Computers, Environment and Urban Systems 77 (2019) 101344

Contents lists available at ScienceDirect

Computers, Environment and Urban Systems

journal homepage: www.elsevier.com/locate/ceus

# Improving urban trash reduction tracking with spatially distributed Bayesian uncertainty estimates

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ARTICLE INFO

*Keywords:*
Stormwater
Trash
Water quality
Bayesian

ABSTRACT

Urban stormwater runoff is among the most significant sources of trash delivery to waterways, degrading aquatic habitats and contributing to oceanic trash gyres across the globe. Municipal water quality permits that require elimination of trash inputs to stormwater systems employ visual trash assessments on city streets to demonstrate litter reduction progress. We present a novel method to increase the utility of these assessments by quantifying their degree of certainty at a granular spatial scale via Bayesian credibility intervals. Using data collected in the City of Salinas, California, we illustrate how the outputs can be used to determine effective trash controls and prioritize areas for management actions. Spatial dependence was incorporated to the uncertainty estimates within individual stormwater drainages and results were interpolated to adjacent parcels. After 3–6 observation periods over 20 months, we found approximately 30% of the city area showed minimal litter accumulation at an 80% certainty level. The outputs provide a practical alternative for cities to determine compliance with stormwater trash regulations, update understanding of trash accumulation patterns, and iteratively adjust sampling designs in response to new observations. The methods described have been implemented as a web-based geospatial decision support tool to help stormwater managers target implementation actions and report progress to regulators.

## 1. Introduction

### 1.1. Urban stormwater trash regulations and management knowledge needs

With growing understanding of the magnitude of trash delivery to oceans, the need for action to prevent further aquatic habitat degradation is now widely recognized (Day, Shaw, & Ignell, 1989; Hammer, Kraak, & Parsons, 2012; Law et al., 2010; Moore, 2008). Urban trash (alternatively termed anthropogenic litter) is a water pollutant that impairs beneficial uses, degrades aquatic habitats and causes entanglement, death from ingestion, and transport of invasive species (Sigler, 2014). While the relative contributions of various sources to ocean trash gyres like the Great Pacific Garbage Patch (Dautel, 2009) are not fully understood, urban stormwater contributes to the overall marine debris problem (EPA, 2011; Wheeler & Knight, 2017). Many communities throughout the United States, including City of New York (NYSDEC, 2015), City of Los Angeles (SWRCB, 2015a), San Francisco Bay Area (SFRWQCB, 2015), and the City and County of Honolulu (Hawaii Department of Health, 2012), have implemented water quality permit regulations to reduce or eliminate trash from urban stormwater. Recent amendments to the California Ocean Plan (SWRCB, 2015a) and the Water Quality Control Plan for Inland Surface Waters, Enclosed Bays, and Estuaries of California (SWRCB, 2015b) require California cities to reduce trash inputs to storm drain systems by 2030 to levels that do not adversely impact aquatic habitats.

Stormwater programs require a means to prioritize locations for mitigation actions, quantify urban trash reduction effectiveness, and provide meaningful reporting of annual progress to regulators. California cities have two options to meet National Pollutant Discharge Elimination System (NPDES) permit compliance: 1) install trash 'full capture systems' that separate or prevent downstream movement of all trash particles > 5 mm in diameter or 2) implement a combination of institutional controls (e.g. street sweeping, trash pickups, education and outreach) to eliminate trash sources to the stormwater system. Areas not served by full capture systems require monitoring to demonstrate that they are clean enough to achieve 'full capture equivalency' with minimal trash available for transport into the storm drain system (SWRCB, 2015a).

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https://doi.org/10.1016/j.compenvurbsys.2019.05.001
Received 2 February 2019; Received in revised form 29 April 2019; Accepted 4 May 2019

### 1.2. Quantifying urban trash conditions

Measuring the effectiveness of urban trash mitigation measures requires a reliable means to characterize patterns of trash accumulation within a city (e.g. Marais & Armitage, 2004; Marais, Armitage, & Wise, 2004). Various qualitative and quantitative field protocols have been used to characterize trash accumulation and impacts in waterways, with methods oriented to different study objectives such as understanding trash sources and types (Rosevelt, Los Huertos, Garza, & Nevins, 2013), transport dynamics and delivery to receiving waters (Moore, Cover, & Senter, 2007; Moore, Sutula, Bitner, Lattin, & Schiff, 2016; San Diego Bay Debris Study Work Group, 2016), habitat impacts (Hoellein, Rojas, Pink, Gasior, & Kelly, 2014), and community impacts (Muñoz-Cadena, Lina-Manjarrez, Estrada, & Ramon-Gallegos, 2012). Methods employed have included stream bank surveys (City of Los Angeles, 2016; SFRWQCB, 2004; Moore et al., 2007), flux estimates in rivers (BASMAA, 2016b), repeated roadway surveys (City of Los Angeles, 2017), and drone-based imagery analysis (Deidun, Gauci, Lagorio, & Galgani, 2018; Hengstmann, Gräwe, Tamminga, & Fischer, 2017). Since the amount of trash entering the stormwater system is dependent on the levels of trash that accumulate on streets, sidewalks, and other impervious surfaces (Wheeler & Knight, 2017) and other factors that influence transport (Moore et al., 2007), a measure of trash accumulation can provide an appropriate metric to estimate loading to receiving waters.

Visual assessments of trash accumulation on roadways are a rapid, qualitative method to measure the accumulated trash available for transport into the storm drain system within a certain area, which we refer to hereafter as *trash condition*. For this study, we employ a variation of a previously developed visual assessment protocol, termed the On-Land Visual Trash Assessment (OVTA), which has shown empirical association with measured trash loads (volume/area) (BASMAA, 2014), and has been accepted by the California State Water Resources Control Board (SWRCB) as a means to comply with water quality permit requirements (SWRCB, 2018). Compliance is achieved via OVTA results by demonstration that areas are in the 'Low' OVTA trash condition category (SWRCB, 2015a). The Low trash condition category is described as having a maximum of "a few small pieces of trash" within a city block length and has been estimated to have equivalent trash loading to the stormwater system as installation of full capture systems (BASMAA, 2014).

