National **Environmental Science** Programme

Emerging Priorities Project - EP1

Assessing the effectiveness of waste management in reducing the levels of plastics entering Australia's marine environment

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Milestone:

5 - Final Report

December 2017




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Preferred Citation

Hardesty, B.D., Schuyler, Q., Willis, K., Lawson, T.J. and Wilcox, C. (2017). Assessing the effectiveness of waste management in reducing the levels of plastics entering Australia's marine environment. Report to the National Environmental Science Programme, Marine Biodiversity Hub. CSIRO.

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Acknowledgement

This work was undertaken for the Marine Biodiversity Hub, a collaborative partnership supported through funding from the Australian Government's National Environmental Science Programme (NESP). NESP Marine Biodiversity Hub partners include the University of Tasmania; CSIRO, Geoscience Australia, Australian Institute of Marine Science, Museum Victoria, Charles Darwin University, the University of Western Australia, Integrated Marine Observing System, NSW Office of Environment and Heritage, NSW Department of Primary Industries. We thank Clean Up Australia, Keep Australia Beautiful National and Keep South Australia Beautiful for sharing data. We also thank Tangaroa Blue Foundation for providing data used in this project (see list of contributers in Appendix D). We also thank the many volunteers that participated in clean up activities and provided data to be used in analyses in this project.

Important Disclaimer

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Executive Summary

Marine debris (or marine litter) is a growing issue of international concern. Defined as any persistent, manufactured or processed solid material discarded, disposed of or abandoned in the marine and coastal environment (UN Environment Program, 2009), it results in a multitude of impacts in coastal and marine environments. Not only does debris impact wildlife, have detrimental economic consequences, result in navigation hazards and transport invasive species, but it also has aesthetic and toxicological impacts on communities and wildlife, respectively. Common items that end up as marine debris include plastic bottles, food packaging, fishing nets or gear, cigarette butts and plastic bags.

Marine debris and its upstream source, land-based waste, is a growing environmental, economic and social issue that spans council, state, national and international boundaries. Addressing this complex issue and reducing waste inputs to the marine environment is a challenging undertaking. Managing the issue will benefit from understanding the plastic pollution problem from a large-scale, holistic perspective. This involves conceptualizing the sources and drivers, the distribution and dynamics of debris in the environment as well as identifying and quantifying the impacts on wildlife and humans, and identifying and assessing a suite of potential management responses.

Monitoring marine debris (land-based waste) in Australia

We know that an estimated 80% of debris entering the oceans comes from land-based sources and the remaining 20% from at-sea activities (Derraik 2002; Jambeck et al. 2015). Hence, understanding the movement of anthropogenic waste on land is fundamental to addressing the issue *before* it reaches the ocean. In this report, we summarise many of the types of data that are collected and we discuss programs that are currently in place to remove and monitor marine debris within Australia. Perhaps most importantly, we provide a framework and a structure that laypeople, citizen scientists and policy makers may want to consider as any group sets out to design and conduct surveys. This is relevant as the way surveys are structured determines what information, such as hotspots or time trends, can be extracted from them.

Identifying Key Driving Factors for Debris Loads on Land

We identified a number of important variables driving debris loads on land in Australa. In particular, land use, socio-economics, and site types were important, in addition to population density and other more widely assumed variables. Interestingly, we found significant differences between the data types we evaluated in terms of our ability to identify clear patterns and driving variables. The volunteer clean up data we evaluated was much more variable, and potentially has two major issues that make it difficult to extract patterns from: 1) an upward bias in debris densities, possibly due to selection of accumulation or ‘dirty’ sites, 2) poor information on sampling effort leading to difficulty in estimating accurate densities of debris. These features are common to volunteer clean up data, as the organisers typically have to balance volunteer engagement and methodological rigor. In contrast, we were able to identify clear patterns in the Keep Australia Beautiful data we analysed, likely because it is designed as a survey, and has tight controls on proceedures and metrics. The KAB data indicated that the NT and WA had the highest levels of debris overall, and the influence of state was the most significant factor driving debris distribution. Additionally, debris levels increased with economic resources within 50km of a study site, and decreased with education/occupation levels within 5km of a site.

