplastics and PFAS Abundance and Composition in Municipal Production Well Water and Potentially Interacting Surface Waters

A. Introduction

Despite widespread detection of microplastics in surface waters, studies experimentally determining their abundance and composition in groundwater at the level of drinking water production are rare (Lee, 2024; Goeppert, 2021). Despite their ubiquity and toxicity, PFAS in groundwater at depths comparable to drinking water supply wells have not been systematically characterized either (Tokranov, 2024). This knowledge gap is a public health concern. Microplastics and PFAS pose threats to human health via ingestion, with drinking water representing a major exposure pathway for both (Rochman, 2019; Tokranov, 2024). Millions of Americans rely on groundwater as their primary drinking water source (USGS, 2019), and microplastics and PFAS were recently added to the Safe Drinking Water Act Contaminant Candidate List 6 (CCL 6), reflecting growing regulatory recognition of their risks to human health through drinking water exposure (Federal Register, 2022).

Microplastics and PFAS are each diverse suites of persistent contaminants of emerging concern. Microplastics have been defined as plastic particles ranging from 1 μm to 5 mm in their longest dimension (California SWRCB), composed of a wide variety of polymer types including polypropylene (PP), polyethylene (PE), polyvinyl chloride (PVC), and polyethylene terephthalate (PET) (Rochman, 2019), among others. They are classified as either primary or secondary microplastics. Primary microplastics are intentionally manufactured within the 1 μm to 5 mm size range, while secondary microplastics are generated through the physical and photochemical disintegration of larger plastic items.

Microplastic morphology is equally diverse, encompassing fibers, fragments, spheres, pellets, films, and foams (Rochman, 2019). Microplastics can adsorb co-occurring contaminants from the surrounding aquatic environment, including PFAS, facilitating the transport and bioaccumulation of these associated chemicals (Sforzi, 2024; Alijagic, 2024). Contaminant mixtures formed through this association may exert greater toxicity than individual components alone (Cassio, 2021; Soltanighias, 2024).

PFAS are a group of highly fluorinated synthetic compounds characterized by multiple carbon–fluorine (C–F) bonds, which confer exceptional chemical stability and resistance to environmental degradation (Wee, 2023). They are widely used in industrial manufacturing of non-stick coatings, textiles, aqueous film-forming foams (AFFF), and food packaging and other plastic packaging, among other applications, where they provide oil and water repellency and thermal resistance (Dickman & Aga, 2022; Alijagic, 2024). PFOA and PFOS are among the most frequently detected PFAS across environmental compartments and are recognized endocrine disruptors with documented associations with plastic pollution (Wee, 2023). Exposure to PFAS has been associated with a range of adverse health outcomes including immune dysfunction, thyroid disease, liver damage, and cancer, with effects varying by sex and age, raising particular concern for vulnerable populations (Güzel, 2025).

Surface waters receive microplastics and PFAS from a variety of point and non-point sources, including wastewater effluents, industrial discharges, and urban stormwater runoff (Desgens-Martin, 2023; Lee, 2024). Both contaminants can enter shallow groundwater systems via infiltrating surface waters that serve as natural aquifer recharge sources (Goeppert, 2021). Microplastics and PFAS may also reach the underlying groundwater

through exfiltration of sewage from wastewater infrastructure, and through exfiltration of reclaimed water from recycled water infrastructure (Lee, 2015). Within wells themselves, plastic casings, pipes, and pump components in contact with water may serve as additional internal sources of secondary microplastics (Viaroli, 2024). The Mission Creek watershed in Santa Barbara, California represents a useful system in which to investigate these pathways: the watershed's main stem serves as a primary recharge source for Santa Barbara Groundwater Basin Storage Unit I (Paulinski, 2018). The watershed receives urban stormwater runoff and recycled water irrigation and overlays a sewage system that is separated from the city's stormwater infrastructure. Each of these represents a documented potential pathway for microplastic and PFAS inputs to surface waters and potentially to the underlying aquifer.

This study determines the baseline concentration and composition of microplastics and PFAS in municipal production well water and in the surface waters and wastewater with the potential to interact with the underlying aquifer and contribute contaminants to the groundwater supply.

B. Methods

1. Study Area

This study was conducted in the Mission Creek watershed in the City of Santa Barbara, California (population ~88,000), located on the California central coast approximately 150 km northwest of Los Angeles. The city is situated on uplifted marine terraces that border the Santa Ynez Mountains to the north and the Pacific Ocean to the south. Commercial and residential land use dominate the area.

Three creeks, Arroyo Burro, Mission, and Sycamore, influence the hydrology of the study area, located in the west, center, and east of the city, respectively (Paulinski, 2018). The watershed of interest is that of Mission Creek, a 12 km long stream channel that drains approximately 30 km² and flows in a southeastern direction, with headwaters on the southern slope of the Santa Ynez Mountains.

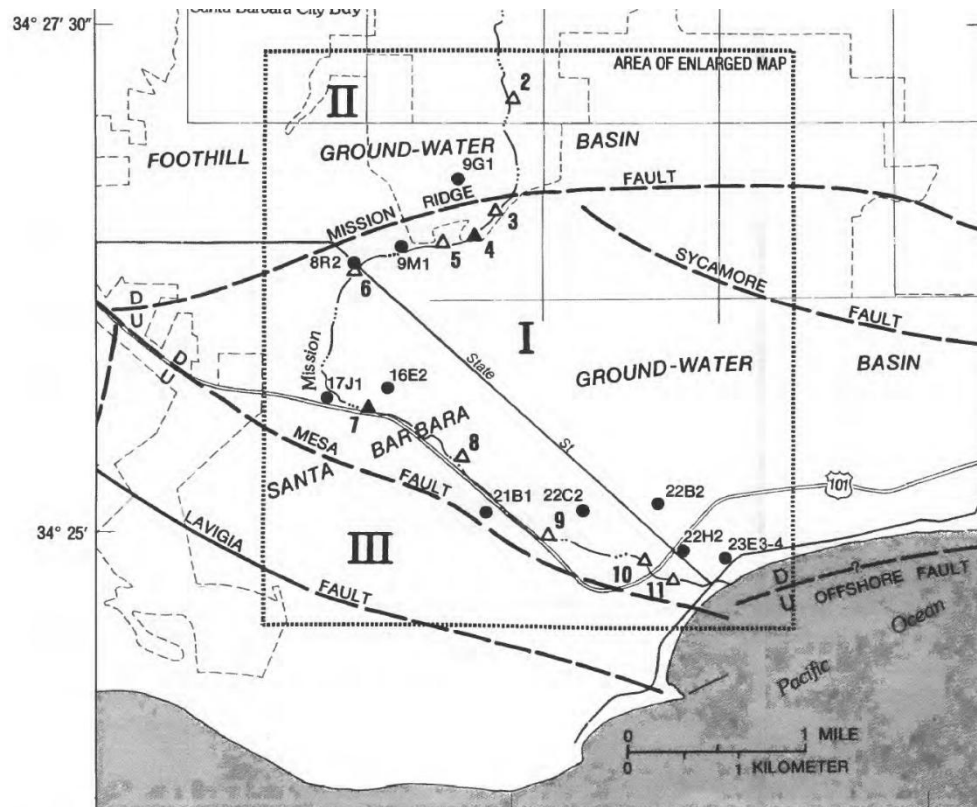


Figure 1. Map adapted from McFadden (1991) showing measurement sites along Mission Creek. Creek sampling for this study occurred near the upstream (site 4) and downstream (site 7) boundaries of the losing reach.

The lower half of Mission Creek constitutes a losing reach, where streamflow seeps into the underlying aquifer. A 1987 USGS study, in which water was twice released from an upstream reservoir into Mission Creek during the dry season, found that total seepage loss between Rocky Nook Park (site 4) and a station near Mission Street (site 7) averaged 4341.85 cubic meters per day (McFadden, 1991). The greatest losses to seepage during both

releases occurred within the 0.99-mile section between Alamar Avenue (site 6) and Mission Street (site 7). Because potential evapotranspiration is less than 0.3 m/day, losses were predominantly attributed to seepage (McFadden, 1991). When little to no groundwater is pumped from Storage Unit I, groundwater discharges from the basin into Mission Creek near its outfall (site 9); however, the water table has historically been substantially below the streambed between sites 2 and 9, and more recently, concrete lining has reduced groundwater influence on the lower creek (Paulinski, 2018). The upper half of Mission Creek is steeply graded (>161 m/km) with a boulder-dominated streambed, while the lower half is more gradual (<14 ft/mile) with a streambed of small cobbles, gravel, sand, and silt (Martin, 1984). Creek sampling occurred near the upstream (site 4) and downstream (site 7) boundaries of the losing reach (Figure 1).

2. Hydrogeology

The study basin, Santa Barbara Groundwater Basin Storage Unit I, spans a shallow saddle between two foothill regions to the northeast and southwest. The basin is bounded by three faults to the northeast, southwest, and northwest, which are assumed to act as barriers to groundwater flow. To the southeast lies the Pacific Ocean, with an unnamed fault approximately 0.4 km offshore thought to further impede groundwater flow (Paulinski, 2018). Consolidated basement rocks are marine in origin and have low permeability where they are unfractured. Unconsolidated terrestrial deposits, comprising silt, sand, and gravel deposited by alluvial fans and floodplains, overlie the basement and constitute the primary water-bearing formation. These deposits are thin in the northwest and pinch out toward the southwest. They are divided into five distinct units: the shallow zone, upper producing zone, middle zone, lower producing zone, and deep zone (Paulinski, 2018).