While the field protocol for OVTA is well-developed, sampling recommendations from (SWRCB, 2017) are based on very limited data and analysis (BASMAA, 2016a). Temporal and spatial variability of trash conditions create a substantial challenge for cities to determine appropriate frequency and spatial density of observations to achieve adequate levels of confidence or power for detecting changes. While important considerations for sampling design and spatial analysis have been addressed (Wheeler & Knight, 2017), they have not been incorporated to monitoring requirements from SWRCB. Moreover, sampling recommendations provided by a post-hoc sample size and power analysis are not responsive to new information as monitoring data are acquired. Since the variance of trash condition estimates may be nonstationary over both time and space (Lippiatt, Opfer, & Arthur, 2013; Moore et al., 2016; Ryan, Moore, Van Franeker, & Moloney, 2009), patterns of uncertainty are likely to shift as more data are collected. Since the implementation period for cities to achieve trash compliance will span at least a decade (SWRCB, 2015a), a dynamic approach to the problem can help cities efficiently allocate monitoring and implementation resources as their understanding of municipal trash patterns improves.

### 1.3. Bayesian uncertainty estimation

Uncertainty should be a fundamental dimension of quantifying the status of environmental conditions to support resource management decision making, since it has direct bearing on our capacity to use data and models to test hypotheses about patterns or changes (e,g. Beven, 2001; Beck, 1982). While use of models, both numeric and statistical, can facilitate wise decisions, dealing with uncertainty in the outputs is among the greatest challenges facing practitioners (Barton et al., 2012). Understanding of the applicability of Bayesian methods to environmental decision-making has grown in recent years (Barton et al., 2012; Ellison, 1996; Wikle, 2003), partly driven by development of new computational tools that make them available to a wider audience of researchers and development of more efficient implementation methods (e.g. Blangiardo, Cameletti, Baio, & Rue, 2013; Brown, 2015; Lunn, Spiegelhalter, Thomas, & Best, 2009). Bayesian methods have been widely applied to the problems of measuring uncertainty in environmental variables (Clark & Gelfand, 2006; Cressie, Calder, Clark, Ver Hoef, & Wikle, 2009; Pulkkinen, 2015) and been shown to have several advantages over frequentist counterparts for experimental design elements such as sample size determination (De Santis, 2007; Joseph, Du Berger, & Bélisle, 1997; Sahu & Smith, 2006).

The problem of ongoing trash condition assessment lends itself to an iterative sampling design that can incorporate new information as it becomes available. Bayes Theorem provides a formal method to update prior knowledge with new evidence wherein a prior expectation (previous belief) is combined with a likelihood function (new data) resulting in a posterior distribution (updated belief) that is used for statistical inference. The less information available in any given year to define trash conditions, the more influence the prior expectation has on the updated belief, and as more data are collected, the importance of the prior belief is diminished. The Bayesian approach allows use of diverse information types in the form of the prior and can be used to make probabilistic statements about trash conditions for specific years—which is important for regulatory compliance, and discrete locations—which is useful for targeting trash management actions and evaluating the effectiveness of those actions. A primary advantage is that it provides a direct accounting of uncertainty associated with parameter values (e.g. mean trash condition) owing to the fact that these parameters are treated as probability distributions rather than point values as they are in a frequentist framework. Accessibility to Bayesian methods has been facilitated by tools built in the R programming language to sample the posterior distributions via Markov Chain Monte-Carlo (MCMC) or estimate them via Integrated Nested Laplacian Approximations (INLA) (Blangiardo & Cameletti, 2015; Martins, Simpson, Lindgren, & Rue, 2013). In this study we provide a new application of Bayesian methods to quantify uncertainty associated with visual trash assessment data for the purpose of iteratively informing regulatory compliance, sampling design, and management actions.

## 2. Data and methods

### 2.1. Visual trash assessments

Visual trash assessment data were collected throughout the City of Salinas from spring 2017 to winter 2018 to estimate trash condition on city streets and sidewalks. Salinas is located on California's Central Coast with a population of 160,000 and an area of approximately 60 $km^2$ (Fig. 1). The City is mostly surrounded by agricultural fields and stormwater flow to receiving waters is governed by eight sub-drainages primarily defined by the stormwater infrastructure. Three of the streams flowing through the City are listed as having impaired beneficial uses by the State Water Resource Control Board (SWRCB, 2016) and persistent trash is evident on roadways and alongside urban stream channels adjacent to commercial, industrial, and high-density residential areas. Trash condition assessments were made 3–6 times throughout the entire city, with observations spaced at least 30 days apart, using the OVTA field protocol. The OVTA approximates an exponential relationship between the trash condition categories and the