Sydney Transport Case Study

We modelled the load of debris on a 300 square metre grid across the entire Sydney region, covering 5,800 square kilometres. We built models of wind and water transport across this region, and used them to explore the variation in debris loads across the region. Using the Keep Australia Beautiful data, we were able to discern relationships between wind and water transport and the levels of debris at a particular site. Water transport generally had a significant positive correlation with higher than expected debris loads, while wind transport had a significant positive correlation with lower than expected debris loads. We were not able to discern such effects from analysis of the Clean Up Australia data. We suggest this lack of transport effects observed in the CUA data is due to complexities in the clean up data. Potentially, this could be addressed with a more extensive analysis, but such analyses were beyond the scope of this project.

Policy Analysis

We were able to distinguish a number of policies that are effective in reducing marine debris, based on our comparison of local policies and the load of marine debris along the coast of 40 councils around the country. All of the programs we evaluated were correlated with some improvement in marine debris loads. This might be an indication of a general awareness and focus on waste management issues at a local scale and the improvement in local coastal conditions. There was substantial variation among the policies in their impact on debris loads, suggesting that it might be possible to identify a small subset of policies that return the greatest benefit.

Hotspots

We used four datasets to map debris hotspots around the country, including KAB litter surveys, CUA clean up data, CSIRO coastal survey data, and CSIRO ocean surveys. We found general concordance among the KAB and CSIRO data sets. Urban centres had higher levels of debris, along with specific areas such as the coastal margin of the Great Barrier Reef and the western coasts of the mainland and Tasmania. The CUA data provided significantly more coverage of the continental areas, however, it was likely affected by extreme values in remote areas of the northwest of the continent. As with the identification of driving variables, this is likely due to issues related to site selection and sampling effort.

Recommendations

Based on the various activities conducted in this project and the current activity in the international sphere around marine debris, below we make six recommendations for the Department to consider in moving forward.

- The Department invest in an improved understanding of the issues limiting the use and utility of these data for monitoring marine debris in Australia. There are a number of existing sources of data. Our analysis uncovered significant differences between them, and some issues that make their use for marine debris monitoring difficult. These issues are potentially resolvable, allowing the Department to make use of the large volume of exisiting data for decision-making, reporting, and assessment.

- The Department prioritise further evaluation of key driving variables and transport processes affecting marine debris in Australia. This would complement the next recommendation (below);
- The Department articulate its monitoring targets, design advice for surveys to ensure the available data can address these targets, and that important reporting standards are clearly identified (with standards selected to address particular questions or criteria of interest). Such guidance could support future Department programs (such as Caring for Country or similar), and assist outside organisations in providing data in a form that is complementary to that may be collated by or for the Department.
- We found clear evidence that some policies adopted by local governments are effective in reducing marine debris. The Department might extend this work, and promote cost-effective solutions based on a national analysis to states, regional bodies, and local councils to support their policy development;
- The Department prioritise the development of a national hotspot map for plastic pollution, covering both terrestrial and marine habitats, and incorporating debris loads away from urban centres.
- The Department could integrate hotspot mapping with an assessment of risk to Department targets, key ecological features, protected species, and important marine ecosystems.

1. Existing approaches to monitoring marine debris or litter on land within Australia

Key points:

- Most waste comes from land-based sources, so focusing on waste reduction and removal before it reaches the ocean is critical.
- Method standardization is challenging and depends upon the questions being asked.
- Clean up events and designed surveys are the two main activities in which data are generally recorded and reported.
- There are challenges to using clean ups as data sources, due to the trade-off between rigor and volunteer engagement.
- Site bias, replication, survey effort and observation bias and are each important considerations when designing and implementing monitoring programs if one wishes to assess litter quantities, source reduction, relative inputs and other basic questions of interest.

1.1 Debris Monitoring

An estimated 80% of debris entering the oceans comes from land-based sources and the remaining 20% from at-sea activities (Derraik 2002; Jambeck et al. 2015). Understanding the movement of anthropogenic waste on land is therefore fundamental to addressing the issue *before* it reaches the ocean, and was the focus of this project. Litter or debris moves in the environment through a variety of pathways. The primary pathways through which this debris or plastic pollution moves include human movement and behaviour (littering, dumping), losses during transport or storage of waste, and via wind and water transport (along rivers, creeks, streams and stormwater outfalls) (See Hardesty et al. 2016).