Three of these units represent the primary water-bearing packages, described in stratigraphic order: the upper producing zone, composed of medium- to coarse-grained sand and fine gravel; the middle zone, composed of fine-grained deposits with sporadic coarse-grained lenses; and the lower producing zone, composed of medium- to coarse-grained sand and fine gravel (Paulinski, 2018; Martin, 1984). The upper and lower producing zones extend throughout the basin and into the northern aquifer, while the middle zone pinches out approximately 1–2 miles northwest of the coastline (Paulinski, 2018; Martin, 1984).

Historical recharge to Storage Unit I has been estimated at approximately 1,110,000 cubic meters per year from rainfall infiltration, 986,784 cubic meters per year from irrigation, 616,740 cubic meters per year from stream seepage, and 370,044 cubic meters per year from subsurface inflow (Martin, 1984). Since 1991, recycled water has become the dominant source of irrigation water (approximately 986,784 cubic meters per year) for high-water-use sites including golf courses, parks, and schools throughout the watershed (City of Santa Barbara Public Works, n.d.). Average annual precipitation in the watershed is approximately 508 mm (20 inches), based on a 72-year record (Santa Barbara County Flood Control District, n.d.).

3. Well Characteristics

Four municipal production wells were sampled with permission from City of Santa Barbara water managers; sampling was not available at any other production or monitoring wells and was constrained to a quarterly frequency to coincide with mandated operational testing. Well depths were reported in units of feet below ground surface (ft bgs), referring to the vertical distance measured downward from the ground surface at the wellhead to the depth of interest. Feet below ground surface (ft bgs) can be converted to meters below

ground surface (m bgs) by multiplying the measurement by approximately 0.305. The depths of the four wells sampled varied (Figure 2): Alameda (162 m bgs), Corp Yard (210 m bgs), and City Hall (194 m bgs) draw from the lower producing zone of Storage Unit I, whereas San Roque (183 m bgs) is located in the East Foothill groundwater basin, which is a separate basin sharing similar lithology with Storage Unit I but recharged primarily by San Roque Creek rather than Mission Creek seepage. San Roque was included to provide a comparison well representing a distinct recharge regime within the broader Santa Barbara groundwater system. All four wells have stainless steel casings and 1.0–1.3 mm (0.04–0.05 inch) slot screens (SAE 304 stainless steel) with varying screen intervals. Alameda, Corp Yard, and City Hall share similar sediment packages including the middle zone, whereas San Roque lacks the middle zone. Corp Yard is the only artesian well in this study, meaning

groundwater pressure in the aquifer is sufficient to cause water to rise above the well casing without pumping.

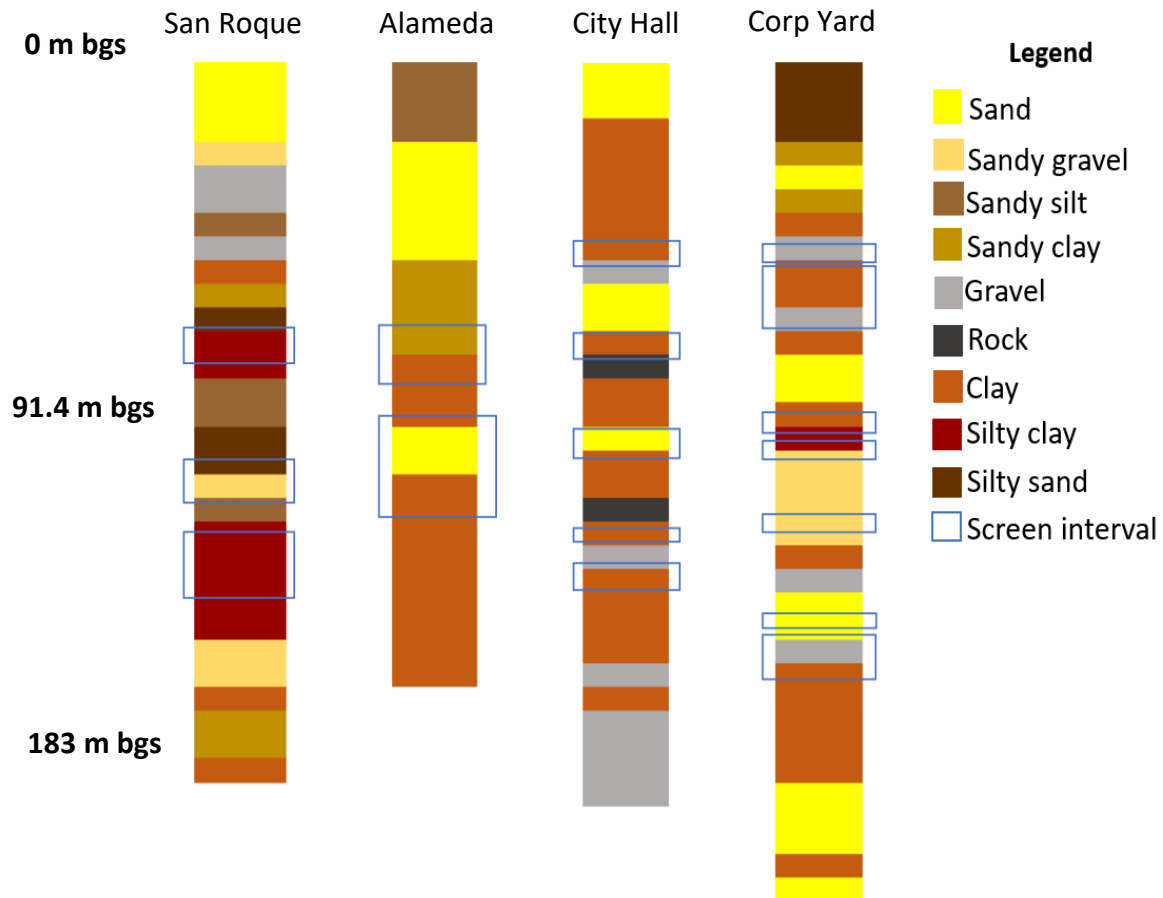


Figure 2. Lithology and depth of San Roque, Alameda, City Hall, and Corp Yard wells with screen intervals included. Screen Intervals for Alameda are: 85-110, 116-146 m bgs; San Roque: 88-101, 131-143, 158-175 m bgs; Corp Yard: 58-62, 69-83, 116-120, 125-131, 137-140, 149-155, 177-184, 187-201 m bgs; City Hall 55-66, 91-96, 131-134, 155-158, 163-172 m bgs.

4. Wastewater Treatment and Distribution

The City of Santa Barbara operates two separate drainage systems: a sanitary sewage system and a municipal separate storm sewer system (MS4). The sanitary sewage system collects mixed residential and commercial wastewater and conveys it to the El Estero Water Resource Center, a publicly owned treatment works (POTW). Industrial wastewater undergoes pretreatment before discharge into the main sewer system.

Secondary effluent from the POTW undergoes tertiary treatment to meet Title 22 of the California Code of Regulations (CCR) for non-potable recycled water reuse. Tertiary treatment includes filtration and UV disinfection. Recycled water is distributed through a dedicated non-potable distribution system (colloquially known as the purple pipe system), which is separate from the potable drinking water distribution system. The MS4 collects and conveys urban stormwater runoff, with Best Management Practices implemented to reduce pollutant loading prior to discharge to receiving water bodies. Stormwater is not diverted to the POTW for treatment.

5. Sampling Design

Samples were collected between October 2024 and May 2025 to capture variability across dry and wet seasons. Samples collected before December 2024 were collected under dry conditions, with no measurable rainfall in the preceding six months (Montecito Water District, n.d.). Seven sampling locations were established (Figure 3): four municipal production wells drawing from confined aquifers between 162 and 210 m bgs, two locations along the losing reach of Mission Creek - one near the upstream boundary (Rocky Nook Park) representing relatively lower upstream urbanization, and one near the downstream boundary (Oak Park) representing relatively higher upstream urbanization - and the El Estero Water Resource Center, from which raw sewage influent and recycled water were collected. Alameda, City Hall and Corp Yard wells form a northwest-to-southeast transect spanning the width of Storage Unit I.