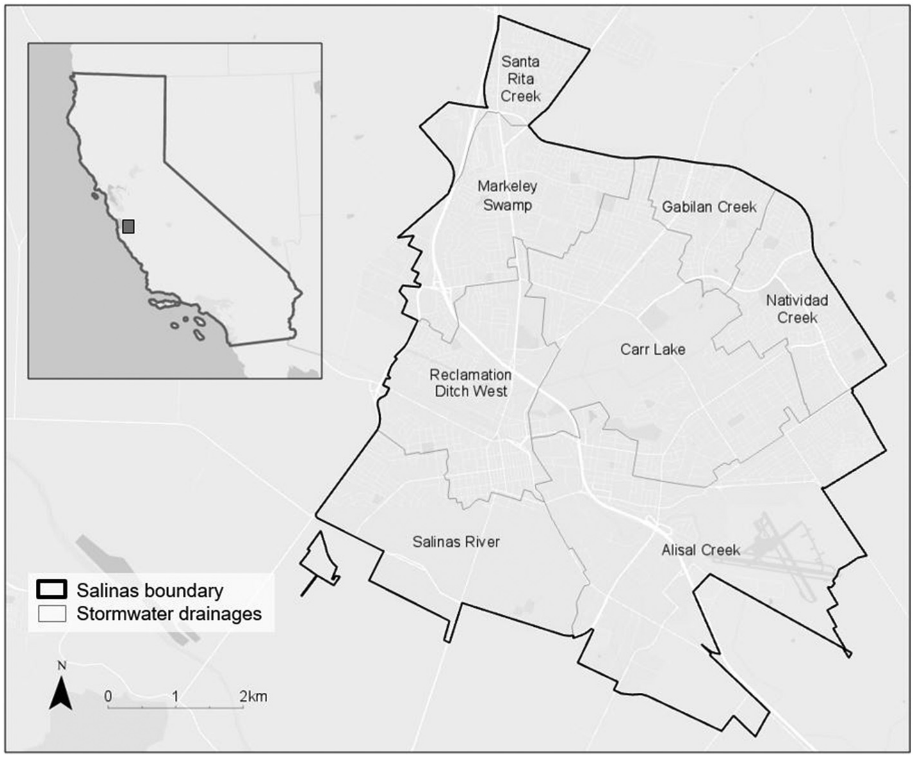


**Fig. 1.** City of Salinas and stormwater drainages.

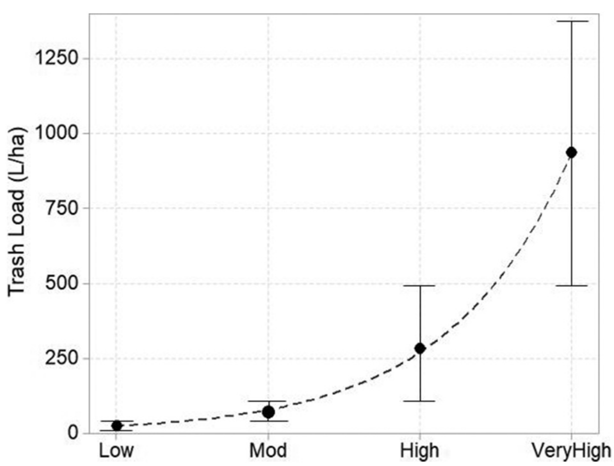


**Fig. 2.** Trash condition score category relationship to measured mean trash loads (volume/area) adapted from BASMAA (2014).

median value of measured trash volumes within that category (BASMAA, 2014) (Fig. 2).

Rather than surveying discrete sites, field teams conducted assessments via a continuous streaming of condition categories while moving along road segments with data recorded via a smartphone mobile app built using Collector for ArcGIS from Environmental Systems Research Institute (ESRI). This allowed rapid coverage of large areas and reduced effort required to translate data from field data sheets to a GIS. Data were collected by field teams of two driving slowly in a vehicle with the passenger assigning the trash category to the road segment. When vision of the road shoulder or curbside was substantially obstructed, usually due to parked cars, field teams would park and complete the road segment survey while walking. In this way, field teams surveyed nearly the entire road network of Salinas at least 3 times on each side of the road during the study period (20 months). Since field personnel changed the trash condition category while moving, and several surveys were conducted on each road, the resulting data set were line segments of different lengths, collected on different dates for various areas of Salinas. Assessments were conducted at least 48 h after substantial rainfall events and at midpoints between regular street sweeping intervals, both of which have strong potential to affect observed trash conditions.

### 2.2. Spatial data processing and analysis

Trash condition data were summarized using a 30-m grid with each cell value calculated as the length-weighted average of the lines that occurred within each cell for each assessment period. For each assessment, the trash condition score for a grid cell ($s_g$) was calculated as the sum of the products of each assessment segment length ($L_1 \ldots L_i$) and the segment trash condition score ($s_1 \ldots s_i$).

$$s_g = s_1 * L_1 + s_2 * L_2 \ldots + s_i * L_i \tag{1}$$

While each observation was assigned the median value of the trash condition category (Fig. 2), combining observations of different lengths made at different times within each grid cell resulted in values on a continuous scale with possible scores ranging from 23 to 935 L/ha for (Fig. 3). For each grid cell, the mean condition was calculated for all of the assessment periods along with observation count and variance, which both serve as inputs to the uncertainty analysis. A nearest-neighbor interpolation was performed in ArcGIS using a maximum distance of 2 grid cells (60 m) to estimate values for cells with no data, which made up approximately 5% of remaining road length. The road network was used to subset the interpolation so that grid cells were filled in only along roads.

Whenever spatial autocorrelation is present, trash condition depends on the covariance structure of the data (e.g. Aubry & Debouzie, 2000). We conducted a spatial analysis to quantify patterns of trash condition and spatial dependence using the R package geoR (Cressie, 1993; https://www.r-project.org/) and the spatial statistics toolbox in ArcGIS, and the outputs were used to inform the uncertainty analysis. Since the spatial processes that result in autocorrelation may exhibit