The questions of how, where and why to monitor debris are fundamental. These questions have implications for how data can be analysed, what we can learn from it, how we can estimate or make predictions or projections for areas we have not been able to sample, the ability to infer changes and responses to interventions, and many other questions we may wish to address. From the 1990s through to the present day, peer-reviewed studies have summarised marine litter monitoring programs, focusing on methods and national-scale surveys (Rees and Pond, 1995; Ribic et al. 1992). There have also been a variety of recommendations for guidelines and approaches to monitoring marine litter on land (see Cheshire and Adler, 2009; Galgani et al. 2010; Opfer et al. 2012; NOAA 1992, 2011; others) and at sea (Directive 2013; Ryan et al. 2009; Mace et al. 2012).

There are myriad ways in which people carry out clean up activities, conduct surveys and monitor debris in programs around the world. To date, however, there has been no global consensus reached on a single survey method, nor has there been a robust comparison of all survey methods. This significant knowledge gap is considered in this emerging priorities project. In September 2017, a global working group through the Group of Experts on Scientific Aspects of Marine Protection (GESAMP) commenced to address this topic. The working group is working specifically on harmonisation of monitoring methods, and includes experts from around the world.

Why has the standardisation of methodologies proven so difficult? One of the fundamental challenges of standardisation comes back to the question(s) being asked. A question as seemingly straightforward as 'How much debris do we find on the coast of New South Wales?' leads to a number of considerations. Is this to be measured in number of items, weight, or volume? Is there interest in the material, manufacturer, or source? How many people are collecting information, and how big an area are we considering? What do we consider coastline? Is it only sandy beaches, or are rocky slabs or other coastal areas considered? What about mangroves? How far from the waterline do we sample? Do we sample big items, small items, and how do we decide? How can we get an estimate if we can't survey every metre of the coastline? Over how much time are we sampling?

As is apparent, what seems like a simple question quickly can become quite challenging. Is it correct, accurate, appropriate or relevant to compare the coastal litter in New South Wales to that of coastal South Australia (given how many people live in each state, not to mention the different length of coastline and infrastructure and resources in each of the two states)? How do we account for the difference in the number of people in a state – is that something we need to consider when we present our results? All these (and many other) questions come in to focus as one considers design and implementation of monitoring programs. If we want to ask if there has been a change in time, do we compare count (or weight or volume) differences between years, or do we need to account for the fact that more people live in a survey region now than they did when an area was surveyed 10 years ago?

There are a number of goals or reasons for carrying out marine debris monitoring. Monitoring or clean ups may take place to increase community engagement and raise awareness, to quantify the amounts of debris, to predict hotspots, to identify sources, to determine sinks or debris accumulation areas, to identify interdiction points, to determine the cost effectiveness of litter bins and signage, to measure changes with time or responses to interventions, and many other reasons. Not all of these are mutually exclusive; many methodogies can address a number of goals.

To contextualise the topic and provide a framework for considering how one might establish a monitoring program (or relevant components to consider), we developed a structure to think about marine debris from survey design through to analysis and interpretation (Figure 1.1). When we identify what we want to know, we can then determine how and/or what we measure – and the appropriate approach or method to employ. If the goal is to have a national monitoring system in place which addresses particular questions, assesses changes through time (and is statistically robust and appropriate), there could be significant benefit in the development of such a monitoring system at the national scale.

We provide a summary of many of the types of data that are collected and programs that are currently in place to remove and monitor marine debris within Australia. Critically, and perhaps most importantly, we provide a framework for the conversation and a structure that laypeople, citizen scientists and policy makers may want to consider as any group sets out to design and conduct surveys (Figure 1.1).