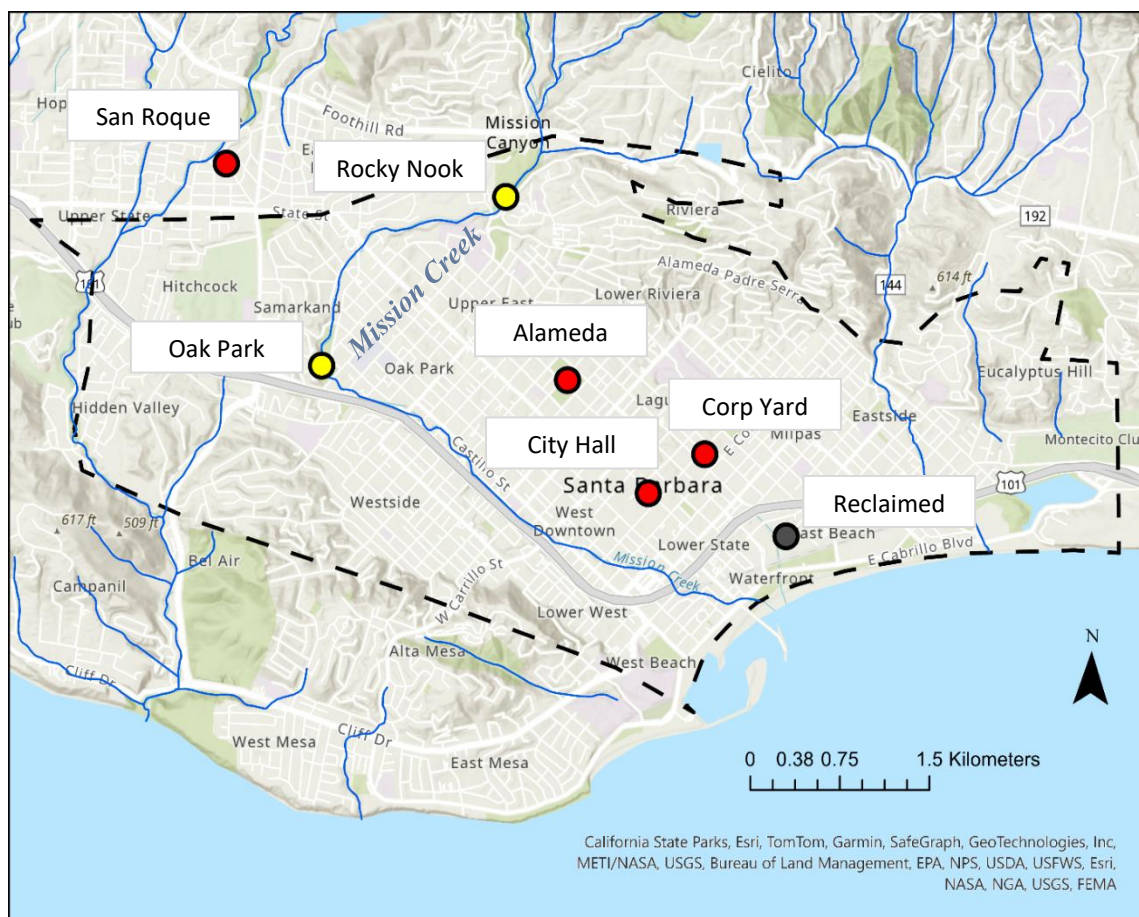


Figure 3. Map of sample sites in Santa Barbara, California. Wells are represented by red circles, and the El Estero Water Resource Center is represented by a grey circle. The two yellow circles indicate the sites where Mission Creek was sampled. Santa Barbara Basin is outlined with a dashed black line.

6. Field Sampling

6.1 Grab Samples

Discrete grab samples for PFAS analysis were collected in duplicate 1 L amber glass bottles for all sample types. Each bottle was rinsed three times with sample water prior to collection, consistent with EPA PFAS field sampling guidance. Grab samples for sewage microplastics analysis were collected as five discrete 10 L aliquots in glass carboys that had been acid-washed with 10% HCl and triple-rinsed with Nanopure water prior to use.

Grab samples for stable isotope analysis ($\delta^{18}\text{O}$ and $\delta^2\text{H}$) were collected in 30 mL plastic bottles with no headspace to prevent isotopic exchange. Each bottle was rinsed three times with sample water prior to filling. All grab samples were immediately placed on ice at approximately 4°C for transport and stored at 4°C until processing.

6.2 Flow-Through and Composite Filtrate Samples

Flow-through samples for microplastics analysis were collected using a field-duplicate inline filtering apparatus designed to retain microplastics across 180, 60, and 25 μm stainless steel mesh filters from 100 L of sample water (creek water, groundwater, and reclaimed water). A sample volume of 100 L was filtered on-site to minimize sampling bias associated with small volumes (Lee, 2022). For every 10 L of sample water filtered, 1 L of filtrate was collected into a 10 L glass carboy, producing a composite of ten 1 L aliquots for subsequent laboratory filtration through a 10 μm stainless steel mesh filter using an all-glass filtration system. Sewage samples were collected and processed at a smaller volume (50 L) due to solids content that rapidly clogged filters when attempting onsite filtration, and due to the practicality of safely transporting and processing large volumes of raw sewage.

The in-field filtration apparatus consisted of a silicone tube connected to a brass hose splitter that diverted sample water into two identical parallel inline filter trains (split-flow field duplicates). Each filter passed water sequentially through 180 μm and 60 μm stainless steel mesh filters (25 mm diameter) encased in 19.05 mm brass fittings adhered to 19.05 mm silicone washers using liquid silicone, followed by a 25 μm stainless steel mesh filter (47 mm diameter) housed in a polycarbonate filter housing (Pall 1119). It is noted that the polycarbonate housing represents a plastic component in contact with sample water; this potential source of microplastic contamination was accounted for in field blank processing.

The split-flow field duplicate design enabled assessment of within-sample analytical precision. Total microplastic counts for each sample were calculated as the sum of particles recovered from both filter trains across all size fractions.

Creek water was drawn from a stainless steel basket suspended in the creek channel (51–102 cm from the right bank at a water depth of 33–56 cm, varying by sampling date and flow conditions) via 1 inch silicone tubing and pumped through the filtration apparatus using a peristaltic pump (Proactive Alexis Peristaltic Pump), consistent with methods described in Harold et al. (2022).

Groundwater samples were collected from stainless steel sample lines diverted from the main pumping lines of the municipal wells. Prior to sampling, wells were purged until at least three casing volumes had been displaced, and sample lines were purged for 15 minutes. Reclaimed water samples were collected from a polyethylene sample line at the point of discharge from the El Estero Water Resource Center recycled water system, which operates continuously and was therefore in a purged state prior to each sampling event. Sewage samples were collected from the raw influent line using an ISCO automated sampling system.

6.3 Water Quality Parameters

Temperature, pH, dissolved oxygen, and specific conductivity were measured for groundwater, creek water, and reclaimed water samples using a YSI EXO3s multiparameter sonde, following USGS best practices for field water quality measurements (USGS, 2023). For groundwater and reclaimed water, approximately 8 L of sample water was collected in a container, and measurements were recorded in triplicate once readings stabilized. For creek water, replicate measurements were made at the sampling location, and where feasible the

probe was deployed continuously downstream of the intake point. Water quality parameters were not measured in sewage samples to prevent instrument damage.

7. Sample Processing and Analysis

7.1 PFAS

PFAS samples were processed following EPA Method 1694 as described in Desgens-Martin et al. (2023). A 500 mL aliquot of each water sample was measured into a glass flask, pH-adjusted to 2.0 ± 0.5 using 37% hydrochloric acid (HCl) and stabilized with 250 mg (0.6 mmol) of tetrasodium ethylenediaminetetraacetate dihydrate ($\text{Na}_4\text{EDTA} \cdot 2\text{H}_2\text{O}$). Targeted analytes were extracted by solid-phase extraction (SPE) using Oasis HLB cartridges (Waters WAT106202), conditioned sequentially with methanol, deionized water, and pH-adjusted reagent water, following Desgens-Martin et al. (2023). The 500 mL extract was concentrated to a 1 mL final volume, yielding a concentration factor of 500; reported concentrations in ng/L were calculated as the instrument-reported concentration (ng/mL in extract) $\times 1000 / 500$.

Samples were analyzed for selected PFAS compounds following Adeleye et al. (2024) using an Agilent 1290 HPLC coupled to an Agilent 6470 Triple Quadrupole LC/MS. Chromatographic separation was achieved using an Agilent Polaris C18-A column with mobile phases of 0.1% (m/v) ammonium formate and 0.1% (v/v) formic acid in water (phase A) and 1:1 (v/v) methanol:acetonitrile (phase B). PFAS were quantified using external calibration curves; isotope-labeled internal standards were not used in this study, which represents a recognized limitation. Within-batch precision and accuracy were assessed using mid-run re-injections of calibration standards at 25 and 100 ng/mL. Results were exported

from Agilent MassHunter Quantitative Analysis software for quality assurance processing and visualization in RStudio.

7.2 Microplastics

Microplastics were analyzed from two sources: (1) the stainless-steel inline mesh filters (180, 60, and 25 μm) collected at field sites, and (2) 10 μm stainless steel mesh filters onto which the 10 L composite filtrate samples were subsequently filtered in the laboratory. Composite filtrate samples and sewage samples were processed as follows: each 10 L sample was pumped through a vacuum filtration apparatus consisting of a 250 mL glass cup clamped to a glass filter support head holding a 47 mm diameter, 10 μm stainless steel mesh filter, draining into a 1 L Erlenmeyer flask, using a peristaltic pump (Proactive Alexis Peristaltic Pump). Sewage samples were first passed through 180, 60, and 25 μm inline stainless steel mesh sieves, and the filtrate was then processed through the 10 μm filter using the same glass apparatus.

Sewage samples had low (<4 g dry equivalent) solids mass and were spread on aluminum trays in a biological safety cabinet and allowed to dry until mass stabilized. Dried sewage residues were processed following Keller et al. (2024). Briefly, solids were transferred to glass beakers with a 1.4 g/mL calcium chloride (CaCl_2) solution for density separation. The solution was sonicated, allowed to settle, and the supernatant was decanted, centrifuged, and filtered sequentially through 180, 60, 25, and 10 μm stainless steel mesh filters using an all-glass filtration apparatus. All glassware was heat-treated at 450°C for 4 hours in a muffle furnace prior to use.