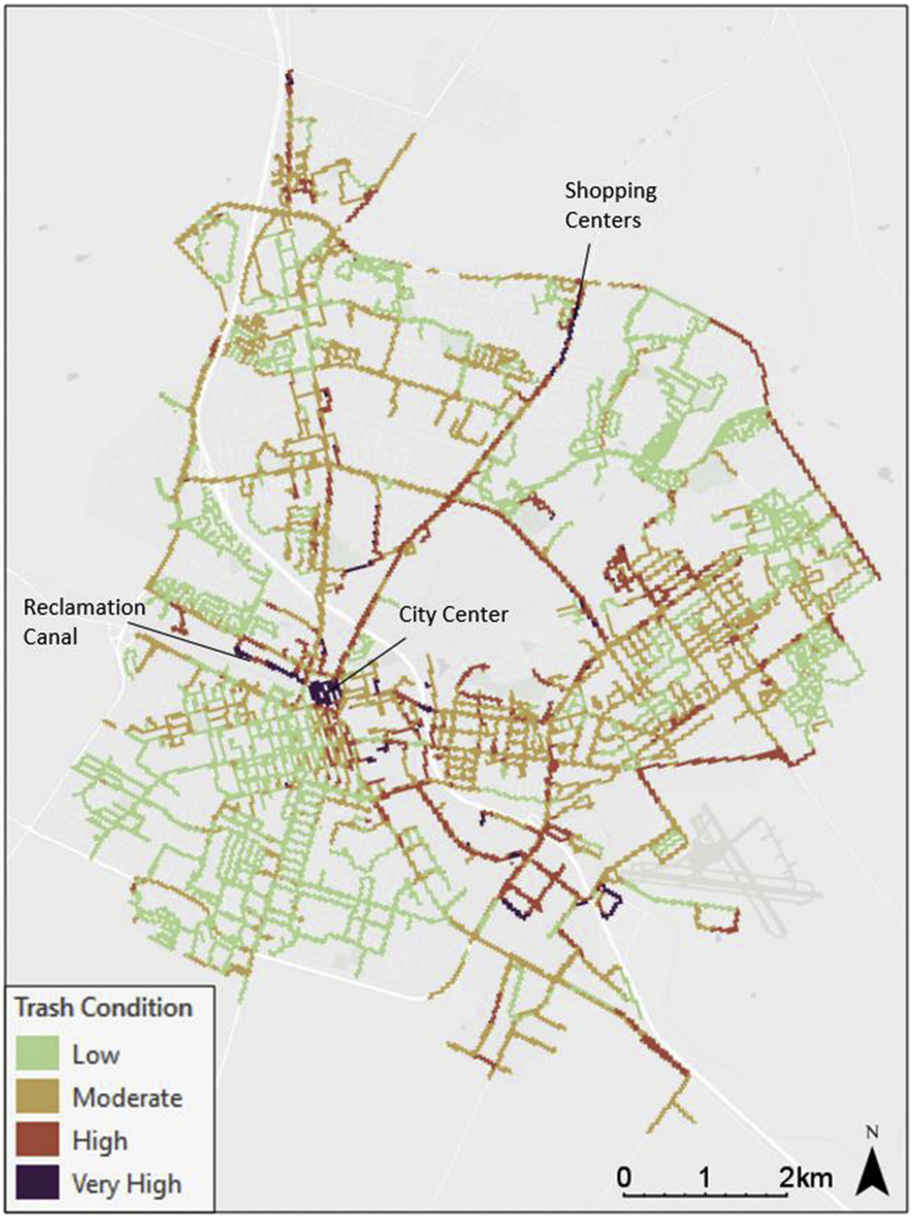


**Fig. 3.** Mean trash condition for observations made from 2017 to 2018 as OVTA categories.

non-stationarity across the City, the range and strength of spatial dependence can also vary by location (Risser, 2016; Smith, Higdon, Swall, & Kern, 2000). To accommodate such spatial effects that may operate at scales finer than the entire City, we subset the trash data using the 8 stormwater drainages shown in Fig. 1 to perform an incremental autocorrelation analysis (Global Moran's I) within each of these drainages. This analysis was done in an area-discrete manner so that locations were only influenced by other locations within their own drainage, since these drainages are often separated by physical barriers on the surface (e.g. railroad tracks, highways), topography, or the subsurface stormwater infrastructure. To assess the potential influence of more granular spatial patterns, we also used a local indicator of spatial association (LISA): Anselin Local Moran's I (Anselin, 2017).

Since there are only 3–6 observations available for each road segment, we explored ways to pool mean trash condition variance by quantifying autocorrelation at various distances. The incremental autocorrelation analysis calculates the Global Moran's I for a series of increasing distances (see Getis & Ord, 1992) and associated z-scores that reflect the intensity of spatial clustering. Since stormwater infrastructure is an important vector for trash transport, these drainages provide a physically meaningful unit of analysis to quantify the spatial dependence. The outputs of this analysis indicated distances of the most pronounced autocorrelation effects within each drainage, providing an appropriate distance at which to pool these variance estimates, which are a key input to the uncertainty calculation.

### 2.3. Quantifying trash condition uncertainty

Using a Bayesian approach, uncertainty is quantified as the width of a specified interval over the posterior distribution, often referred to as a 'credibility interval.' To quantify uncertainty, we used Bayesian functions written in R by (Joseph et al., 1997; Joseph & Belisle, 2015) to calculate the number of additional observations required to reach various posterior credibility interval coverage probabilities for a normal mean (e.g. 0.95). The number of additional observations ($m$) required is calculated using the R function *mu.varknown*, for a specified length ($L$) and coverage probability level ($p$) for the posterior credible interval for the unknown mean as

$$m = \left[\frac{(p+1)/2}{L/2}\right]^2 * \sigma^2 - n0 \quad (2)$$

where *n0* is the number of previous observations and $\sigma^2$ is the variance. The R package 'raster' (Hijmans, van Etten, et al., 2018) was used to call the function *mu.varknown* to apply to each grid cell where trash condition data had been collected, using the number of prior observations (*n0*) and variance ($\sigma^2$) calculated for each grid cell as inputs to calculate *m*. The length over the posterior distribution (*L*) was kept fixed at approximately 10% of the range of the trash condition data. The posterior credibility interval coverage was varied between from 0.50 to 0.99 at intervals of 0.05, resulting in gridded outputs of additional observations required to achieve various levels of certainty as reflected by the credibility interval coverage. The number of additional observations required at each location reflects the measurement uncertainty given each combination of trash condition variance and number of previous observations. These raster layers were combined to create a map of certainty with each cell value reflecting the highest credibly interval coverage level that required no additional observations.