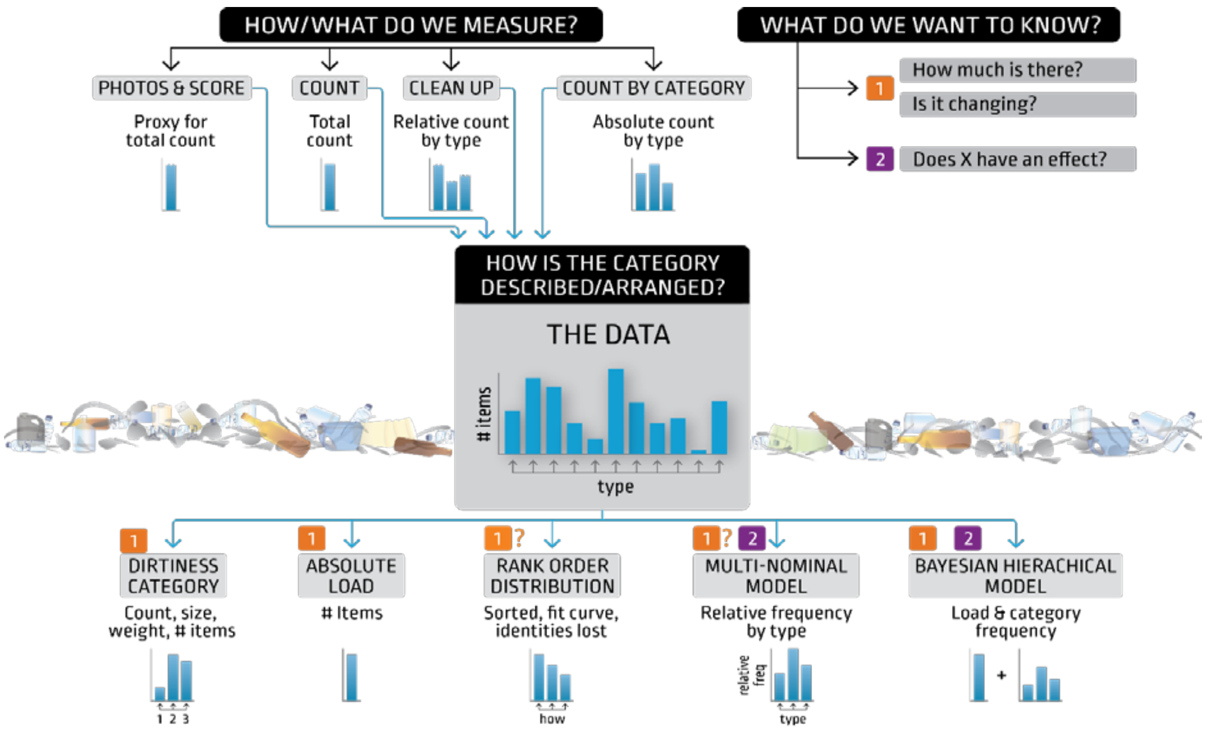

Figure 1.1. Description of what questions might be asked of data (1, 2 in orange and purple), how or what is measured, with how the data may be collected, described or arranged and what questions and analyses that can be conducted to address particular questions

At one extreme, data can be aggregated up into a total count of items across all categories or a total weight (Figure 1.1, lower left). The advantage of this approach is that by using a single category of data, modelling efforts can focus on the full complexity of space and time patterns, incorporating both driving variables, such as local population size, and nuisance variables, such as sampling effort. At the other extreme, one might model the abundance of items in each category, across the tens of categories that are recorded in various data collections. The challenge in this approach is that models describing the abundances in each category may differ, leading to a very complex interpretation of the data (lower right). Furthermore, categories may be positively or negatively correlated, so the direction of the link between items and abundance may be difficult to interpret. Intermediate tools such as richness curves or rank order distributions, as typically used in fields like community ecology (Figure 1.1, central bottom) do not seem to be particularly linked to useful questions in this context, though this is something we explored.

1.2 Monitoring marine debris in Australia

There are two main categories under which monitoring activities tend to fall: clean up events and designed surveys. In the following paragraphs, we discuss both of these with respect to data quality, concerns and constraints and information presently available. We also provide recommendations to improve statistical power, reduce data collection effort, improve inference, and maximise insights related to marine debris monitoring going forward.

