Contents lists available at ScienceDirect

Environmental Pollution

journal homepage: www.elsevier.com

Anthropogenic litter cleanups in Iowa riparian areas reveal the importance of near-stream and watershed scale land use☆

Win Cowger[a, b, *], Andrew B. Gray[a], Richard C. Schultz[b]

[a] Department of Environmental Science, University of California, Riverside, 900 University Ave, Riverside, CA, 92521, United States
[b] Department of Natural Resources Ecology and Management, Iowa State University, 2310 Pammel Dr, Ames, IA, 50011, United States

ARTICLE INFO

Article history:
Received 3 August 2018
Received in revised form 5 April 2019
Accepted 9 April 2019
Available online xxx

Keywords:
Plastic pollution
Anthropogenic litter
Citizen science
Riparian litter
Cleanup

ABSTRACT

Volunteer cleanup operations collect large datasets on anthropogenic litter that are seldom analyzed. Here we assess the influence of land use in both near-stream and watershed scale source domains on anthropogenic litter concentration (standing stock, kg km^{-1}) in riparian zones of Iowa, USA. We utilized riparian litter concentration data on four classes of anthropogenic litter (metal, recyclable, garbage, and tires) from volunteer cleanup operations. Anthropogenic litter data were tested for correlation with near-stream and watershed scale land uses (developed, road density, agricultural, and open lands). Road density (road length/area) and developed land use (% area) were significantly correlated to anthropogenic litter, but agricultural (% area) and open lands (% area) were not. Metal objects correlated to near-stream road density ($r = 0.79$, $p = 0.02$), while garbage and recyclable materials correlated to watershed scale road density ($r = 0.69$, $p = 0.06$ and $r = 0.71$, $p = 0.05$ respectively). These differences in the important spatial scales of land use may be related to differences in transport characteristics of anthropogenic litter. Larger, denser metal objects may be transported more slowly through the watershed/channelized system and thus, dependent on more proximal sources, whereas smaller, less dense garbage and recyclable material are likely transported more rapidly, resulting in concentrations that depend more on watershed scale supply. We developed a linear regression model that used near-stream road density and the total amount of observed litter to predict an average anthropogenic litter density of 188 kg km^{-1} and a standing stock of 946 t in all Iowa streams (>4th Strahler order). The techniques employed in this study can be applied to other professional and volunteer litter datasets to develop prevention and cleanup efforts, inform investigations of process, and assess management actions.

1. Introduction

Anthropogenic litter causes economic, environmental, and human health issues. For example, the concentration of anthropogenic litter on coastal beaches increases with a greater number of tourists (Oigman-Pszczol and Creed, 2007) and negatively impacts tourism if unmanaged (Nelson and Botterill, 2002). In addition, the indirect economic cost of people driving further to less littered destinations amounts to millions of dollars a year in some United States counties (Stickel et al., 2012; Leggett et al., 2014). Worldwide, approximately 2 million tonnes of plastic are delivered to the ocean via streams each year (Lebreton et al., 2017). In transit to the ocean, anthropogenic litter can adversely impact and kill aquatic life (Gall and Thompson, 2015). In oceans and in streams, wildlife entanglement and ingestion has affected over one thousand known species (Tekman et al., 2018), and humans can also be exposed to hazards from anthropogenic litter types such as sharp objects, hygiene products, and toxic substances (Moore et al., 2007). These impacts have engendered interest from citizen, government, and academic sectors and created opportunities for interdisciplinary collaborative research to overcome the challenges of anthropogenic litter pollution through scientifically informed management actions.

Citizen science surveys of anthropogenic litter are common (Rech et al., 2015; Nelms et al., 2017), but their use for scientific analysis is challenging (van der Velde et al., 2017). Volunteer cleanup operations can be a type of citizen science survey which attempts to remove all anthropogenic litter from an area. Cleanups may quantify litter by tallying the number of items found (Ocean Conservancy, 2018) or weighing the total mass collected (Project AWARE, 2017). Data from volunteer cleanups often have poor spatial descriptions (e.g., point or line locations representing area surveyed), a lack of controlled effort, and bias in site selection because of a goal to find sites with the most anthropogenic litter (Hardesty et al., 2016a,b). However, by assuming unbiased reporting of anthropogenic litter composition, managers and policy makers commonly use volunteer cleanup data to assess the most common items found in the environment (Zettler et al., 2017; Ocean Protection Council, 2018; Schuyler et al., 2018). Some robust citizen science surveys have been less likely to include the cleanup of anthropogenic litter (Rech et al., 2015) but more likely to control for the area surveyed, effort, and site selection (Vincent et al., 2017). These rigorous survey designs have been used to address sources and hotspots of anthropogenic litter (Rech et al., 2015; Nelms et al., 2017;

☆ This paper has been recommended for acceptance by Dr. Sarah Harmon.

* Corresponding author. Department of Environmental Science, University of California, Riverside, 900 University Ave, Riverside, CA, 92521, United States.

Email addresses: wcowg001@ucr.edu, wincowger@gmail.com (W. Cowger); agray@ucr.edu (A.B. Gray); rschultz@iastate.edu (R.C. Schultz)

https://doi.org/10.1016/j.envpol.2019.04.052
0269-7491/ © 2019.

Kiessling et al., 2019), but data from volunteer cleanups have not produced comparable results (Hardesty et al., 2016a,b). Uncertainty persists regarding what information volunteer cleanups should collect to assess sources and hotspots of anthropogenic litter.

The need for riverine anthropogenic litter management throughout the United States is growing, which will require new hotspot identification tools to inform effective litter prevention and cleanup strategies. The Clean Water Act requires that streams in the United States are monitored to assess potential pollution from a wide range of contaminants, including anthropogenic litter (Moore et al., 2007). The listing of a waterbody as “impaired” (polluted) triggers further investigation on the part of state agencies to develop plans for rectification through development of a total maximum daily load (the maximum allowed concentration or flux of a substance). Streams that have been identified as impaired by anthropogenic litter are now managed with no allowable discharge of anthropogenic litter on a daily basis (Maryland Department of the Environment, 2010; LARWQCB, 2007). To reach the zero allowable anthropogenic litter discharge limit, managers must identify the most abundant types of litter and hotspots, which can be derived by first determining the appropriate spatial scale for predictors of litter supply and subsequent modeling of the litter transport pathways (EOA Inc., 2014). Once the most abundant litter items and hotspots are identified, prevention strategies such as improved waste management and bans and mitigation strategies including cleanups or separation inlets in storm drains can be applied. Management of anthropogenic litter in the United States waterways costs hundreds of millions of dollars annually (LARWQCB, 2007; Mid Atlantic Solid Waste Associates, 2009). Furthermore, anthropogenic litter studies to date focus primarily on beach and marine litter (Botero et al., 2017; Willis et al., 2017; Hidalgo-Ruz et al., 2018) with relatively few discussions of riverine litter (Rech et al., 2015; McCormick and Hoellein, 2016). Government and volunteer cleanups overlap in their effort to remove and quantify anthropogenic litter, which presents an opportunity to determine if volunteer cleanups can be used as a management asset to determine litter properties, hotspots, and sources.