Suspected microplastics on all filters were identified at 40 $\times$ magnification using a stereomicroscope (Olympus SZ40) following morphological guidelines established by

Rochman et al. (2019). Particles identified as potential microplastics were transferred to 5 mm aluminum discs and analyzed using μ FTIR following standard protocols established by the Moore Institute for Plastic Pollution Research, using a ThermoFisher Nicolet iN10 MX instrument at the Southern California Coastal Water Research Project. Spectra were validated using the Open Specy QA/QC pipeline in RStudio, with spectral matches required to exceed a Pearson's R correlation of 0.65. Only validated plastic spectra were retained for analysis, resulting in conservative particle counts for all samples.

7.3 Stable Isotopes

Oxygen ($\delta^{18}\text{O}$) and hydrogen ($\delta^2\text{H}$) isotope ratios were measured at the UC Davis Stable Isotope Facility using GasBench isotope ratio mass spectrometry (GasBench-IRMS). Additional oxygen ($\delta^{18}\text{O}$) and hydrogen ($\delta^2\text{H}$) isotope ratios were sourced from previous records published by USGS and the California State Water Resources Control Board.

8. Quality Assurance and Quality Control

8.1 Cleaning Equipment

PFAS sampling and processing equipment was cleaned in compliance with EPA Method 1694: glassware was washed with laboratory detergent, rinsed with tap water, and given a final rinse with LC/MS grade water. Sample bottles were additionally baked in a muffle furnace at 450°C for 6 hours. Microplastics sampling glassware was acid-washed with 10% HCl for 30 minutes, triple-rinsed with Nanopure water (Thermo Scientific Barnstead GenPure Pro UV/UF), and covered with aluminum foil until use. Stainless steel filters, brass fittings, and silicone components were sonicated (Branson CPX8800H) with Nanopure water and approximately 20 g of laboratory detergent (Alcojet) for 25 minutes, triple-rinsed

with Nanopure water, and covered with aluminum foil. All tubing was flushed three times with Nanopure water by volume prior to use. All filtration was performed inside a biological safety cabinet to minimize atmospheric microplastic contamination. Field duplicate filtration systems were assembled in the biological safety cabinet, and all stainless-steel mesh filters, silicone washers, and fittings were inspected at 40× magnification prior to deployment to confirm the absence of particle contamination. Cotton lab coats were worn during all sampling and processing steps to minimize contamination from synthetic fibers.

8.2 Field Blanks

PFAS field blanks consisted of cleaned 1 L amber glass sampling containers filled with LC/MS grade water at the point of sample collection, which subsequently underwent the same collection, transportation, storage, and analysis procedures as samples. Instrument blanks consisting of reconstitution solvent were included in each LC/MS analytical batch to quantify instrument-level contamination.

For microplastics, field blanks consisted of empty 10 L glass carboys opened at the point of sample collection for the duration of sampling and then sealed, to account for atmospheric particle deposition. Field blanks were processed identically to samples in the laboratory. Additionally, duplicate inline filter assemblies were transported to and from each field site and examined upon return to assess potential contamination of field equipment during transport and deployment. One field blank per sample type per sampling event was collected.

Sample-specific minimum detectable amounts (MDA_B) were calculated following Lao et al. (2023), using the background particle count from field blanks (N_b) for each sample:

$$MDA_B = N_b + 3 + 4.65\sqrt{N_b}$$

Blank subtraction was performed following Munno et al. (2023), in which particle chemistry and morphology identified in field blanks were subtracted from corresponding samples.

8.3 Filter Recovery Efficiency

The recovery efficiency of the inline filtration apparatus was assessed in triplicate by filtering 10 L of Nanopure water spiked with known counts ($n = 30\text{--}41$ particles per replicate, counted under $40\times$ magnification prior to spiking) of polyethylene microspheres in three size fractions ($600\text{--}710\text{ }\mu\text{m}$, $300\text{--}355\text{ }\mu\text{m}$, and $75\text{--}90\text{ }\mu\text{m}$) and 1 mm cellulose acetate microfibers. Larger particle sizes were selected to minimize uncertainty in spike counts, since accurate enumeration of smaller particles prior to spiking is difficult and would introduce bias into the recovery estimate. Recoveries were high: $98.8 \pm 1.9\%$ (mean $\pm$ SD) for $600\text{--}710\text{ }\mu\text{m}$ spheres, 100% for $300\text{--}355\text{ }\mu\text{m}$ spheres, $95.8 \pm 3.8\%$ for $75\text{--}90\text{ }\mu\text{m}$ spheres, and 100% for 1 mm microfibers. Notably, a substantial proportion of microfibers were recovered on the $25\text{ }\mu\text{m}$ filter rather than the 180 or $60\text{ }\mu\text{m}$ filters, indicating that fibers oriented longitudinally during filtration and passed through filters with pore sizes considerably larger than their diameter, which is a known phenomenon in microplastics filtration that may result in underestimation of fiber concentrations at coarser size fractions.

9. Data Visualization and Statistical Analysis

All data visualization and analysis were performed in RStudio (version 2026.01.1) using the following packages: `dplyr`, `tidyr`, `ggplot2`, `stringr`, `readr`, and `scales` for data processing and visualization, and `vegan` for multivariate community analysis.

Blank-corrected microplastic counts by polymer class were calculated and visualized by sample type and collection date. Microplastic concentrations in particles per liter were calculated by dividing blank-corrected particle counts by the filtered sample volume (100 L for all sample types except sewage, for which 50 L was filtered). Samples with total blank-corrected counts below their sample-specific MDA_B were reported as not detected.

Microplastic polymer composition was characterized using centered log-ratio (CLR) transformation of proportional abundance data to address the compositional nature of the dataset, with a pseudocount of 0.001 added prior to transformation to handle zero values. Principal components analysis (PCA) was performed on the CLR-transformed matrix using the `prcomp()` function in base R, and results are visualized as a biplot showing sample scores and polymer class loadings. Similarity percentages analysis (SIMPER; Clarke, 1993) was performed on untransformed proportional abundance data using the `vegan` package to identify polymer classes contributing most to compositional dissimilarity between sample types.

PFAS concentrations were converted from instrument units (ng/mL in SPE extract) to water sample units (ng/L) using the SPE concentration factor ($500 \text{ mL sample volume} / 1 \text{ mL final extract volume} = 500$; $\text{ng/L} = \text{ng/mL} \times 2$). Reported concentrations reflect averages of field duplicate samples where both replicates were above the lower limit of quantification (LLOQ) and below the upper limit of quantification (ULOQ). Results below the LLOQ but above zero were reported as detected but below LLOQ. Field blank qualification flags were applied where field blank concentrations exceeded the LLOQ (J* flag) or where sample concentrations were at or below the corresponding field blank concentration (J-B flag), consistent with standard EPA data usability frameworks.

C. Results

1. Microplastics and PFAS in Sampled Waters

The lowest microplastic concentration (0.03 particles per liter) was observed in Corp Yard production well water collected on October 2, 2024, while the highest (1.94 particles per liter) was detected in raw sewage collected on November 25, 2024; this was more than three times higher than the next highest sewage sample. Municipal production well water samples generally had the lowest microplastic concentrations relative to other sample types. However, five well water samples exceeded concentrations observed in at least one creek sample: City Hall (January 9, 2025; 0.26 particles per liter), Alameda (January 13, 2025; 0.17 particles per liter), Alameda (October 8, 2024; 0.16 particles per liter), Corp Yard (January 9, 2025; 0.14 particles per liter), and Alameda (April 8, 2025; 0.10 particles per liter). Notably, three of these five exceedances occurred during the January 2025 sampling event across three different wells. The highest creek concentration (Mission Creek at Rocky Nook, November 9, 2024; 0.38 particles per liter) was above all the well sample concentrations. All five well samples that exceeded creek concentrations also exceeded the reclaimed water concentration range of 0.04 to 0.11 particles per liter. These results are visualized in Figure 4.