Survey design is one of the first key components in developing a quality data set. It is useful to consider design at a number of levels in a hierarchical fashion. First, surveys should be balanced across any variable for which one wishes to make inference. For temporal trends, for example, surveys must have been conducted over the time period in question. Similarly, to evaluate spatial trends, surveys would ideally be carried out across all locations in a consistent manner. If, for example, the effects of river outlets are of concern or interest, sampling would need be structured keeping the location of river outlets in mind. Surveys would also need to be balanced across factors that may influence the effects of river outlets (e.g. population within the watershed, road networks, etc.). Deviations from balanced sampling, for instance variations in sampling over time or location, can confound the data, making it difficult to interpret in light of the multiple factors that influence the results.

Second, it is important to control the bias in how sites are sampled. This is particularly true where there is a relationship between the chance of choosing a site and the variables that affect the site. For example, ready access to coastal sites might be part of the survey location choice, but is also likely to affect visitation rates by the public (and thus influences the deposition rates for debris). By using tools such as randomisation, we can avoid these biases. When or where biases cannot be avoided, it is important to collect data that will allow one to estimate the effects of biases in the analysis.

Next, due to variation at sites, it is valuable to have replication within the sites. Replication at the site level, and stratification of replicates across the conditions at each site (for example, substrate types at a survey site may include boulders, sand, and rocky slab) can assist in reducing variability at each site. This is valuable for allowing estimation of the driving variables for the variation where it occurs.

Finally, controlling survey effort and observation error is very important. Ideally, any item in a survey should have an equal probability of detection, irrespective of size, shape, location, and observer. This is clearly an impossibility. Thus, it is important to control observer effort and detection probability as well as possible. This can be done through (1) standardising the search area; (2) standardising the search time; and (3) standardising the rate or speed of the search. Recording information on the size and color of items can help with standardising observations for detection error, particularly when considered in the context of survey conditions like substrate type and colour. Ultimately, if one of the goals of the study includes the ability to make predictions in areas where surveys were not carried out, (e.g. predicting outside the observed conditions or locations) it is essential that the sampling hierarchy includes the full range of conditions for which predictions will be made.

Analysis of different data types requires a variety of statistical approaches or tools. It is useful to identify the main questions or goals of the project at the outset (though we acknowledge that goals can change through time). This is the fundamental first step which allows for appropriate analysis and interpretation of data that will be collected. For example, if the goal is to identify the baseline level of litter on the coastline and one wishes to be able to make projections outside of where data was collected or reported, it is important to stratify the sampling such that various coastal types are sampled in proportion to their occurrence (see Hardesty et al. 2016 for one example based on a national coastal survey of Australia). If survey sites only include one substrate type or are of one shape, aspect, or slope, it is much more difficult to make predictions about the amounts of debris that are likely occur at other sites that do not have the same substrate (or slope, aspect, etc.). However, if that is not a goal of the monitoring, such factors need not be incorporated into the survey design. One cannot add such analyses post-hoc however if the project goals expand to encompass such changes. This is often a fundamental difference between designed survey monitoring and clean up events.

At one end of the spectrum are the hundreds to thousands of clean up activities that take place on beaches, in parklands, along waterways, highways and in communities around Australia. For example, Clean Up Australia (initiated in 1989; http://www.cleanup.org.au/au/) engages more than half a million volunteers who removed waste from more than 7,000 sites around the country in 2016 alone. Surfrider, another volunteer-based international civil society group (started in 1984; http://www.surfrider.org.au/; http://www.adessium.org/), also participates in beach clean up activities and awareness campaigns, often in remote or difficult to access parts of the country. Tangaroa Blue Foundation (TBF, started in 2004; http://www.tangaroablue.org/) is another national group that organises numerous clean ups on beaches (and rivers) around the country. Tangaroa Blue Foundation also hosts data collected by other clean up groups (including Surfrider, and numerous local clean up organizations), compiling it into a national database as part of the Australian Marine Debris Initiative (AMDI). The International Coastal Cleanup (ICC) first organized more than 30 years ago by The Ocean Conservancy, is a global clean up effort whereby volunteers clean up sites around the world over a single week or day (generally in September of each year). Ocean Conservancy hosts a publically accessible global database where information is stored and made available to the public. *These are by no means **all** of the organisations and individuals that conduct clean ups; these are but a few examples of some relevant groups and are provided for indicative purposes*.