One would expect that both near-stream and watershed scale land use would be important riparian litter sources. However, only near-stream land use has been demonstrated to correlate to standing stock riparian litter concentration (White, 2010; Moore et al., 2016; McCormick and Hoellein, 2016), while measurements of litter flux within the water column have been found most strongly related to watershed land use (EOA Inc., 2014; Rech et al., 2015). Why have riparian standing stocks and fluvial fluxes of anthropogenic litter been found to correlate with different spatial scales of land use? We know that the fate of stream-transported litter is determined by an expression of watershed and stream characteristics. The characteristic transport length and storage time for any given piece of litter in a fluvial system is dependent on physical characteristics of the litter (e.g., size, density, shape), the characteristics of the water flow (i.e., watershed hydrology and hydraulics), and stream morphology (e.g., channel composition and geometry) (Williams and Simmons, 1997; Cowger and Schultz, 2015; Aguilera et al., 2016; EOA Inc., 2016; McCormick and Hoellein, 2016; Romans et al., 2016; Besseling et al., 2017). Therefore, we expect that both near-stream and watershed scale land use should represent important sources of riparian anthropogenic litter. Here, we test the correlation between riparian litter concentration and near-stream and watershed scale land use as a first step toward a better understanding of riparian litter dynamics.

The overarching goal of this study was to investigate sources and hotspots of riparian anthropogenic litter collected from streams in Iowa, USA. We first evaluated the anthropogenic litter categories native to our dataset to assess the categorization approach employed by the data collectors and potential management opportunities. Second, we identified the most important land use types and spatial scales by testing the hypothesis that near-stream and watershed scale population pressure variables correlate to anthropogenic litter concentration and investigated the role of bias from differences in effort across surveys. Next, we used the strongest predictors of trash concentration to construct a model, compared this to a simple extrapolation, and estimated the quantity of anthropogenic litter in Iowa riparian areas. Finally, we discussed how the results of this model could directly inform litter management actions in Iowa. This work supports the development of simple analytical and modeling approaches to better inform management and scientific questions associated with anthropogenic litter worldwide.

2. Methods

2.1. Study region

Iowa is a 145,000 km^2 state in the center of the USA geomorphically dominated by Quaternary glacial processes, currently with land primarily used for agriculture, and a humid continental climate (Fig. 1, top left panel). Iowa is bordered on the east by the Mississippi River and on the west by the Missouri River, a major tributary of the Mississippi River. Glacial erosional processes have contributed to low topographic relief in Iowa, with a maximum elevation difference of 363 m across the state. Iowa's Molic soils are high quality agricultural land which is used primarily for the cultivation of corn and soybeans, and cattle grazing. Over four seasons, Iowa's temperatures range on average from −29 to 38 °C. The state receives an average 86 cm of precipitation per year, most of which is delivered between April and September as rain.

2.2. Anthropogenic litter data

The Iowa Department of Natural Resources (Iowa DNR) selected sample sites for the annual volunteer cleanup organized by Project AWARE (A Watershed Awareness River Expedition) based on access to boat launches and campgrounds but not based on an expectation of a greater amount of anthropogenic litter (Iowa DNR, *personal communication*). Cleanups were conducted primarily on larger, navigable streams, as reflected by high Strahler stream order, a system of fluvial network classification where headwater streams are 1st order, and stream order increases downstream of like ordered confluences (Strahler, 1952). Three of the eight stream cleanups began on a 4th order stream: 2008 (27 km stream distance), 2012 (90 km), and 2013 (56 km) and continued into 5th order and greater streams; the remaining cleanups began on 5th order streams. The beginning and end points of each stream cleanup were mapped using a geographic information system. Total cleanup distance for each cleanup event ranged from 77 km to 164 km (SI Table 1). The planned cleanup distance was determined by number of days available on the water and access to boat ramps. Two cleanups (2011 and 2010; Fig. 1.) were split between two non-connected channels within the same watershed; the rest of the cleanups were conducted over a continuous stream segment. After determining the sample site, the Iowa DNR invited volunteers to attend the cleanup event through the news and social media.

Each year during Project AWARE, hundreds of volunteers canoed down Iowa streams for 5–7 days to collect anthropogenic litter in riparian areas (SI Table 1; Fig. 1.). Project coordinators counted the number of volunteers every day. More than 80 volunteers collected

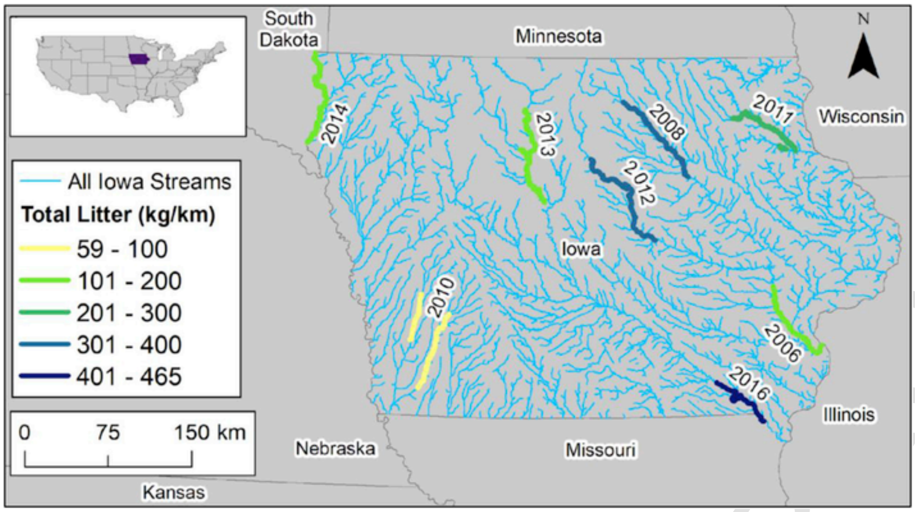

Fig. 1. The study location (top left panel), Iowa (in dark purple), is in the center of the United States. The litter collected from the eight Project AWARE cleanups (main panel) during a 10 yr period are indicated by the color of the river reaches surveyed. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

trash during any average day (SI Table 1). There was a wide range in volunteer skills (scientists to civilians) and age (5–80). Volunteers were given instructions to collect every piece of anthropogenic litter they saw and finish a segment of the total route by a specific time each day which depended on locations of portages. Cleanups only happened during daylight hours. Most anthropogenic litter was collected in the riparian area as the streams were often too turbid to observe benthic litter, which was rarely collected. When trash was spotted from the canoe, volunteers would dock their canoe, collect the trash, return to their canoe, and continue downstream. Distance from the stream that volunteers could collect trash was limited by the time the volunteers had before the time required to reach the next location and their ability to see the trash. Therefore, volunteers rarely traveled further than 10 m from the stream edge (Iowa DNR, *personal communication*). Private property in the riparian area was avoided when entering the land would obviously be an intrusion (e.g., when a fence or private boat dock was present). Typically, a motor boat followed behind the group of canoes and was used to transport large objects. Dams or log jams were avoided by portaging canoes around impoundments and continuing the cleanup directly downstream. At the end of each stream segment, all collected anthropogenic litter was deposited at a designated pickup location.