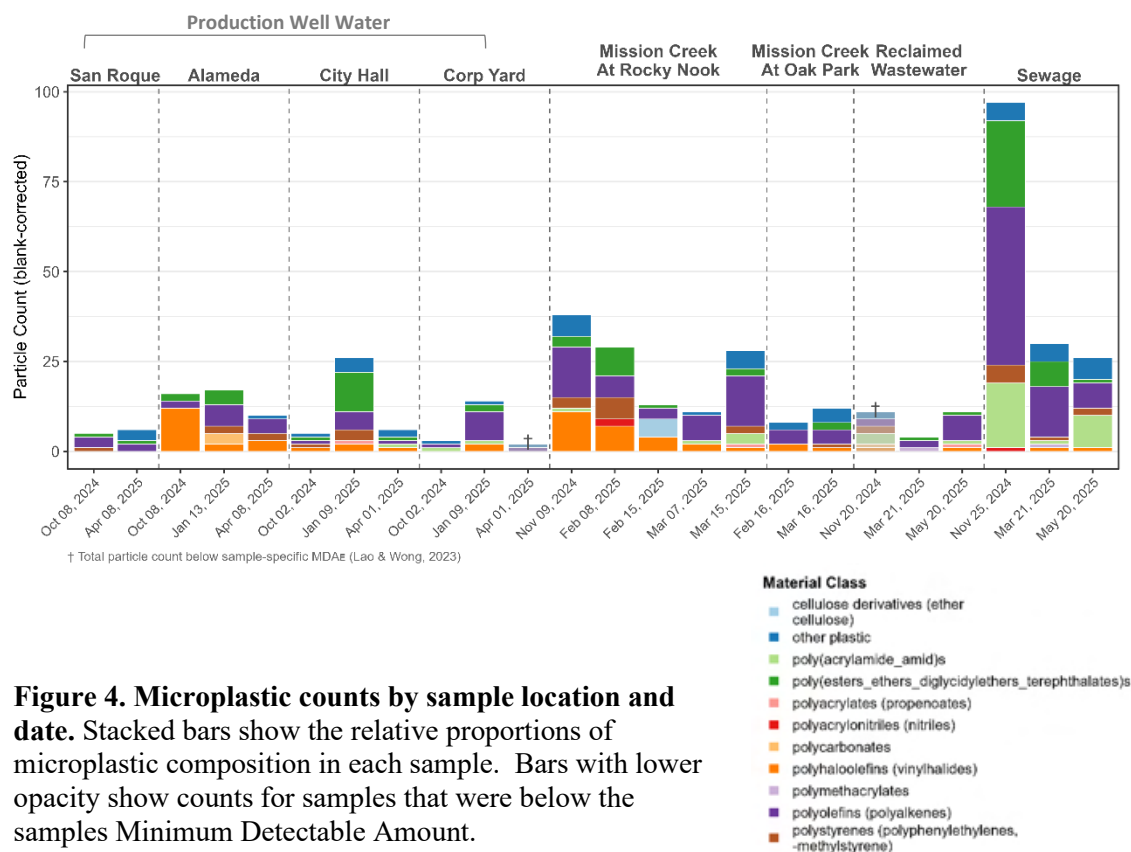


Figure 4. Microplastic counts by sample location and date. Stacked bars show the relative proportions of microplastic composition in each sample. Bars with lower opacity show counts for samples that were below the samples Minimum Detectable Amount.

Microplastics were detected in 22 of 24 samples at concentrations ranging from 0.03 to 1.94 particles per liter. Corp Yard (April 2025, corrected count = 2, $MDA_B = 3$) and Reclaimed Wastewater (November 2024, corrected count = 11, $MDA_B = 11.6$) fell below their sample-specific minimum detectable amounts calculated following Lao et al. (2023) and are reported as not detected.

Microplastic polymer composition was explored using principal components analysis (PCA) of centered log-ratio (CLR)-transformed proportional abundance data and similarity percentages analysis (SIMPER). PCA scores and polymer class loadings are shown in

Figure 5. The first two principal components explained 36.8% and 23.9% of total compositional variance, respectively, for a combined 60.7%. Sample types showed substantial overlaps in compositional space, with no group occupying a distinct region of the biplot, consistent with broadly shared urban microplastic sources across water types. SIMPER analysis of untransformed proportional abundance data identified two compositionally distinctive signals across pairwise comparisons: poly(acrylamide)s consistently contributed to dissimilarity in all comparisons involving sewage ($p < 0.05$ in multiple pairs), consistent with polyacrylamide use in urban settings and entry into the sewer system; and polyhaloolefins (vinyl halides) contributed significantly to dissimilarity in comparisons involving Alameda well water relative to Corp Yard ($p = 0.011$), San Roque ($p = 0.009$), sewage ($p = 0.007$), and reclaimed water ($p = 0.029$), consistent with infrastructure-derived contamination at that well. Across all pairwise comparisons, polyolefins, polyhaloolefins (vinyl halides), and other plastics together accounted for approximately 60–75% of compositional dissimilarity, reflecting their dominance across all

sample types and the absence of a single diagnostic polymer class that cleanly distinguishes one water type from another.

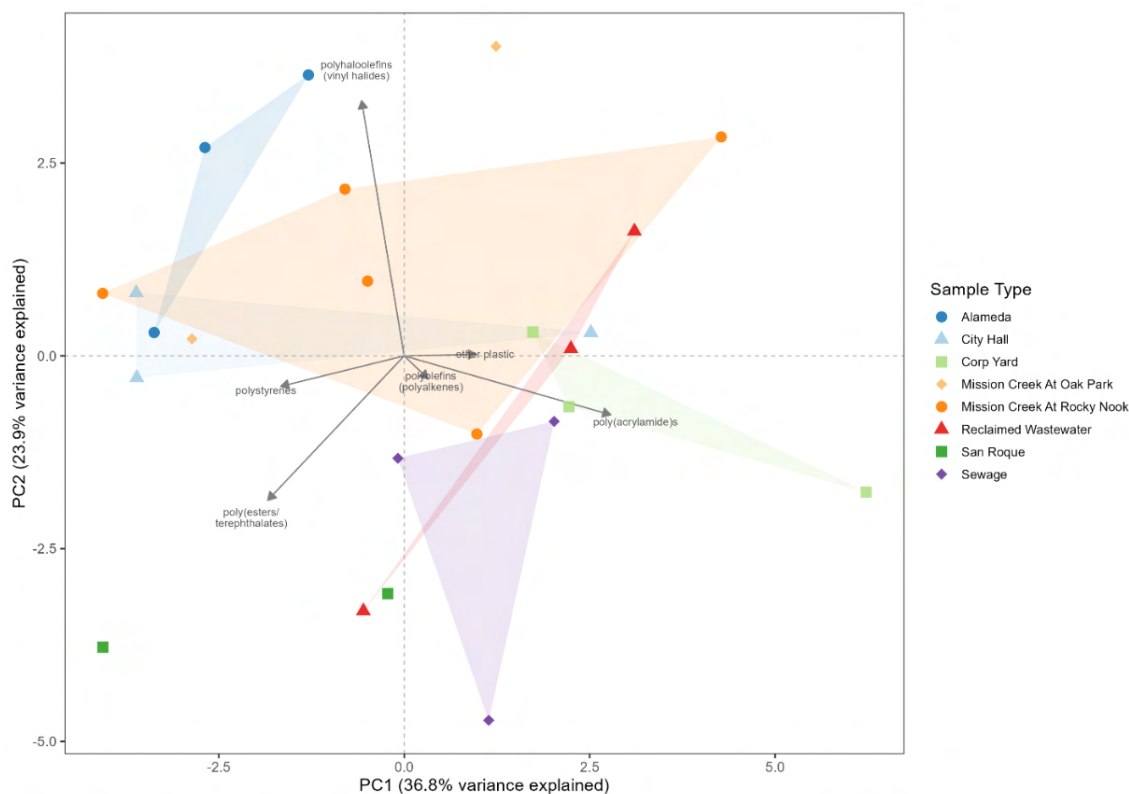


Figure 5. Principal Component Analysis biplot of microplastics composition across all water samples. No single polymer class distinguishes one sample type from another.

PFAS concentrations reported in this study are semi-quantitative. QC standards consisted of mid-run re-injections of calibration standards at 25 and 100 ng/mL in the SPE extract rather than independently prepared reference materials and therefore confirm within-run instrument stability but cannot independently verify quantification accuracy in environmental sample matrices. Within-batch precision was acceptable for all compounds (median RSD <12%). Results should be interpreted as semi-quantitative estimates suitable for characterizing occurrence patterns and relative concentrations within analytical batches,

but not for precise quantitative comparisons across batches or between sample types analyzed in different runs.

PFCAs were the most frequently detected PFAS class across all sample types. Neither chlorinated PFAS (9Cl-PF3ONS or 11Cl-PF3OUdS) was detected in any sample. PFHxA was detected in all samples, and was quantified above the LLOQ in the majority of sample types, exhibiting a clear concentration gradient from reclaimed water (43.6–107.8 ng/L) to sewage (13.0–21.7 ng/L) to Mission Creek at Rocky Nook (1.3–25.2 ng/L) and Oak Park (6.5–11.4 ng/L), with detections predominantly below the LLOQ in groundwater production wells; where PFHxA was quantified, concentrations ranged from 1.1 to 1.8 ng/L across five of twelve well samples from three of the four wells sampled, with the remaining seven combinations below the LLOQ of 1 ng/L. PFHpA was quantified in reclaimed water (3.1–4.5 ng/L), sewage (2.0–7.3 ng/L), and one Mission Creek at Rocky Nook sample (2.6 ng/L on February 8, 2025), but was detected only below the LLOQ in all groundwater well samples. PFOA was quantified in reclaimed water (1.3–17.2 ng/L), sewage (8.4–12.5 ng/L), Mission Creek at Rocky Nook (1.3–3.2 ng/L) and Oak Park (1.4–2.3 ng/L), and in Alameda well water on two unqualified sampling dates (January 2025: 1.12 ng/L; April 2025: 1.09 ng/L). PFOA detections in Alameda October 2024, City Hall October 2024, and Corp Yard October 2024 were qualified with J-B or J* flags indicating that field blank concentrations were at or above sample concentrations on those dates; these results are not attributed to the environment. PFOS was quantified only in reclaimed water (5.6–11.6 ng/L) and sewage (3.2–8.6 ng/L), with two detections just above the LLOQ at Mission Creek at Rocky Nook (2.5 ng/L each on February 8 and March 15, 2025) and was not detected above the LLOQ in any groundwater well sample. PFNA was quantified exclusively in sewage (19.8–39.0 ng/L)

and was not quantified above the LLOQ in any other sample type. PFBS was quantified in reclaimed water on two of three sampling dates (21.0–30.9 ng/L) and at Mission Creek at Rocky Nook on February 8, 2025 (26.8 ng/L), the same date on which anomalously elevated PFHxA (25.2 ng/L) was also observed. PFAS detections are visualized with those of microplastics in Figure 6.