For waste or debris monitoring that is based on clean up activities, site choice (i.e. where clean ups take place) is driven in part by volunteer initiative. Often, people focus clean up efforts at sites identified as areas that would benefit from such activities (i.e. accumulation or 'dirty' sites). Some volunteers adopt a site that they clean regularly, often because they live nearby or have a connection to the site. Replication and randomisation typically are not a feature in the decision making process for clean up locations. Generally, there is some level of information recorded on sampling effort (such as number of volunteers or how much time was spent on the activity), but little prescription about how effort is expended in the field, and detection probability is generally not controlled. While it is possible to control for biases introduced by this approach to some extent, the survey methods introduce sampling variation and to some extent reduce the inferences that could be made from a similar sized dataset collected in a more structured manner. For example, while extracting information from clean up data that would allow you to estimate overall debris loads and distribution patterns is challenging, you can readily use these data for other purposes, such as identifying the sources of debris that are found at a particular site.

Many of the organisations, individuals and community groups that participate in and record information from clean up activities, report data from their removal and clean up efforts to their local communities or on data portals hosted by other organisations (such as Tangaroa Blue Foundation's AMDI, the Atlas of Living Australia (ALA) or the CSIRO national marine debris database). Data provision in many clean ups is a side benefit of an activity that was not initially designed as a data collection exercise (though it may have become that through time). Thus, any changes to the protocols need to recognize this situation and accept any limitations imposed by the primary goals of the clean up activity. There are certainly ways to control survey effort and detection probability by providing guidance on the search pattern and minimum item size reported for the surveys. Other information that can improve the analytical utility of the data recorded during clean ups include the person-effort involved, total time spent undertaking the activity and the area sampled.

In contrast to many clean up efforts, the Keep Australia Beautiful (KAB) and CSIRO methods are typical of designed surveys. Both include stratification and randomisation at both levels in the hierarchy (site choice and survey location choice). We have less information about the details of stratification and randomisation for KAB site selection than is known for the CSIRO approach, as the underlying methods are not publically available. In each of these, however, observation effort is tightly controlled, with area surveyed and survey effort constant across surveys. Both are structured in a manner that reduces variation between surveys. Detection error is controlled by standardising visual acuity among surveyors (i.e. controlling for the distance between the observer's eye and the area searched) and the rate at which items are encountered. Both were established without focusing on reporting data from 'dirty' or 'clean' areas *per se*, and instead are representative of various types of sites.

There are always trade-offs in survey design. By reporting or collecting only larger items, observers can cover a larger area, and the variability in the sampling is therefore reduced. However, selecting for larger items potentially biases the sample more towards littered items as opposed to ocean-borne debris, which is usually smaller in size (e.g. fragments). Furthermore, certain areas are likely to be more prone to littering, while others may have a higher abundance of ocean-sourced debris. If the methods differ such that ocean-sourced debris is less represented in some data sets, estimates of hotspots and trends even at the same sites based on differing methods can be completely different (see Hardesty et al. in revision).

There are a range of options that could help improve the data quality. Considering design principles such as stratification, randomisation and replication are all valuable. Developing a better understanding of the site selection process and search dynamics of volunteer participants to attempt to develop better spatial and temporal coverage in the survey designs would also be useful. Some of these proposed improvements can likely be done through interviews or detailed evaluation of the existing data in retrospect, others may require modification of methods or survey designs and can only be applied to future efforts. Some improvements may require field experiments to understand human dynamics during clean ups. These are all valuable considerations for future aspects of this work.

It is clear that regulations, economic and market based instruments and community-based solutions also have a role to play (Vince and Hardesty 2016). By better understanding the types of litter and the pathways through which it moves, we will be better able to manage litter before it reaches the ocean. The landscape is dynamic and changing rapidly in Australia, particularly as policies such as bag bans, container deposit legislation (CDL) and other governance arrangements are being considered at state and national levels. There is much to be learned about land-based litter inputs to the ocean and systematic surveys will be needed to differentiate successes, challenges, and opportunities to reduce these inputs.