### 2.4. Output mapping

Since cities require an area-based metric to demonstrate trash condition compliance guidelines (SWRCB, 2017), we explored two methods for interpolating the trash condition data collected on roads to adjacent parcels, Nearest Neighbors (NN) and Empirical Bayesian Kriging (EBK) (Krivoruchko & Gribov, 2014). For the NN approach, grid cells were buffered to intersect parcels adjacent to road segments and the parcels were assigned the trash condition of that grid cell or an area-weighted average of grid cells that intersected the parcel. EBK is a geostatistical approach that was implemented in ESRI's Geostatistical Analyst wherein the interpolation is not constrained to the roads, so that data values influence grid cells in all directions. The parcel layer was clipped to the EBK and NN outputs to classify parcels as the area-weighted average of the grid cells within each parcel.

To facilitate reporting and trash action prioritization, we used the data interpolated from the on-road grid cells to create parcel-scale maps that reflect compliance with trash regulations or indicate trash mitigation priority areas. Compliance results were mapped using the trash condition category of Low (see Fig. 2) and the calculated certainty levels. Similarly, trash priority areas were mapped for parcels that fell into trash condition categories other than Low by combining their mean scores ($\bar{s}$) with the certainty estimates ($c$) to calculate the priority area score ($f$) as

$$f = \bar{s} - (1 - c) * \bar{s} \quad (3)$$

which were mapped as quartile categories defined for the entire City of Salinas.

## 3. Results

### 3.1. Urban trash condition and certainty patterns

Mean trash condition for the study period ranged from 2.5 to 935 L/ha. and the mean trash condition for all of Salinas was 70 L/ha, which falls near the median of the Moderate trash condition category. The majority of the 30-m grid cell values were in either the Low (42%) or Moderate (44%) categories and were low in the High (12%) and Very High (2%) categories (Fig. 3). Areas of the city with the most trash (High and Very High trash condition) were concentrated in commercial areas of the city center, large industrial parcels near the city center, along the reclamation ditch waterway, and shopping centers near main arterial roads, especially where they approach the perimeter of the City.

Results of the autocorrelation analysis for trash condition variance at 90-m increments shows moderate differences between stormwater drainages (Fig. 4). Because the Moran's I index is dependent on the calculated spatial weights, these index values cannot be interpreted directly and must be evaluated within the context of the null hypothesis as a z-score (e.g. Getis & Ord, 1992). The z-scores on the y-axis indicate the intensity of spatial clustering; z-scores > 1.96 represent significant positive spatial clustering with a 90% level of confidence. The peaks in each plot represent the strongest spatial autocorrelation within each stormwater drainage. All drainages exhibit similar patterns of a decline of spatial autocorrelation towards insignificant levels beyond 2 km for most of the drainages, though the trajectory and steepness of the falloff vary. The peak autocorrelation distance ranged from 120 m in Alisal Creek to 460 m in the Gabilan Creek drainage (highlighted points in Fig. 4). These peak distances were used as the radius for calculating pooled variance estimates for each stormwater drainage for input to the uncertainty analysis. In this way, the uncertainty estimates incorporated heterogeneity of the covariance structure that arises from differences in spatial processes operating within each stormwater drainage.

The LISA analysis showed that most areas within the city (84% of grid cells) showed no significant local clustering of trash condition variance (Table 1). Few areas (< 1% of grid cells) showed High-Low or Low-High outliers that indicate high spatial frequency variance heterogeneity. Local clustering, primarily Low value clusters, were identified throughout the city, and together with High value clusters accounted for 15% of grid cells. Often, these clusters had at least one axis that was similar in length to the strongest autocorrelation distance calculated using the Global Moran's I. Since the Global metric appeared to largely represent the dominant mode of autocorrelation and was also easier to automate, we used the results from the incremental autocorrelation analysis (Global Moran's I) as the basis for pooling variance estimates over space.

The spatial pattern of trash condition certainty calculated using Eq. 1 for each road grid cell are shown in Fig. 5. Lighter areas that indicate lower certainty (high uncertainty) in trash condition have either fewer observations and/or have greater time-variance in those observations. High certainty areas tended to be cleaner areas of the City away from the city center and main arterial roads, consisting largely of single-family residential areas. These areas receive less vehicle and pedestrian traffic and employ parking ordinances that allow street sweepers to reach most curb and gutter areas where trash often accumulates. Most of the areas with high certainty have a Low or Moderate mean trash condition, while areas with low certainty (< 70%) are particularly prevalent in High and sometimes Moderate trash condition areas (Figs. 3 and 5). This is partly due to the exponential nature of the trash condition – trash loading rate relationship (Fig. 2), wherein High and Very High values disproportionately increase variance used in the uncertainty analysis. In areas that have High or Very High trash conditions episodically, more observations may be needed to increase certainty of mean trash condition estimates.

### 3.2. Mapping compliance and identifying priorities

Outputs of the interpolated mean trash condition from roads to parcels using each of the two methods, nearest neighbor (NN) and Empirical Bayesian Kriging (EBK), are shown in Fig. 6. Given the empirically estimated parameters for EBK (nugget, slope, power) with a power semivariogram model, EBK provides greater coverage throughout the city compared to NN which leaves substantially more area unclassified. Correspondence between EBK and NN for the trash condition categories are summarized in Table 2, with the Low and Moderate condition categories showing < 10% deviation and the High trash category showing a 30% difference. Near the center of the City (Fig. 6), a large agricultural parcel is classed as High using EBK (panel B) but is left unclassified using NN (panel A) because it is surrounded by other agricultural fields not roads. Another example is in the southeast portion of the city, where the Airport was classified in the Moderate category using NN (panel A) but in the High category with EBK (panel