At the pickup location, anthropogenic litter was segregated into four categories (tires, metal, recyclable, and garbage) and measured by Iowa DNR staff. Tires ranged in sizes from bicycle to tractor tires. Metal included all objects primarily composed of metal, with objects like tractor and car bodies and fences. Recyclable material included electrical appliances, hazardous materials (chemicals), cardboard, plastic, and redeemable beverage containers. The garbage category included everything not covered by the other categories (e.g., textiles, lumber, or nonredeemable plastic such as plastic film and food wrappers) and included materials that may have been categorized as recyclable, metal, and tires when those materials were not accepted at collection facilities nearby. After collection and sorting, the anthropogenic litter was trucked to local waste and recycling facilities where the mass of litter was measured with truck scales (±20 kg error as per Standard Requirements (NIST, 2018)). A minimum of 100 kg of trash, and commonly in excess of 1 t, was weighed in each load. Over the course of the study, 243 t of litter were removed from Iowa streams (SI Table 1). Data from the truck scale measurements were tallied and aggregated after the cleanup by Iowa DNR staff.

To avoid complicating the analysis, we only used data from river reaches with no known previous cleanup and normalized the anthropogenic litter data by stream length. Three data points from the records between 2006 and 2016 were removed from the dataset because they overlapped with a previous cleanup or included trash mass from cleanups not conducted in the stream. To calculate standing stock concentrations, the total mass of anthropogenic litter and subset categories of litter were normalized to stream length (kg km^{-1}) to develop five response variables: *Tires, Metal, Recyclable, Garbage,* and *Total Litter* (sum of all categories). These litter variables were subsequently assessed for their relationship to land use and effort explanatory variables.

2.3. Spatial data

Geospatial datasets on land use, hydrographic data, and roadways were acquired from the following open access datasets: the National Land Cover Dataset (NLCD) (Homer et al., 2015), the National Hydrography Dataset (2015), Iowa DNR Geospatial Database (Iowa, 2017), and the 2018 Topologically Integrated Geographic Encoding and Referencing (TIGER) Database (US Census, 2018). The NLCD is a United States Geological Survey (USGS) raster image that identifies 16 land use types (USGSa,) that can be generalized to 3 land use categories (Developed, Open Lands, and Agriculture) at a 30 m resolution. The National Hydrography Dataset is a USGS vector dataset that includes watershed delineations and stream centerlines used in this analysis (USGSb,). By utilizing the National Hydrography Dataset, we assumed that streams were characterized by simplified stream centerlines as derived from digital elevation models. Strahler stream orders for each surveyed stream reach were acquired from an Iowa DNR Geospatial Database (Iowa, 2017). Data on roadways were extracted from the 2018 TIGER Geodatabase (US Census, 2018), a database created by the US National Census Bureau that consisted of centerlines of primary and secondary roads in vector line shapefiles for the entire United States.

Land use variables were refined and their aerial extent was extracted at five spatial scales each: four near-stream buffer zones incorporating increasing distances from the channel and the watershed scale (similar to analyses from White, 2010; EOA Inc., 2014; Moore et al., 2016). First, stream centerlines were clipped from the National Hydrography Dataset using Project AWARE's beginning and end points to designate the study stream reaches in ArcMap 10.2 (ESRI, 2013) (Fig. 1). The areal extent of land use variables in near-stream scales were extracted with circular buffer distances around both sides of the cleaned stream centerline at 200, 400, 600, and 800 m (SI Fig. 1). Watershed boundaries were modified from the National Hydrography dataset using the USGS Topographic Basemap in ArcMap to fit to the endpoint of each cleanup and then used to extract the watershed scale land use variables (SI Fig. 1). In 2010 and 2011, two Project AWARE streams did not share the same endpoint (Fig. 1); both watersheds were delineated for each stream segment and merged. The NLCD values of open, low, medium, and high developed land use represent different ranges of impervious surfaces (the proxy for development), which were aggregated to create the *Developed* land use classification composed primarily of buildings, roads, and lawns. The two agricultural land use variables in the NLCD, pasture/hay and cultivated crops, were summed to create the *Agriculture* land use class. All other variables in the NLCD were combined to create the class *Open Lands* composed of forests, prairie, water, and other nonagricultural, undeveloped land types. The sum of all areas defined as *Developed*, *Agriculture*, and *Open Lands* in the NLCD raster were divided by the total area of the riparian buffer zone or watershed and multiplied by 100 to create the three land use percentages for each of the five spatial scales. Road centerlines from the Roads dataset (US Census, 2018) were clipped at each scale in the same way and the total distance of roads (m) was divided by the total area of the spatial scale (m^2) to create the *Road Density* variable (m^{-1}).

2.4. Effort

Effort has been shown to confound cleanup data in other studies (Hardesty et al., 2016a,b) and was therefore, investigated for its importance in this study. We determined effort by multiplying the duration of each cleanups by the average number of daily volunteers to create the *Person Days* variable. *Person Days* was then analyzed for its potential as an explanatory variable.

2.5. Analysis

The correlative analysis and model development that we tested were all post hoc analyses, and we analyzed data and assessed results cautiously. Land use variables were investigated for correlation with the response variables of riparian anthropogenic litter mass in order to identify land use controls on litter concentration, explore the spatial dependence of the relationship between litter concentration and land use, and identify potential confounding influences of unequal effort. Normality was tested with the Shapiro test ($p < 0.1$), which indicated that all variables were normally distributed with the exception of *400 m Open Lands, 200 m* and *600 m Agriculture, Garbage, and Recyclable*. Homogeneity of variances were tested with Levene's test ($p < 0.1$), which has a low sensitivity to non-normal data, and indicated that none of the explanatory and response groups had homogeneous variances. Because of concerns over potential violations of linear correlation assumptions, Spearman Rank correlation (r and p values) was used to test correlations without dependence on normality, homoscedasticity, linearity, and outliers. A hypothesis test (alpha = 0.1) was used to accept or reject the null hypothesis that the correlation was zero. We decided to use a p value of 0.1 instead of the traditional 0.05 because the level of aggregation in each data point (>80 km stream lengths and thousands of hours of effort) had the potential to represent average conditions well but resulted in a small population size (8 data points) and thus, lower statistical power. We assumed that variation in sampling distance from the stream, percentage of overlooked objects, percent of mischaracterized materials (e.g. water and dirt attached to the waste), and other errors in sampling were normalized in the dataset.