2. Investigating patterns in marine debris data and identifying key drivers

To investigate patterns in debris distribution and the drivers associated with patterns observed, we accessed a variety of data sets, as well as biogeographic information on sites around Australia. We modelled these data using a generalised additive model (GAM) to identify which factors were most influential in determining the distribution of debris across the landscape.

Key findings

- Through this analysis we compared designed survey and clean up approaches in their capacity to identify important drivers affecting marine debris distribution.
- We applied a General Additive Model (GAM) to the Australia-wide data set for KAB and CUA data. We found the KAB model explained a significantly higher amount of the variability in the data.
- We found that the NT and WA had the highest levels of debris overall. State was the most significant factor driving debris distribution.
- Debris levels increase with economic resources within 50km of a study site, and decrease with education/occupation levels within 5km of a site.
- Volunteer clean up methods can introduce site selection biases into the data. Further work on correcting for these biases is essential if they are to be useful for marine debris monitoring and evaluation.

2.1 Data and predictor variables

For this analysis we accessed data from Clean Up Australia, CSIRO Marine Debris Program, Keep Australia Beautiful (KAB) and Keep South Australia Beautiful (KESAB), and Tangaroa Blue Foundation (TBF). These data are quite distinct in nature. KAB and KESAB were originally designed to gather data on the effectiveness of container deposit legislation, CSIRO protocols were developed to assess general debris loads around the country, TBF data collection is aimed at developing source reduction plans, and CUA programs are focused on removing debris from the environment. Some of the programs are designed specifically as surveys (KAB, KESAB, CSIRO), while others collect or aggregate data from community-based clean ups (CUA, TBF). The data sources also have different sampling focuses, with some focused on large items (CUA, KESAB, KAB), others on specific sources (KESAB, KAB, TBF), or more general debris loads (CSIRO). The differences in the program goals and survey designs imply differences in characteristics of the data, underlying biases, spatial coverages, and site selections. The sourced survey data cover different periods of time, use different categories to audit the mix of debris types, practice different survey techniques, and are provided at different geographic scales. All of these factors have strong effects on the utility of the data for measuring plastic pollution in the environment. For a more thorough description of the data, please see Appendix B.

A variety of predictor variables was collected to characterise each sample site and determine if site characteristics have a discernible influence on debris load and type. Where relevant, variables were calculated within 5 different buffer sizes; 1, 5, 10, 25, and 50km radius around each survey point, to assess the scale of influence relevant to each variable (Appendix C).

Predictor variables included distances to transport routes such as roads and railway stations, as well as the total length of various road types within each buffer. Land cover, population density, and four different socio-economic indices were also considered: economic advantage, economic advantage/disadvantage, economic resources, and education/occupation (see Appendix C for more detail).

2.2 GAM MODELLING

Note that we have previously employed similar methodologies in the Brisbane region (Hardesty et al. 2016). The analyses presented here were run in a parallel fashion, with minor adaptations and improvements on this previous work. Clearly both the geographies and results vary between the studies, but we would like to explicitly acknowledge that some of the text in sections 3 and 4 is similar to the Hardesty et al. report as the methodologies employed were similar.

To explore patterns in the large scale datasets in this project, identify key drivers, and develop a predictive model that can be used in the Sydney transport study, we fit a Generalised Additive Model (GAM) to the full Australia-wide KAB and CUA data sets. We did not use CSIRO data in this analysis as there were only 3 survey sites that were conducted in the Sydney watershed region, and we did not use TBF data as we did not have a full Australia-wide dataset against which the models could be fit. The focus of GAM models is on fitting functional relationships between a variable of interest, in this case the debris load at a site, and potential explanatory variables. This allows us to understand how debris load varies at different levels of the predictor variables as they interact with each other, and using those relationships once established, predict loads in other sites.