There does not appear to be a correlation between microplastics and PFAS detections across sampled waters (Figure 6), although it is noteworthy that sewage samples had the highest PFAS and microplastic concentrations compared to all other sample types. This aligns with current understanding of the major sources of these contaminants: microplastics and PFAS are released during the use and disposal of consumer and industrial products, which typically occurs in indoor residential and industrial settings where these contaminants enter wastewater systems via drain discharge and concentrate in raw sewage (Hale, 2022). By comparison, deposition of microplastics and PFAS in the natural environment via pathways such as atmospheric deposition, infrastructure, vehicle wear and urban runoff is relatively more diffuse (Rafiei, 2023; Bouarafa, 2026), resulting in lower and more spatially variable concentrations across surface waters and groundwater.

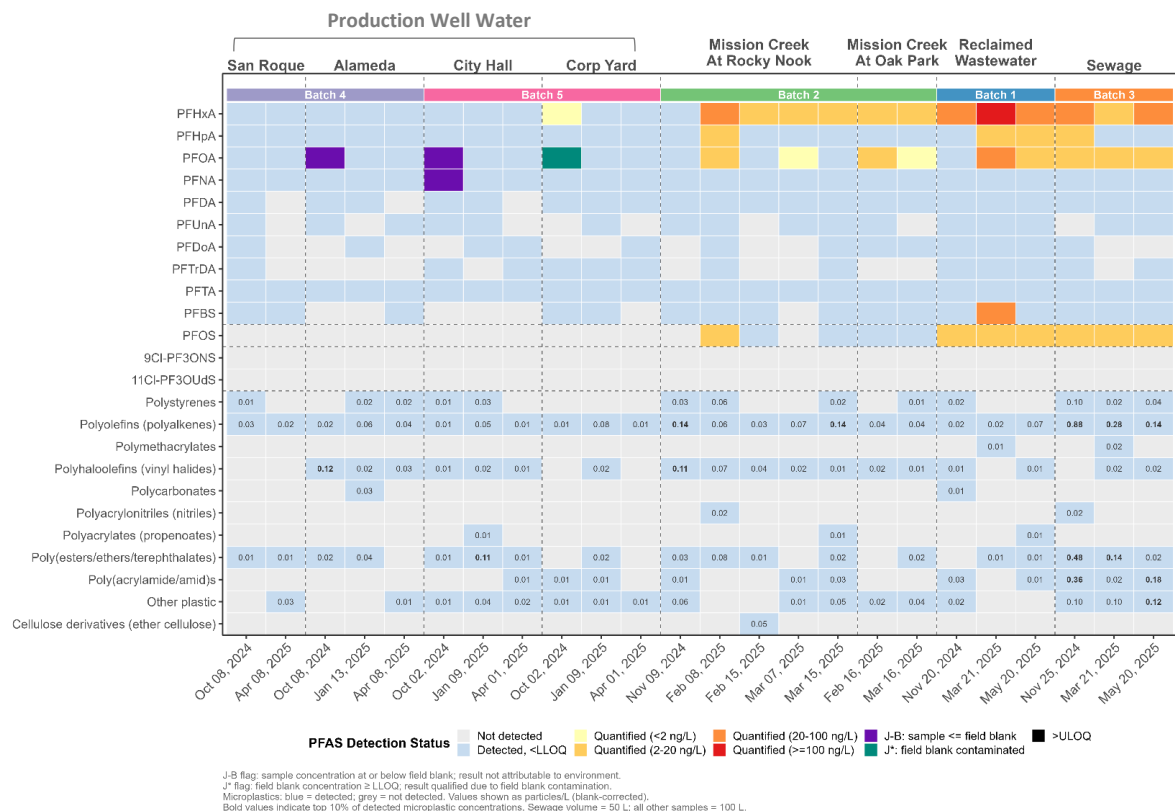


Figure 6. Heatmap visualizing PFAS and microplastic polymer class presence across water samples. Detections below the lower limit of quantification are shown in blue, and non-detects are grey. PFAS concentrations (ng/L) falling within quantitation limits are indicated in increasing scale from yellow to light orange, and dark orange to red. Batch labels denote the analytical batch in which PFAS were analyzed using LC-MS/MS, and do not apply to microplastics. Microplastics concentrations (microplastics/L) are noted in each cell where microplastics were above the minimum detectable amount after blank correction. Bold text indicates the top 10% of microplastics concentrations observed across all samples. Note that for microplastics, the volume of sewage samples was 50 L while the volume of all other samples was 100 L; all PFAS samples were 500 ml.

D. Discussion

Detecting low concentrations of microplastics in groundwater presents substantial methodological challenges. The μ FTIR method used in this study has a practical size limit of detection of approximately 10–20 μ m and exhibits reduced accuracy for fibrous particles, which tend to orient longitudinally during filtration and pass through filters with larger nominal pore sizes than their diameter would suggest (Cai, 2020; Munno, 2023). This is

particularly relevant for interpreting groundwater results, because the physical transport of solid particles from the surface to confined aquifer depths requires passage through very narrow pore throats in fine-grained sediments, which are usually in the range of microns to less than 1 millimeter (mm) (Auset, 2006). Particles small enough to traverse these pore spaces cannot be reliably identified as plastics using current spectroscopic methods. Emerging techniques including time-of-flight secondary ion mass spectrometry (ToF-SIMS) and pyrolysis gas chromatography-mass spectrometry (Py-GC/MS) offer the potential to chemically validate sub-20 μm particles and are under active development for microplastics applications. Groundwater samples collected as part of this study have been archived following best practices for contamination minimization and are available for future analysis once these methods are more fully validated.

Contaminants like microplastics and PFAS could enter wells as a result of leakage at well heads through gaps in well caps or seals, not just at the well where samples are collected, but at other monitoring and private wells nearby (UNESCO, 2025). However, the microplastics detected in municipal production well water in this study are more likely attributable to disintegration of plastic materials in the wetted components of the well pump, motor, pipes, and associated fittings rather than to contaminated surface water entering around the well infrastructure or contamination of groundwater in the aquifer. Several lines of evidence support this interpretation. First, all well heads are sealed City Hall and Corp Yard wells draw from the lower producing zone at depths of 635 and 690 ft, equivalent to 193.5 and 210.3 m, below ground surface, respectively, separated from the surface by the fine-grained middle zone which acts as a confining layer. Paulinski (2018) report calibrated horizontal hydraulic conductivity end members for Storage Unit I of 8.58 ft/day (2.6 m/day)

for coarse-grained producing zone sediments and 0.023 ft/day (0.007 m/day) for fine-grained confining materials. This difference in hydraulic conductivity reflects the fundamental difference in pore geometry between the producing zones and the fine-grained confining units that separate them, making physical transport of microplastic particles detectable by μ FTIR ($\geq 10 \mu\text{m}$) from the surface through the confining layer unlikely under natural groundwater flow conditions. Second, the polymer classes detected in well water, specifically polyolefins, polyhaloolefins (vinyl halides), and poly(esters/terephthalates), are consistent with materials used in well infrastructure. The submersible pumps installed in City Hall and Corp Yard are Grundfos SP-series pumps with all-stainless steel hydraulic components including impellers and diffusers; polymer-containing wetted components are limited to NBR nitrile rubber O-rings and bearings, a polyphenylene sulfide (PPS) neck ring, and a PTFE/carbon-graphite bearing washer. NBR wear would produce polyacrylonitrile-class particles, and PTFE wear would produce polyhaloolefin (vinyl halide)-class particles. This is consistent with μ FTIR spectra detected from microplastics observed in these well water samples. Column pipe, wellhead fittings, lubricants, and thread tape in municipal well systems, represent additional potential sources of polyhaloolefin (vinyl halide) particles. The detection of polyolefins points to PVC or HDPE components in the above-pump infrastructure as additional sources, consistent with findings reported by Viaroli et al. (2024) who documented infrastructure-derived microplastics in well water. Third, two well sample/date combinations, City Hall (January 2025, 0.26 particles per liter) and Corp Yard (January 2025, 0.14 particles per liter), exceeded concentrations observed in some Mission Creek and reclaimed water samples. Rather than indicating environmental contamination,

this is consistent with variable rates of polymer wear from infrastructure materials across sampling events, which would be expected to vary with pump age and runtime.

Alameda well, which is located adjacent to Mission Creek, draws from the upper producing zone at 162 m bgs. This is shallower than City Hall and Corp Yard and with a more direct hydraulic connection to creek recharge. Its polymer composition showed a distinctively elevated polyhaloolefin (vinyl halide) signature relative to other sample types in SIMPER analysis ($p < 0.05$ in multiple pairwise comparisons), which could reflect infrastructure sources including thread tape, PVC pipes, and other lubricants and adhesives. Additionally, stable isotope analysis of water samples collected in this study provides evidence that Alameda well water may not reflect recent recharge. The $\delta^{18}\text{O}$ and $\delta^2\text{H}$ values of Alameda well water (mean $\delta^{18}\text{O} = -6.19\text{‰}$, mean $\delta^2\text{H} = -38.2\text{‰}$) (see SI) cluster with other production wells sampled in this study and with the California State Water Resources Control Board Groundwater Ambient Monitoring and Assessment (GAMA) Program production well samples collected from Storage Unit I in 2011, and does not overlap substantially with $\delta^{18}\text{O}$ and $\delta^2\text{H}$ values of Mission Creek water collected at Rocky Nook and Oak Park ($\delta^{18}\text{O}$: -5.1 to -6.4‰ , $\delta^2\text{H}$: -26.8 to -36.3‰) and from reclaimed water ($\delta^{18}\text{O}$: -3.3 to -4.4‰ , $\delta^2\text{H}$: -15.8 to -29.1‰). The similar isotopic composition of Alameda well water and GAMA wells sampled from Storage Unit I in 2008 suggests that the isotopic character of pumped groundwater has been stable over 15 years, consistent with either long groundwater residence times or a consistently isotopically stable recharge source. This isotopic evidence strengthens the infrastructure source attribution for microplastics detected in Alameda well water, as it indicates that even the relatively more hydraulically connected

production well in this study may not be drawing meaningfully from recent Mission Creek recharge at the timescales relevant to microplastic contamination.