Extrapolative and process-based models were developed to predict the anthropogenic litter concentration in Iowa rivers. When planning model development we considered that 1097 km of Iowa streams had been sampled and only 5018 km were to be modeled, suggesting that direct extrapolation of average survey results could be informative. We used a bootstrapping routine (n = 1000, resampling with replacement) to estimate the mean concentration of *Total Litter* and 90% confidence intervals, and the resulting 5%, 50%, and 95% quantile values were multiplied by total population of Iowa streams > 4th order to predict the standing stock of riparian litter. Bootstrapping was used because the small sample size decreased our certainty in the assumptions of the *t*other tests commonly used to create confidence intervals were valid. Next, we decided to pursue a simple linear regression to better account for the role of processes associated with land use. Model fitness was determined by Root Mean Squared Error (RMSE), the lowest Akaike information criterion corrected (AICc) (Burnham et al., 2002), and the relative likelihood described with the AICw (Wagenmakers and Farrell, 2004). Random 70 km and greater stream segments in Iowa streams >4th order and greater were discretized by splitting the stream networks at major confluences or where the stream sections would be equal to or above 70 km. Land use data were extracted from the discretized streams in the same way as the observed streams. The model was then used to predict anthropogenic litter in all of the random segments by bootstrapping (n = 1000, resampling with replacement) the model coefficients and using the discretized stream land use data to generate the distribution of model outputs and extract the 90% confidence intervals from the output distribution. By not incorporating litter transport criteria, we assumed that variation in hydrologic and geomorphic factors were equivalent across sample locations. In support of this assumption, we noted that all sampled streams were perennial and rainfall in the region was relatively evenly distributed across each year of the study. In addition, there was little topographic relief throughout Iowa, and the study focused only on stream reaches from Strahler 4th to 7th order. Statistical analyses were conducted in R 3.5.2 with RStudio (R Core Team, 2018). Figures were created in R, Inkscape, and ArcGIS 10.2.2, and supporting code is available (Supplemental Material).

3. Results and discussion

3.1. Litter composition analysis

The anthropogenic litter mass was compared by litter type for the entire study and between years. On average, *Metal* was the most abundant anthropogenic litter material, followed by *Tires*, *Garbage*, and *Recyclable* (Fig. 2). In 2008 and 2010 the most common type of anthropogenic litter was *Garbage,* but in all other years, *Metal* or *Tires* were the most abundant. In every year except 2010, *Recyclable* was the least abundant material. These findings elicited discussion of the categorization scheme used and assessment of management opportunities in Iowa.

The anthropogenic litter categorization scheme used in this study negatively impacted comparability to other studies and may explain the concentration of *Garbage*. We do not know of any other groups that collect litter data with the same categorization scheme as Project AWARE. Other anthropogenic litter studies based on counts of items

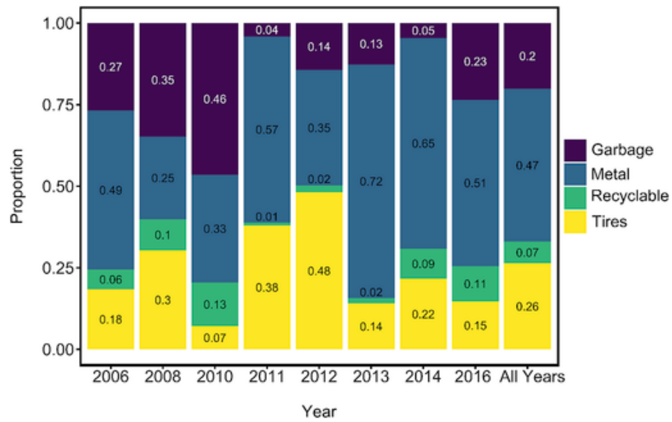

Fig. 2. Ratio of anthropogenic litter masses found between 2006 and 2016 in Iowa streams and "All Years", the summed proportion from the entire data set.

found plastic to be the most abundant material (Moore et al., 2016). While *Garbage*, *Tires*, and *Recyclable* all likely contain plastic materials, the design of this dataset precludes an assessment of plastic concentration in Iowa riparian litter. Additionally, this study used mass instead of count. Since mass is a conserved unit (unlike count), this likely aided our ability to detect relationships that other studies could not. *Garbage* was the most common trash type during two years, but in some cases, *Garbage* masses included materials that would have been classified in other categories and were rejected by transfer stations. The uncertainty introduced from this categorization strategy may undermine assessment of the *Garbage* category and decreases certainty in the assessment of the other categories. Classifying anthropogenic litter by standardized and consistent categories that are comparable to other studies, in any litter categorization scheme would facilitate the advancement of knowledge on litter production and transport dynamics (McCormick and Hoellein, 2016). These considerations make the *Total Litter* category the most consistent and viable for comparison within this study between years and with other studies. However, *Recyclable* is especially low in all years, which merits further consideration.

Recyclable could be the least abundant material in part because Iowa has a time-of-purchase redemption fee on some recyclable beverage containers. Iowa could address other more abundant anthropogenic litter types by requiring manufacturers and consumers of *Tires* and *Metal* objects to be responsible for their disposal and create redemption fees at time-of-purchase (Schuyler et al., 2018). An assessment of these categories within their spatial context may reveal more process-based information about the litter types.

3.2. Land use and effort analysis

3.2.1. Land use type

The interactions between land use types and anthropogenic litter were compared through Spearman correlation matrices. Most Spearman correlations between litter variables and *Open Lands* (Fig. 3C), *Developed* (Fig. 3B), *or Road Density* (Fig. 3D) were positive, while most *Agricultural* (Fig. 3A) land use correlations were negative. None of the correlations between litter variables and *Agricultural* or *Open Lands* were significant (Fig. 3A and C). However, *Road Density* and *Developed* were both significantly correlated with anthropogenic litter variables (Fig. 3B and D). *Road Density* was significantly correlated to all near-stream scales of *Metal* (buffer *200 m*: r = 0.79, *400 m*: r = 0.81, *600 m*: r = 0.66, *800 m*: r = 0.69), *Total Litter* (*200 m*: r = 0.67 and *400 m*: r = 0.61), *Garbage* (*Watershed*: r = 0.69), and *Recyclable* (*Watershed*: r = 0.69)(Fig. 3D). *Developed* land use was significantly correlated to *Metal* (*200 m*: r = 0.71), *Total Litter* (*200 m*: r = 0.62), and *Garbage* (*Watershed*: r = 0.86) (Fig. 3B). These results confirmed that land use features associated with higher human exposure (roads and developed areas) would result in higher riparian litter concentration. Unraveling the scale at which correlated land use types influence anthropogenic litter is critical to source assessment.