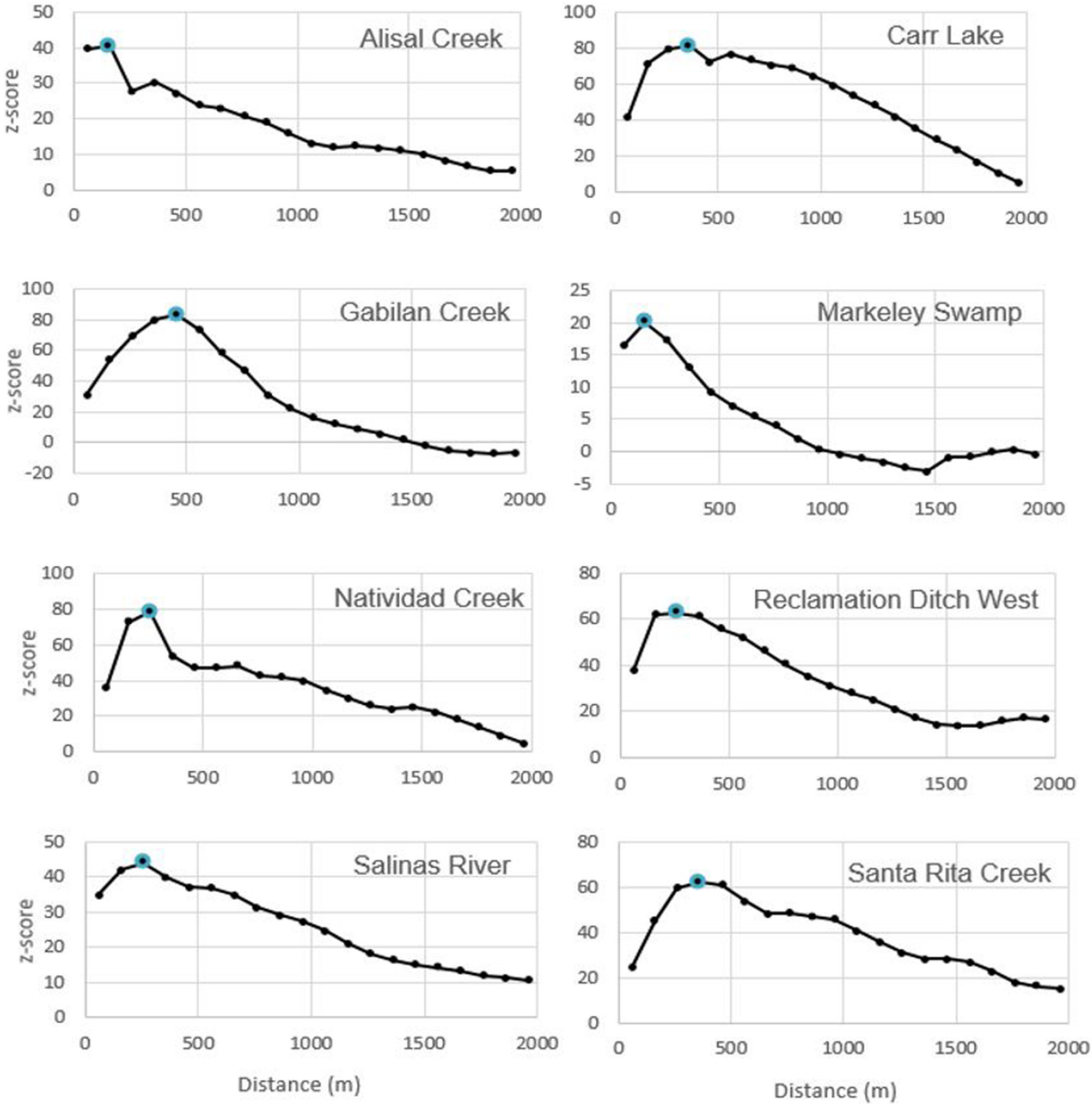


**Fig. 4.** Incremental spatial autocorrelation for Salinas stormwater drainages. Highlighted points indicate distances selected for pooling variance.

**Table 1**
Anselin Local Moran's I ($I_i$) analysis results summary. A 95% confidence level was used for determining significant clusters and outliers.

| | Grid cells (%) |
|---|---|
| Not significant | 84 |
| Low cluster | 13 |
| High cluster | 2 |
| Low-high outlier | 1 |
| High-low outlier | 0.03 |

B).

While EBK provides somewhat greater coverage and has the advantage of accounting for the error in the underlying semivariogram parameters, we selected the NN interpolation for its simplicity of application and interpretation. As we would expect, areas that exhibit the highest standard error using EBK are often left unclassified with NN due to a lack of proximal data (Fig. 6, panel C). Another consideration is that with EBK, the road network does not provide the same degree of constraint for the interpolation as it does for the NN. This is an important consideration given that car traffic, pedestrians, and stormwater flows on roads all move trash more freely than they may across large parcels. Outputs from NN are also easier to explain than those from EBK to users not familiar with spatial interpolation methods,