The global order of polymer abundance in environmental microplastics studies is polyester, polypropylene, polystyrene, polyvinyl chloride (PVC), and polyethylene terephthalate (PET), likely reflecting global plastic production volumes and the tendency of denser polymers such as PVC and PET to settle in aquatic environments relative to lower-density polyolefins (Koelmans, 2019). The polymer composition observed in Mission Creek and sewage samples in this study broadly reflects this pattern, with polyolefins dominating across most sample types.

In contrast to the microplastics detected in production well water samples, which appear primarily attributable to infrastructure materials, PFAS detections in well water may be representative of low-level aquifer contamination via older recharge sources, given that PFAS are dissolved-phase contaminants not subject to the physical filtration barriers that effectively exclude particulate microplastics from confined aquifer zones. The stable isotope data, however, suggests an important caveat: the similar isotopic composition of all four production wells and the 2008 GAMA samples indicates that groundwater in Storage Unit I may have long residence times. If groundwater residence times are on the order of decades or longer, the low-level PFAS detected in production wells may reflect recharge that predates contemporary PFAS monitoring programs, which aligns with legacy PFCAs like PFHxA, PFHpA, and PFNA being detected in well water samples (Xiao, 2021). Tritium samples to age well water collected during this study have been archived for potential future analysis.

PFHxA was the dominant PFAS detected across all sample types and exhibited a clear concentration gradient from sewage and reclaimed water to groundwater, consistent with reclaimed water irrigation as a potential primary PFAS source to the watershed with attenuation along the aquifer recharge pathway as found in (Xingchun, 2022). This pattern is consistent with the behavior of short-chain PFCAs in soil-water systems. PFHxA has a low soil-water partition coefficient (K_d) relative to longer-chain PFAS such as PFOS (Nguyen, 2020), making it more mobile in the subsurface and more likely to reach the water table. The absence of PFOS above LLOQ in any groundwater well sample, despite its detection in creek water and reclaimed water, is consistent with preferential sorption of this long-chain PFAS to soil organic matter during infiltration (Nguyen, 2020). This points to a chain-length-dependent attenuation pattern in which mobile short-chain PFCAs reach the aquifer while longer-chain PFAS are retained in the vadose zone.

E. Conclusion

This study characterized the concentration and composition of microplastics and PFAS across a suite of potentially interacting water resources in a single urban watershed, providing baseline measurements that can inform both source attribution and drinking water management in Santa Barbara, California. Microplastics were detected in 22 of 24 samples at concentrations ranging from 0.03 to 1.94 particles per liter, and six PFAS compounds, namely PFHxA, PFHpA, PFOA, PFNA, PFBS, and PFOS, were quantified above detection limits across one or more sample types, however, these concentrations in waters serving as potential drinking water resources were below any Maximum Contaminant Levels established by either the United States Environmental Protection Agency or California State Water Resources Control Board. Specifically, microplastics concentrations in creek samples

ranged from 0.8 particles per liter to 0.38 particles per liter, which is within the lower range of microplastic concentrations measured in urban creeks (Luo, 2019; Werbowski, 2021). Microplastics concentrations in groundwater ranged from 0.03 particles per liter to 0.26 particles per liter which is also within the lower range of microplastic concentrations measured in groundwater (Lee, 2024). However, direct comparisons of microplastic concentrations across different studies should be approached cautiously as differing sample collection and quality assurance and quality control methods may lead to substantially different measurements.

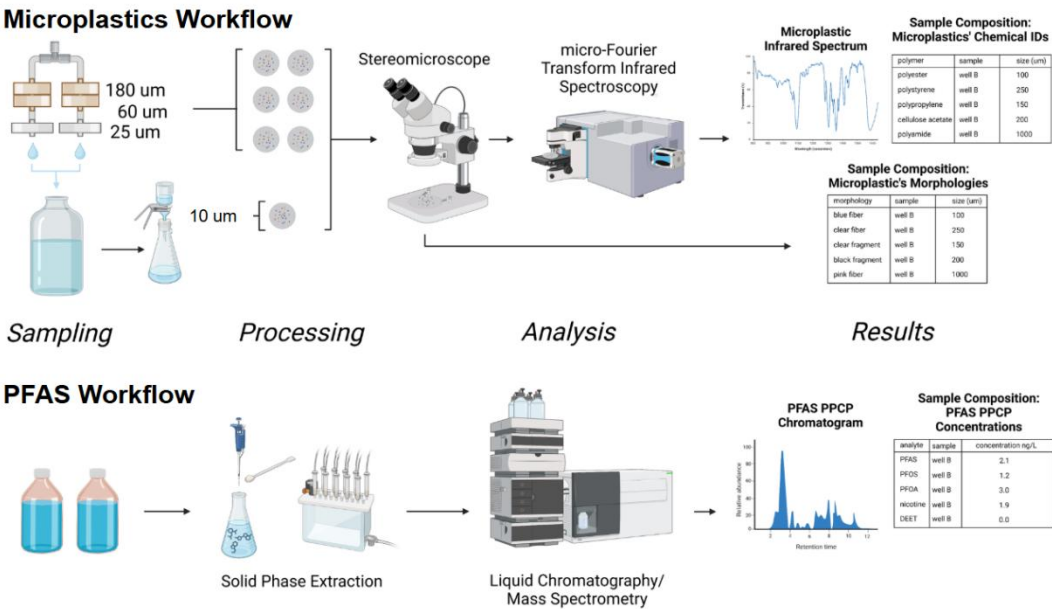
The most environmentally significant PFAS finding is the concentration gradient of PFHxA from reclaimed water through creek water to groundwater production wells, consistent with reclaimed water irrigation as a potential PFAS source to the watershed, albeit with substantial attenuation along the aquifer recharge pathway. These findings establish a baseline against which future PFAS trends in Storage Unit I can be evaluated, particularly as reclaimed water use in the watershed is expected to remain substantial as an alternative to using imported surface water from nearby reservoirs.

Microplastics detected in production well water are most plausibly attributed to disintegration of plastic components and lubricants in well infrastructure rather than transport of environmentally derived particles through the aquifer matrix. These findings suggest that microplastic concentrations measured at the wellhead are not representative of microplastic concentrations in the aquifer itself, and that well infrastructure may be the most proximate source of detected particles. This is an important distinction for interpreting monitoring data from production wells more broadly.

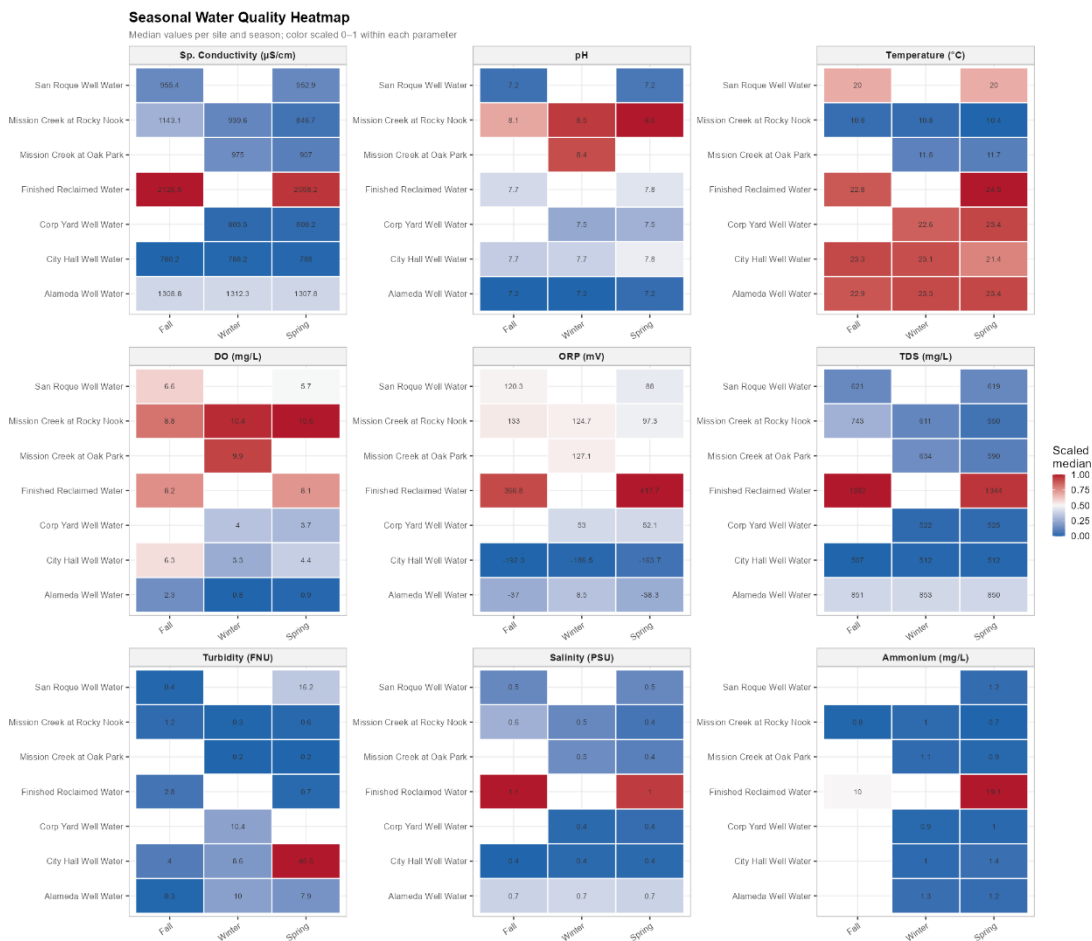
This study provides the first simultaneous characterization of microplastics and PFAS across the full spectrum of potentially interacting water types: sewage, reclaimed water, creek water, and production well water, all within a single urban watershed. The results demonstrate that while PFAS contamination of groundwater is detectable at very low levels, consistent with historical recharge, microplastic contamination of municipal production well water at drinking water depth most likely reflects infrastructure rather than environmental sources. Both findings have direct implications for how stormwater and water resource managers interpret compliance monitoring data, prioritize treatment investments, and design future sampling programs as plastic, microplastic, and PFAS regulations continue to evolve at the state and federal level.