3.2.2. Spatial scales

We assessed the correlation of *Developed* and *Road Density* (at near-stream and watershed scales) to anthropogenic litter categories. At the near-stream scale as spatial extents increased from 200 m to 800 m for *Developed* and *Road Density*, correlation strength to anthropogenic litter tended to decrease (e.g. Spearman correlation be-

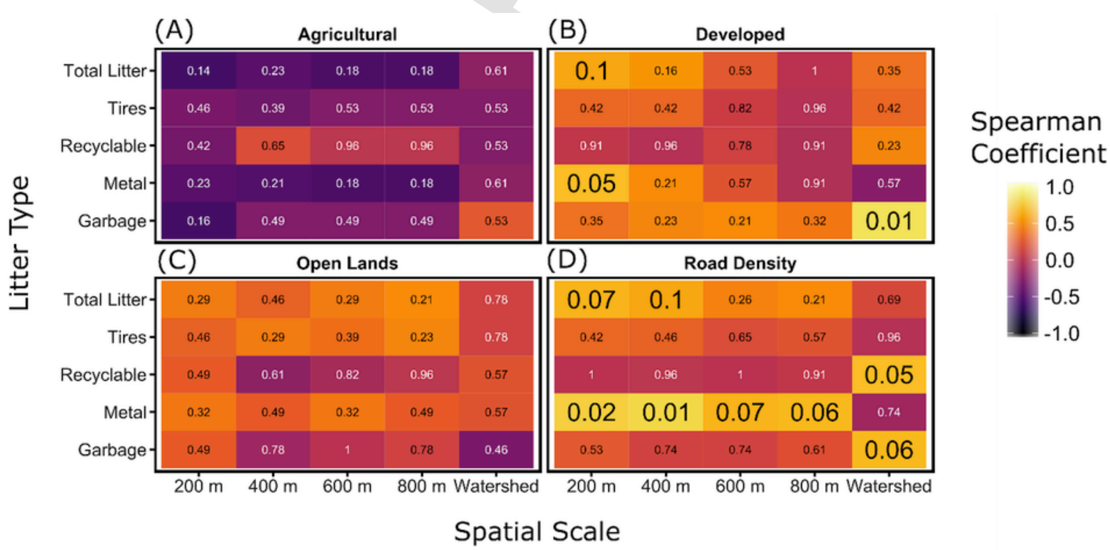

Fig. 3. Results of Spearman correlation analysis between land use types (frames) at multiple scales (x axis) and anthropogenic litter types (y axis). The color of the matrix represents the strength of the correlation (Spearman coefficient). The p value is the text in each pixel. Significant correlation p values (<0.1) are reported in large font, and Spearman coefficients are reported in the Land Use Type section. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

tween *Metal-Road Density* (*200 m*: r = 0.79, p = 0.02 and *800 m*: r = 0.69, p = 0.06). At the watershed scale three significant correlations were found between *Garbage–Watershed Developed* (r = 0.85, p = 0.01), *Garbage-Watershed Road Density* (r = 0.69, p = 0.06), and *Recyclable-Watershed Road Density* (r = 0.71, p = 0.05). This is the first study to demonstrate that both watershed and near-stream land use correlates with riparian anthropogenic litter concentrations, though many other studies have found correlations to near-stream land use (Williams and Simmons, 1999; White, 2010; Moore et al., 2016; McCormick and Hoellein, 2016; Rech et al., 2015). Prior studies surveyed stream reaches of less than 1 km, while each stream reach in this study was a minimum of 76 km long. It may be the case that small scale, high resolution studies favor the identification of local near-stream influences of population pressure while missing watershed scale process signals that may require the larger scale riparian surveys employed in this study.

Relevant land use scales appear to be dependent on anthropogenic litter material type and transport characteristics, which may further inform stream management. *Garbage* and *Recyclable* were generally less dense and smaller litter types, and were most strongly correlated to watershed scale land use factors, potentially because these objects are more easily transported overland and through the fluvial network. Conversely, *Metal* was composed of generally larger and denser materials and was most strongly correlated to the near-stream scale land use. *Tires* were not significantly correlated to any of the land use scales and may have transport characteristics that cannot be explained by near-stream or watershed scale land use. This finding has implications for watershed management. Where watershed scale sources are found to determine litter concentration, further investigation of watershed scale litter production throughout developed sectors may be necessary (EOA Inc., 2016). When near-stream forces are found to be more important, decreasing connectivity between streams and litter production elements such as roads and changing management at stream accesses points may be more effective (McCormick and Hoellein, 2016).

3.2.3. Effort

We explored the influence of the confounding factor effort (*Participant Days*) in terms of all response variables, and all spatial scales of *Road Density* (SI Fig. 2), which has the most significant correlations to litter variables (Fig. 3). *Participant Days* had a significant negative correlation to *Garbage* (r = −0.85, p = 0.01) (SI Fig. 2). We expected effort to have a positive correlation (if any) to litter concentration. A weak and non-significant negative correlation between *Watershed Road Density* (r = 0.57, p = 0.14) might be a factor influencing this result. For these reasons, we concluded that variation in effort was likely not a significant issue for this study, and if so, only for models developed specifically for *Garbage*.

3.3. Litter model

Model overfitting was of great concern with such a highly aggregated dataset. To avoid overfitting, we only evaluated linear models. Only normally distributed variables could be assessed which eliminated the potential for models to be developed using *Garbage* or *Recyclable*. Additionally, *Tires* were not correlated significantly with explanatory variables, so we could not develop independent models for each class. For these reasons, we assessed models only for the prediction of *Total Litter*.

Simple linear regression models were developed using the three land use variables found to be significantly correlated with *Total Litter*: *Developed* (*200 m* stream buffer), and *Road Density* (*200 m* and *400 m* stream buffers) (Fig. 4). The y intercept of each model was not statistically different from zero. All models had wide 90% confidence intervals (e.g. *200 m Road Density – Total Litter*: Slope ±70%). AICc indicated that the linear model of *Total Litter* using *Road Density* in the 200 m buffer was the best model with a 0.53 weighted probability from the AICw.

Issues with non-significant y intercept and wide confidence intervals in the tested models (Fig. 4) were a direct result of the highly aggregated data collection approach used in this study. Because each data point required 5–7 days of data collection and hundreds of volunteers, there were very few data points, which decreased the explanatory power of the dataset. Additionally, aggregating observations over large distances (>77 km) forced the data toward the central tendency for the region, thus obviating the possibility of observing extreme high and low values of anthropogenic litter and explanatory variables.