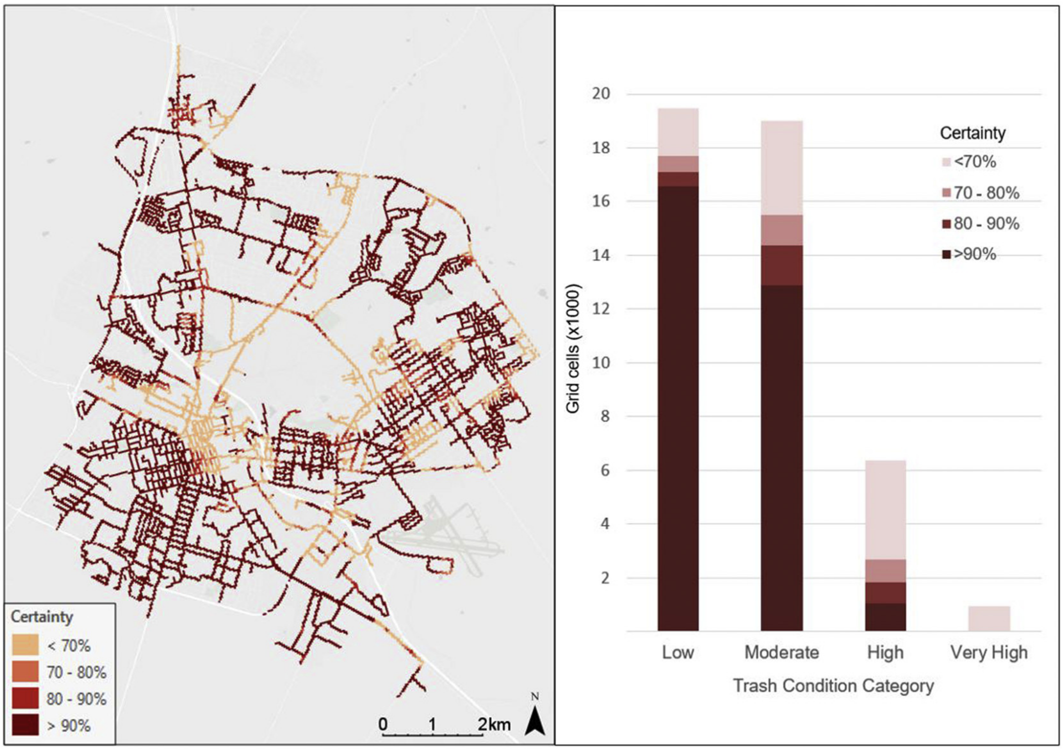


**Fig. 5.** Trash condition certainty scores on roads throughout the City of Salinas.

which can provide cities with a clearer understanding of the link between the trash data collected and analytical outputs.

The result of combining the uncertainty outputs with the trash condition data using the NN interpolation are shown in Fig. 7 to illustrate areas of compliance (top map) and trash priority areas (bottom map) at the parcel scale for part of the Reclamation Ditch West stormwater drainage (Fig. 1). Green parcels are within the range of the Low trash condition category and have > 70% certainty of their calculated mean value, with darker shades representing increasing degrees of certainty. Using a certainty threshold of 80%, the two darkest green categories illustrate parcel area in compliance. Given this example

**Table 2**
Summary of results from Empirical Bayesian Kriging (EBK) and nearest neighbor (NN) interpolation.

| | Trash condition area (ha) | | |
|---|---|---|---|
| | NN | EBK | % Difference |
| Low | 1836 | 1961 | −6 |
| Moderate | 1835 | 1696 | 8 |
| High | 964 | 1301 | −30 |
| Very high | 68 | 67 | 1 |
| Unclassified | 359 | 38 | 162 |

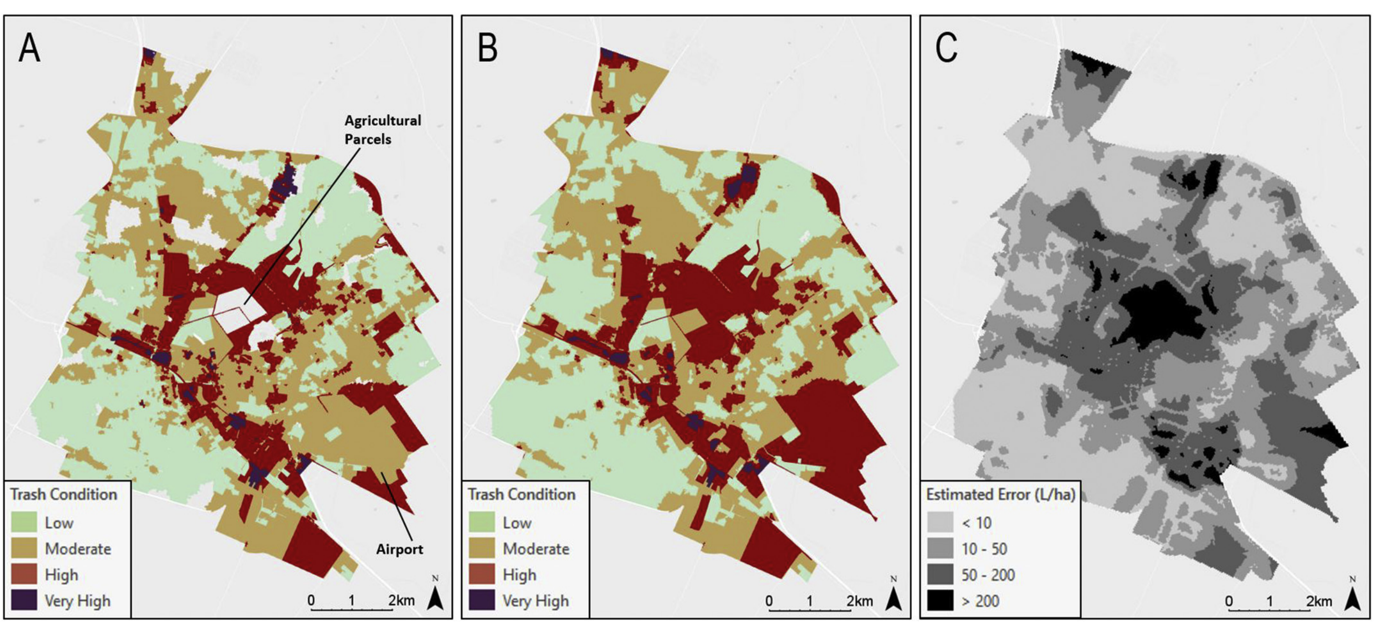


**Fig. 6.** Interpolated outputs using Nearest Neighbor (A) and Empirical Bayesian Kriging (B), and the Standard Error for EBK estimates.