F. Appendix

Visualization of Microplastics and PFAS Analytical Workflow



Heatmap of water quality parameters over time

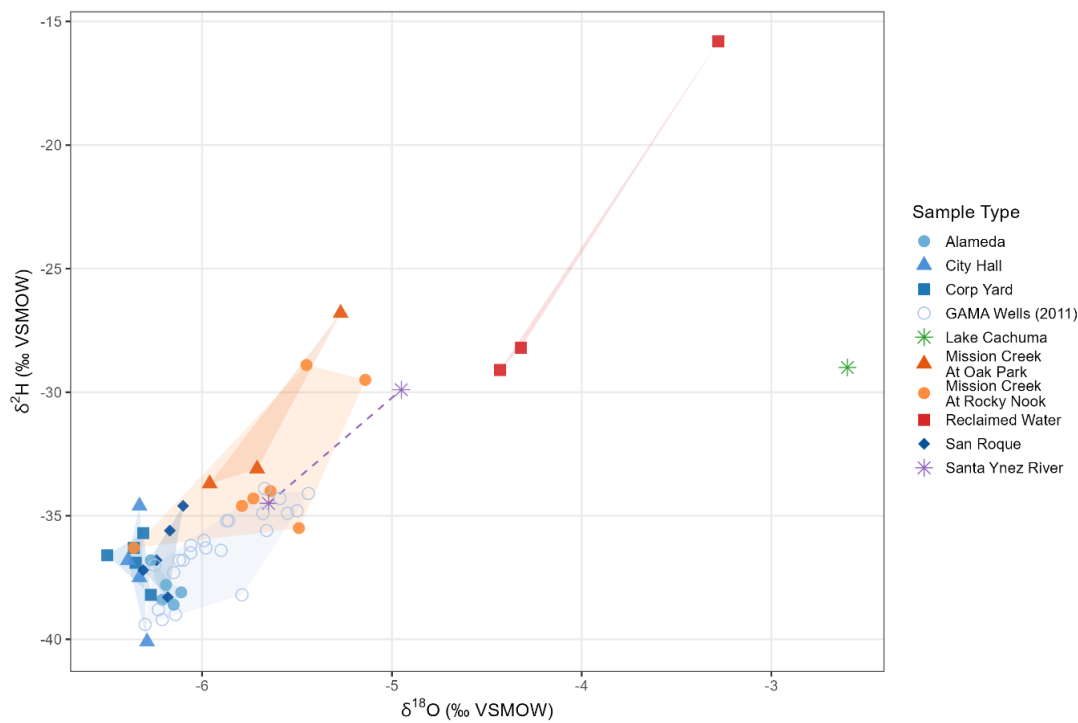


Raw and blank-corrected microplastic particle counts by sample and date. Blank subtraction was performed using the combined-characteristics method (size fraction and material class) per Munno et al. (2023). Bold text indicates samples where blank subtraction reduced the total count. Subtraction was applied only to size fraction and material class combinations present in the corresponding field blank. *Note corrected

counts for Corp Yard on April 1 and Reclaimed Water on November 20th exceeded sample batch minimum detectable amounts and are therefore listed as non-detectable (N.D.)

Sample	Date	Raw Count	Particles Subtracted	Corrected Count
	Apr 08, 2025	11	1	10
Alameda	Jan 13, 2025	17	0	17
	Oct 08, 2024	16	0	16
	Apr 01, 2025	6	0	6
City Hall	Jan 09, 2025	26	0	26
	Oct 02, 2024	5	0	5
	Apr 01, 2025	2	0	N.D. (2)*
Corp Yard	Jan 09, 2025	14	0	14
	Oct 02, 2024	3	0	3
Mission Creek At Oak Park	Feb 16, 2025	8	0	8
	Mar 16, 2025	12	0	12
	Feb 08, 2025	29	0	29
	Feb 15, 2025	13	0	13
Mission Creek At Rocky Nook	Mar 07, 2025	11	0	11
	Mar 15, 2025	28	0	28
	Nov 09, 2024	40	2	38
	Mar 21, 2025	4	0	4
Reclaimed Wastewater	May 20, 2025	11	0	11
	Nov 20, 2024	11	0	N.D. (11)*
	Apr 08, 2025	6	0	6
San Roque	Oct 08, 2024	5	0	5
	Mar 21, 2025	30	0	30
Sewage	May 20, 2025	32	6	26
	Nov 25, 2024	97	0	97

Biplot of Oxygen-18 and Deuterium stable isotopes with convex hulls to illustrate clustering



VI. Summary

The work presented in this dissertation develops and applies novel methods and sampling approaches to quantify terrestrial plastic trash, and microplastics and PFAS in waters across urban environments, providing estimates with measures of uncertainty to support regulatory compliance and inform water resources management.

Chapter II describes the application of multiple-pass removal surveys with depletion modeling to estimate the true abundance of land-based plastic trash with quantified uncertainty and quantifies the degree to which single-pass trash surveys, the current norm for monitoring, underestimate plastic trash count and mass. Single-pass methods were found to substantially underestimate both plastic litter count and mass. The multiple-pass removal survey with depletion modeling approach provides an accessible surveying protocol with an analytical workflow in open-source software, making it available to both expert and non-expert practitioners.

Chapter III evaluated mark-recapture as an additional novel method for surveying terrestrial litter, finding that estimates of true litter abundance derived from mark-recapture and multiple-pass removal surveys with depletion modeling conducted in the same transect converged to nearly identical values with nearly identical standard errors. This demonstrates that two independent methods produce consistent estimates of true litter abundance and provides practitioners with a second accessible surveying approach that can be selected based on transect characteristics and available resources.

Chapter IV scaled multiple-pass removal surveys with depletion modeling to the watershed level and evaluated agreement between depletion-modeled trash mass estimates and qualitative rankings assigned using the On-Land Visual Trash Assessment (OVTA),

California's primary method for monitoring trash compliance under the California Clean Water Act Trash Amendments. OVTA rankings agreed with trash mass estimates in distinguishing sites ranked as "Not Littered" from those ranked as "Slightly Littered" or "Littered"; however, because single-pass surveys underestimate true trash abundance, sites ranked as "Not Littered" by the OVTA may have higher trash loads than the visual assessment alone would suggest. Depletion-modeled litter mass estimates were then used as inputs for Empirical Bayesian Kriging Regression Prediction to interpolate trash mass across the sidewalk networks of three neighboring watersheds, stratified by Priority Land Use type, with prediction uncertainty quantified using a Bland-Altman-like approach. In two of the three watersheds, trash density was consistent with expected contributions from Priority Land Use types; however, in the smallest watershed, trash density was uniformly elevated across all land use types, suggesting that location-specific effects can supersede land use designation as a driver of accumulation and that watershed-wide intervention may be warranted in some cases. Together, these findings provide managers with a spatially explicit framework for assessing trash loading by Priority Land Use type at the watershed scale.

Chapter V determined the concentration and composition of microplastics and PFAS in municipal production well water and surface waters potentially interacting with the underlying source aquifer, within the same study area where litter loads were estimated in Chapter IV. Low levels of microplastics and PFAS were detected in groundwater and in urban creek water known to seep into the underlying aquifer, with relatively higher concentrations detected in reclaimed water and sewage. Detected PFAS concentrations were below all Maximum Contaminant Levels currently established by the United States Environmental Protection Agency and the California State Water Resources Control Board.

These measurements provide a baseline characterization of microplastic and PFAS occurrence in these water resources at a time when state and federal regulations governing their monitoring and removal from drinking water are actively developing.

Together, this body of work advances the methodological and empirical foundations for monitoring plastic trash, microplastics, and PFAS in urban environments and waters, providing tools and data that managers and researchers can apply to support regulatory compliance and protect human and ecosystem health.

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