The best fit simple linear regression model and a basic extrapolation were used to estimate anthropogenic litter concentration in randomly discretized 70 km and longer Iowa stream segments with a Strahler order >4 (SI Table 2). The RMSE of the extrapolation model was 119 kg km^{-1} and the best fit linear model was 78 kg km^{-1}. Therefore, the best fit simple linear regression model was an improvement to basic extrapolation, which resulted in an overestimation of 25% when applied to all Iowa streams (1201 t) relative to the best fit model (964 t) (SI Table 2).

Our best estimate of riparian anthropogenic litter concentration in Iowa streams was highly conservative and comparable to other studies. The model results were closer to average results than the observations (Fig. 5, Fig. 1). While there are 5,018 km of 5th order or greater streams in Iowa, another 122,000 km of lower order streams were not included in our model. The model also did not account for accumulation or export and was meant to be an estimation of standing stock during the study period. Additionally, the model only applied to riparian anthropogenic litter, while some studies found a similar amount

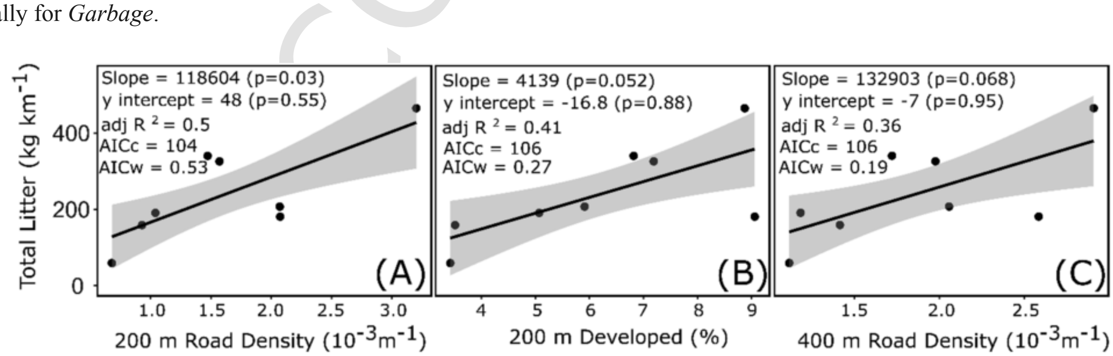

Fig. 4. Linear regression models for the prediction of *Total Litter* on the basis of (A) *Road Density* within a 200 m riparian buffer zone, (B) *Developed* land use within a 200 m riparian buffer, (C) *Road Density* within a 400 m riparian buffer zone. The shaded areas represent the 90% confidence intervals around each regression line.

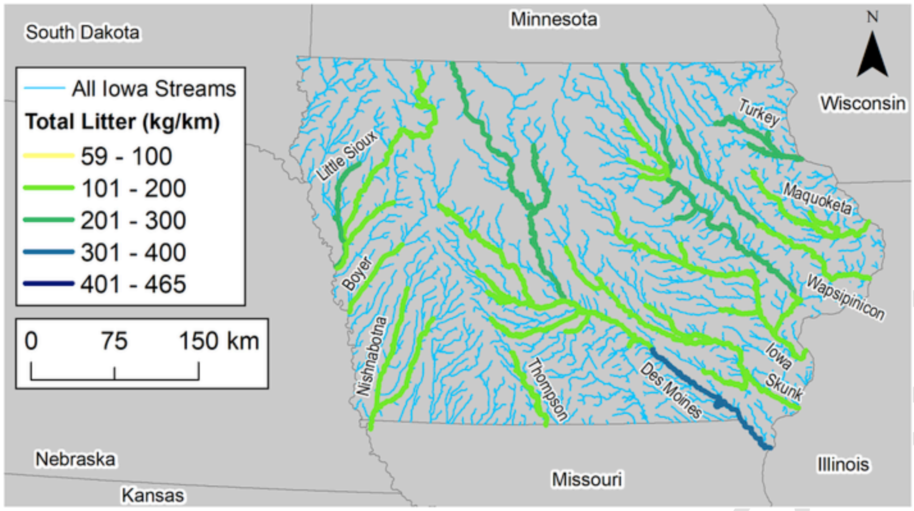

Fig. 5. Modeled results of average anthropogenic litter per kilometer from 2006 to 2016 in randomly selected segments of major Iowa stream networks. For comparability, the color scale is identical to Fig. 1. The lack of the lowest and highest ranges observed shows the model's tendency toward average conditions. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

of benthic anthropogenic litter (McCormick and Hoellein, 2016). During their survey of streams in the Great Lakes region of the US, McCormick and Hoellein (2016) reported 60–1250 kg km^{-1} of riparian anthropogenic litter. This range encompassed the 132–251 kg km^{-1} (Table 1) found by modeling litter in our study, even though the McCormick and Hoellein (2016) study reaches were much shorter (50–100 m), had a wider range of urban development (8–73% Developed land use), and our study lacked exact control of survey width. Model results of ours and similar studies could be used as hotspot maps (Fig. 5) for guiding anthropogenic litter management decisions (Table 1).

We explored insights for regional management at the scale of independent major rivers in Iowa. The Turkey River had the highest mean *Total Litter* concentration at 269 (209, 330) kg km^{-1}, and the Skunk River had the lowest mean concentration at 136 (75, 218) kg km^{-1} (Table 1). Though the highest and lowest total mass of anthropogenic litter were on the Des Moines 297 (217, 377) t and Boyer 12 (8, 18) t. The Turkey River was the most impacted river per kilometer in Iowa, but this river was also one of the smallest of the rivers (227 km) and did not contain a large amount of litter over all 61 (47, 74) t. The two rivers with the highest total mass were the Des Moines and Iowa 218 (155, 291) t which are also the largest rivers in the state and adjacent to the largest cities. The Des Moines and Iowa river watersheds should be considered a top priority for management and policy makers in the state. Yet some rivers were less impacted by anthropogenic litter. For example, the Skunk River had a large watershed with a long stream reach (572 km), but the Skunk River also had the lowest concentration (136 kg km^{-1}), because there were fewer roads near the Skunk River than other streams in this study. The mean amount of anthropogenic litter in all Iowa streams was 188 kg km^{-1} which can serve as a baseline to assess how Iowa reduces or increases its anthropogenic litter pollution problem in future studies.

Table 1
Modeled predictions of riparian anthropogenic litter concentration on segments of major Iowa rivers.