**Fig. 7.** Parcel-based trash compliance and priority areas for a subset of parcels near the Reclamation Ditch West stormwater drainage. Priority areas that do not have a mean condition within the Low category range are shown in the lower map as quartiles.

compliance threshold, approximately 30% of the parcel area in Salinas was in compliance during the 20-month study period. Areas that have relatively poor trash condition and high certainty are good candidates for areas to prioritize for management actions.

## 4. Discussion

The method presented employs a simple Bayesian approach to quantifying the certainty in trash condition estimates, which is intended to align with resources available to make such tools widely available to cities. Understanding patterns of trash condition uncertainty is critical for decision making since there is often little initially known about the variance of trash over space or time and the cost of ongoing assessments limits data collection. While spatial autocorrelation patterns of trash condition variance differed somewhat between stormwater drainages, they mostly had significant influence within a range of 2 km, indicating that full coverage assessments of Salinas are probably unnecessary in the long term. Areas that are consistently trash free will tend to have high certainty and be candidates for reduction of monitoring frequency in upcoming years. By focusing ongoing assessment resources more heavily in areas that have demonstrated severe trash issues to a high degree of certainty, the effectiveness of specific trash mitigation strategies in different areas can be investigated. This can provide stormwater managers with better information to identify effective strategies and to isolate factors that contribute to success or failure in different areas of their cities.

Areas with highly variable trash conditions may require an exceedingly high number of observations to reach an acceptable level of certainty given the trash volume scale used in the OVTA assessments. For example, in an area that showed trash conditions with both Very High and Low conditions at different survey times, > 100 observations may be required to reach a level of certainty above 80% given the level of precision specified in this analysis (10%). Of course, some of the variance must be attributed to errors in trash category scoring itself, which would probably happen most often in discerning between the Low and Moderate trash categories since these two categories have the smallest separation. As observations increase, variance will tend to decrease, particularly if new observations show greater consistency and cleaner conditions. Areas that continue to show relatively high variability of trash conditions *should* require continued observations, since the data would indicate that they are both poorly characterized and represent an ongoing risk of trash delivery to receiving waters. Application of the method presented will require careful consider of tolerances for precision and certainty that would be acceptable within the regulatory frameworks of individual cities.

In this application, spatial effects were not explicitly incorporated in the uncertainty estimates by way of the inference model structure, but via the input data by pooling variance within a radius based on a stratified spatial analysis (e.g. Higdon et al., 1999). Likewise, temporal effects are only accounted for by way of setting a time window over which observations are used to inform prior distributions. Specification of a Bayesian spatio-temporal hierarchical model would allow for more detailed accounting of patterns such as spatial autocorrelation operating at different scales, as well as accounting for interactions between spatial and temporal factors not included in this study (e.g. Barber & Gelfand, 2007; DiMaggio, 2012; Kruschke & Vanpaemel, 2015; Sain & Cressie, 2007; Wikle, 2015). However, such complex hierarchical models can suffer parameter identifiability issues, and such an approach would also increase the computational burden given the need to sample from the posterior distribution (e.g. Wang & Gelfand, 2002), particularly so with large raster data sets that cover entire cities. Cressie et al., 2009, explores several other limitations associated with Bayesian Hierarchical models (along with their benefits) related to the complexity of such models and their practical implementation. Perhaps most importantly, use of more sophisticated models also presents the problem of having more complex relationships between inputs and outputs, which may pose a challenge for practical use by stormwater managers and regulators, who are typically not experts in statistical modeling.

An important constraint on Bayesian inference is the need to specify parameters of a prior distribution, which always involves a degree of subjectivity, similar to specification of other model components including data models, process models and parameter models (Cressie et al., 2009). A typical approach in the context of a sample size problem is to use a non-informative prior, but this can sometime result in unreasonably small or large sample sizes to reach a desired credibility interval (Sahu & Smith, 2006). In this case we parameterized the prior via the variance of trash condition estimates already collected near the same location within a 20-month time window. Another approach to specifying the prior would have been to use data collected throughout the city to specify the prior. However, this would ignore the observed heterogeneity in the covariance structure of the trash data between stormwater drainages. Perhaps most importantly, this approach would not provide location-specific estimates of uncertainty that can be readily updated as additional observations are made to inform compliance and spatial targeting of management actions.

## 5. Conclusions

Given the growing understanding of urban trash impacts and related water quality regulations, there is a critical need for cities to efficiently determine compliance and prioritize actions. This study demonstrated a methodology in the City of Salinas that is responsive to regulatory requirements and includes spatially distributed uncertainty estimates that provide valuable context for stormwater visual trash assessment results. Low levels of certainty were mostly prevalent in trashy areas, but some of these trashy areas also showed high certainty, indicating that they are good places to focus trash mitigation actions. A measure of certainty increases transparency of the compliance process for determining which areas should count towards intermittent progress in annual reporting or whether the data dictate a shift in course for a stormwater program. As with many other environmental data collection problems, determination of adequate number of observations to test hypotheses is dependent upon characteristics of the data. A Bayesian approach allows new data to be incorporated to iteratively inform the sampling design so that monitoring schedules can be adjusted over time for more efficient resource allocation. While results were presented within the context of regulatory requirements of California, USA, the methods used are generally applicable in any city with stormwater trash reduction requirements. To make this approach more widely available, it has been automated and integrated to a web-based stormwater platform (www.2nform.com), now used by several cities working towards the goal of eliminating trash in stormwater.

## Acknowledgements

The authors acknowledge support from the City of Salinas Stormwater Program and contributions from their Stormwater Program Manager, Heidi Niggemeyer. Kevin Butler at the Environmental Systems Research Institute (ESRI) provided valuable suggestions to guide the analysis and interpretation of results along with detailed review of the manuscript.

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