Watershed	Mean Litter Concentration[a](kg km^{-1})	Total Litter Mass (t)	Total Stream Length[b] (km)
Turkey	269 (209, 330)	61 (47, 74)	227
Des Moines	219 (159, 280)	297 (217, 377)	1364
Wapsipinicon	208 (156, 262)	73 (55, 92)	355
Maquoketa	194 (143, 246)	52 (38, 66)	270
Iowa	193 (139, 254)	218 (155, 291)	1161
Little Sioux	188 (136, 246)	107 (77, 140)	574
Thompson	176 (123, 233)	24 (16, 31)	137
Boyer	156 (104, 225)	12 (8, 18)	83
Nishnabotna	139 (80, 217)	38 (22, 59)	275
Skunk	136 (75, 218)	78 (42, 124)	572
All	188 (132, 251)	964 (681, 1278)	5018

[a] 90% prediction intervals in parenthesis.
[b] Total length of streams > order 4 in the watershed.

4. Conclusions

Analysis of land use controls on riparian litter concentration produced new insights into processes controlling riparian anthropogenic litter, recommendations for improving data collection methods, and ideas for improved management. Variables that describe population pressure drove riparian anthropogenic litter concentration. Near-stream and watershed scale *Developed* and *Road Density* land use most strongly correlated to the total mass of anthropogenic litter found in 4th order and greater Iowa stream corridors. The large total stream length sampled in this study appears to have facilitated the identification of both near-stream and watershed scale processes. Differences in average density and object size (metal > garbage), indicated that garbage is likely more mobile than metal objects. Hydrologic and fluvial variables should also be integrated into future riparian litter models at watershed and near-stream scales. A simple linear regression based on the proportion of *Road Density* found in a 200 m buffer around all riparian areas of 5th order and greater streams in Iowa predicted a standing stock of approximately 964 t of litter with an average of 188 kg km^{-1} in large Iowa stream corridors (Table 1). The Iowa and Des Moines rivers were the most litter impacted rivers and should be considered top priorities for riparian anthropogenic litter abatement. In the future, Project AWARE and other cleanup efforts would benefit from repeated visits to the same stream reaches, with increased spatial resolution (data from smaller sub-reaches), control of the survey area extent, and additional anthropogenic litter attributes for materials, items, and brands that are comparable to other studies conducted globally. The data in this study likely benefited by using lines instead of points for the spatial attribute, mass instead of count to quantify litter, large groups of volunteers to collect the litter, and a random site selection process. Existing data sets from cleanups in other regions could be used to inform management in the future, depending on data quality. This study recommends that policy focused on preventing litter in Iowa should be targeted toward near-stream and watershed scale phenomena. Redemption fees may be an effective measure for reducing litter concentrations. The simple analytical methods and modeling approaches used in this study can be adapted elsewhere as a first exploratory step to inform the assessment of process-based phenomena, and guide the prevention of anthropogenic litter.

Conflicts of interest

We commit that there is no conflict of interest in our research.

Acknowledgements

Most of all, we thank the thousands of volunteers who worked hard to clean up the rivers of Iowa 5 days every year. The dataset at the heart of this study would not have been possible without them. We also thank past and present Iowa DNR Staff Lynette Seigley, Garrett Shear, Nate Hoogeveen, Luke Wright, and Mary Skopec for providing us with high quality data and advice during the creation of this model. Dr. Neil Bernstein provided analytical method and writing guidance throughout the development of this manuscript, and the lead author is particularly grateful for Neil's mentorship. Valuable input from two anonymous reviewers and Martin Thiel greatly improved this study. This study was funded in part by the USDA National Institute of Food and Agriculture, Hatch program [A. Gray, project number CA-R-ENS-5120-H] and a National Science Foundation Graduate Research Fellowship [W. Cowger]. The views expressed in this paper are those of the authors and do not necessarily reflect those of funding or employing institutions.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envpol.2019.04.052.

References

Aguilera, M.A., Broitman, B.R., Thiel, M., 2016. Artificial breakwaters as garbage bins: structural complexity enhances anthropogenic litter accumulation in marine intertidal habitats. Environ. Pollut. 214, 737–747.

Besseling, E., Quik, J.T.K., Sun, M., Koelmans, A.A., 2017. Fate of nano- and microplastic in freshwater systems: a modeling study. Environ. Pollut. 220 (Pt A), 540–548.

Botero, C.M., Anfuso, G., Milanes, C., Cabrera, A., Casas, G., Pranzini, E., et al., 2017. Litter assessment on 99 Cuban beaches: a baseline to identify sources of pollution and impacts for tourism and recreation. Mar. Pollut. Bull. 118 (1–2), 437–441.

Burnham, K.P., Anderson, D.R., book (Eds.), 2002. Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach.

Cowger, W., Schultz, R.C., 2015. Bhagsu Clean Watershed Project. Undergraduate Thesis. Iowa State University.

EOA Inc, 2014. San Francisco Bay Area Stormwater Trash Generation Rates. Bay Area Stormwater Management Agencies Association, Bay Area, CA, 95.

EOA Inc, 2016. Tacking California's Trash Project. Bay Area Storm Water Management Agencies Association, Bay Area, CA, 151.

ESRI (Environmental Systems Research Institute), 2013. ArcGIS release 10.2.2, Redlands, CA.

Gall, S.C., Thompson, R.C., 2015. Impact of debris on marine life. Mar. Pollut. Bull. 92.1, 170–179.

, .

Hardesty, D.B., Wilcox, C., Schuyler, Q., Lawson, T.J., Opie, K., 2016b. Developing a Baseline Estimate of Amounts, Types, Sources and Distribution of Coastal Litter – an Analysis of US Marine Debris Data. CSIRO Oceans and Atmosphere, Hobart, Australia, 106.

Hidalgo-Ruz, V., Honorato-Zimmer, D., Gatta-Rosemary, M., Nuñez, P., Hinojosa, I.A., Thiel, M., 2018. Spatio-temporal variation of anthropogenic marine debris on Chilean beaches. Mar. Pollut. Bull. 126, 516–524.

Homer, C.G., Dewitz, J.A., Yang, L., Jin, S., Danielson, P., Xian, G., Coulston, J., Herold, N.D., Wickham, J.D., Megown, K., 2015. Completion of the 2011 national land cover database for the conterminous United States – representing a decade of land cover change information. Photogramm. Eng. Rem. Sens. 81, 345–354.

Iowa DNR, 2017. https://programs.iowadnr.gov/nrgislibx/, Accessed in 2017, the database is now retired but access to downloaded data will be made available upon request.

Kiessling, T., Knickmeier, K., Kruse, K., Brennecke, D., Nauendorf, A., Thiel, M., 2019. Plastic Pirates sample litter at rivers in Germany - riverside litter and litter sources estimated by schoolchildren. Environ. Pollut. 245, 545–557.

LARWQCB (California Regional Water Quality Control Board Los Angeles Region), 2007. Trash Total Maximum Daily Loads Los Angeles River Watershed. 48, Los Angeles, CA.

Lebreton, L.C.M., van der Zwet, J., Damsteeg, J.-W., Slat, B., Andrady, A., Reisser, J., 2017. River plastic emissions to the world's oceans. Nat. Commun. 8, 15611. https://doi.org/10.1038/ncomms15611doi:10.1038/ncomms15611.

Leggett, C., Scherer, N., Curry, M., Bailey, R., 2014. Assessing the Economic Benefits of Reductions in Marine Debris: A Pilot Study of Beach Recreation in Orange County, California. National Oceanic and Atmospheric Administration, Cambridge, MA, 45.

Maryland Department of the Environment, 2010. Total Maximum Daily Loads of Trash for the Anacostia River Watershed, Montgomery and Prince George's Counties. Maryland and the District of Columbia, Baltimore, MD, 79.

McCormick, A.R., Hoellein, T.J., 2016. Anthropogenic litter is abundant, diverse, and mobile in urban rivers: insights from cross-ecosystem analyses using ecosystem and community ecology tools. Limnol. Oceanogr. 61, 1718–1734.

Mid Atlantic Solid Waste Associates, 2009. National Visible Litter Survey and Litter Cost Study. Keep America Beautiful. Stamford, CT, 216.

Moore, S.M., Cover, M.R., Senter, A., 2007. A Rapid Trash Assessment Method Applied to Waters of the San Francisco Bay Region: Trash Measurement in Streams. Storm Water Ambient Monitoring Project, Bay Area, CA, 55.

Moore, S., Sutula, M., Von Bitner, T., Lattin, G., Schiff, K., 2016. Southern. California Bight 2013 Regional Monitoring Program Volume III. Trash and Marine Debris. Southern California Coastal Water Research Project, Southern California, 78.

National Hydrography dataset, 2015. National resource conservation service. In: https://datagateway.nrcs.usda.gov/, accessed 2018.

Nelms, S.E., Coombes, C., Foster, S.C., Galloway, T.S., Godley, B.J., Lindeque, P.K., Witt, M.J., 2017. Marine anthropogenic litter on British beaches: a 10-year nationwide assessment using citizen science data. Sci. Total Environ. 579, 1399–1409.

Nelson, C., Botterill, D., 2002. Evaluating the contribution of beach quality awards to the local tourism industry in Wales—the Green Coast Award. Ocean Coast Manag. 45 (2), 157–170.

NIST, 2018. https://www.nist.gov/pml/weights-and-measures/nist-handbook-44-2018-current-edition.

Ocean Conservancy, 2018. International Coastal Cleanup 2017 Report. Ocean Conservancy, Washington, DC, 28.

Ocean Protection Council, 2018. California Ocean Litter Prevention Strategy: Addressing Marine Debris from Source to Sea. Ocean Protection Council, California, 53.

Oigman-Pszczol, S.S., Creed, J.C., 2007. Quantification and classification of marine litter on beaches along Armação dos Búzios, rio de Janeiro, Brazil. J. Coast. Res. 23, 421–428.

Project AWARE, 2017. A River through Land and Time: Change, Continuity and the Cedar River. Iowa, USA, 4.

R Core Team, 2018. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria, URL https://www.R-project.org/.

Rech, S., Macaya-Caquilpán, V., Pantoja, J.F., Rivadeneira, M.M., Kroeger Campodónico, C., Thiel, M., 2015. Sampling of riverine litter with citizen scientists findings and recommendations. Environ. Monit. Assess. 187 (6), 335.

Romans, B.W., Castelltort, S., Covault, J.A., Fildani, A., Walsh, J.P., 2016. Environmental signal propagation in sedimentary systems across timescales. Earth Sci. Rev. 153, 7–29 https://doi.org/10.1016/j.earscirev.2015.07.012.

Schuyler, Q., Hardesty, B.D., Lawson, T.J., Opie, K., Wilcox, C., 2018. Economic incentives reduce plastic inputs to the ocean Marine Policy. Available from: http://www.sciencedirect.com/science/article/pii/S0308597X17305377.

Stickel, B.H., Jahn, A., Kier, W., 2012. The Cost to West Coast Communities of Dealing with Trash, Reducing Marine Debris. US Environmental Protection Agency, Blue Lake, CA, 50.

Strahler, A.N., 1952. Hypsometric (Area-Altitude) analysis of erosional topography. Bull. Geol. Soc. Am. 1117–1141.

Tekman, M.B., Gutow, L., Macario, A., Haas, A., Walter, A., Bergmann, M., 2018. Alfred-Wegener-Institut Helmholtz-Zentrum für Polar- und Meeresforschung. In: http://litterbase.awi.de/interaction_detail, accessed 2018.
US Census, 2018. 2018 TIGER Geodatabase record layouts. United states Census. In: https://www2.census.gov/geo/pdfs/maps-data/data/tiger/tgrshp2018/2018_TIGER_GDB_Record_Layouts.pdf, last accessed 12/28/2018.
USGSa, National land cover dataset 2011. In: https://www.mrlc.gov/data?f%5B0%5D=category%3Aland%20cover, last accessed 1/4/2019.
USGSb, National Hydrography dataset. In: https://www.usgs.gov/core-science-systems/ngp/national-hydrography/access-national-hydrography-products, last accessed 1/4/2019.
.
van der Velde, T., Milton, D.A., Lawson, T.J., Wilcox, C., Lansdell, M., Davis, G., et al., 2017. Comparison of marine debris data collected by researchers and citizen scientists: is citizen science data worth the effort?. Biol. Conserv. 208, 127–138.
Vincent, A., Drag, N., Lyandres, O., Neville, S., Hoellein, T., 2017. Citizen science datasets reveal drivers of spatial and temporal variation for anthropogenic litter on Great Lakes beaches. Sci. Total Environ. 577, 105–112.
Wagenmakers, E.-J., Farrell, S., 2004. AIC model selection using Akaike weights. Psychon. Bull. Rev. 11 (1), 192–196.
Willis, K., Denise Hardesty, B., Kriwoken, L., Wilcox, C., 2017. Differentiating littering, urban runoff and marine transport as sources of marine debris in coastal and estuarine environments. Sci. Rep. 7, 44479.
White, P.J., 2010. Impacts of Polystyrene Bans on Trash-Impaired Watersheds in the East Bay. Master's Thesis. San Francisco State University.
Williams, A.T., Simmons, S.L., 1997. Movement patterns of riverine litter. Water Air Soil Pollut. 98, 119–139.
Williams, A.T., Simmons, S.L., 1999. Sources of riverine litter: the River Taff, south Wales, UK. Water Air Soil Pollut. 112, 197–216.
Zettler, E.R., Takada, H., Monteleone, B., Mallos, N., Eriksen, M., Amaral-Zettler, L.A., 2017. Incorporating citizen science to study plastics in the environment. Anal. Method. 9, 1392–1403.

ETOC BLURB

Near-stream and watershed scale land use control riparian litter concentration in Iowa streams.