There are two ways variables can be treated in a GAM model; either as terms with a specified mathematical form (called parametric terms) or as terms with an unspecified form that needs to be approximated (called smooth or nonparameteric terms). For instance, one might assume that debris loads increase linearly with population density in an area. In this case the goal is to estimate the slope of that relationship, that is how an increase in population translates into an increase (or decrease) in debris load. In a GAM model, one would represent this as parametric term, as we have specified that it is a linear relationship with two parameters, a slope and an intercept. In contrast, one might not have any expectation as to how debris loads change with population, and thus one might prefer to use a very flexible approach to modelling the relationship. For instance, in this example, debris loads might increase with population in sparsely populated areas, but then decrease in urban areas as solid waste management improves. The increasing and decreasing parts of the relationship might not even have the same shape. In a GAM modelling context, one might use a smooth or nonparametric term to approximate this more complex relationship. A smooth or nonparametric relationship is built using many small functions that, when added together, can represent a complex function such as the one described here between population and debris load in rural and urban areas. A smooth term can capture these types of complex relationships readily, while a parametric term, such as a linear function, would not be able to. However, this flexiblity comes at a price. While smooth terms generally fit the data better, as they can conform to the complex patterns in data, they can be more difficult to interpret.

As reported in Hardesty et al. (2016), the total debris data from KAB surveys varies widely, with loads distributed between 0 and 3345 items/1000m^2. The median value is 40 items/1000m^2, while the mean is 72 items/1000m^2. Because of the large number of small observations, the data are not normally distributed, so we transformed them with a log transform. The distribution of CUA data has a much larger spread, with loads distributed between 0 to 134,000 items per 1000m2. The median value is 2.98, while the mean is significantly higher, at 714.20. This indicates several outlying values in the CUA data. We also log transformed the CUA data (Hardesty et al. 2016).

Because some of the socio-economic variables are significantly correlated, we transformed those variables in order to be able to incorporate some measure of them into our analyses while avoiding correlation among them. Economic advantage and disadvantage were strongly correlated, so we decided to only incorporate the economic advantage variable and not the disadvantage variable. Economic advantage was strongly correlated with both education/occupation as well as economic resource. To address this, we calculated the linear relationship between education/occupation and economic advantage, and included the residuals from this relationship instead of education/occupation itself. In the GAM analyses we also included a spatial smooth to represent the location of sampling sites. We also included site types which were reported in both KAB and CUA datasets.

In contrast to conditional inference tree models (see Section 3.4.1), there is no automated selection process for GAM models to find the best model. As noted in Hardesty et al. (2016), for KAB and CUA data, we began by fitting a model with all smoothed terms. Insignificant smooth terms were dropped from the model. We then graphed each significant smooth term, and where appropriate, moved them into a parametric form, such as a linear relationship. If a parametric term was significant, we left it as parametric; if not, we moved it back into a smooth.

KAB GAM modelling

The final KAB GAM explained 29.4% of the variability in the model. We present the parameter values for each of the terms in the model, the standard error (a measure of uncertainty) for the parameter value, the *t* and *p* values which measure the statistical significance (by convention, a p value < 0.05 is considered to be significant statistically), the median value of the variable for that coefficient, the product of the coefficient and the median (which measures how strong the effect is, and can be compared among predictor variables), and a ranking of the absolute value of these signed products (or effect sizes and direction) (Hardesty et al. 2016) (Table 2.1).

In the GAM modelling for the KAB data, political unit is the most predictive of the total amount of debris, with states having 4 of the 5 highest effect values. In particular, the Northern Territory and Western Australia have significantly higher debris levels than the reference state, the ACT.

Next most influential are the socio-economic factors, with economic resource (50km) and education/occupation (5km) indices falling into the top 10. Notably, economic resource is positively correlated with debris, meaning that the higher the economic resource of the surrounding 50km, the more debris there is, while education/occupation is negatively correlated; the higher the education in a 5km buffer, the lower the debris there is. Education/economic advantage residuals also appear in the final model, but only in a smoothed term, not in a parametric term, and the relationship is not very straightforward to interpret.

Site types, in particular highways, have the next strongest effect size. Interestingly, the reference type, beach, has lower debris levels than any of the other site types. Highways, retail sites, and car parks have the highest debris levels. Land use was also influential in determining debris levels, with production landscapes in relatively natural areas, and water (such as marshes and rivers) having significantly higher debris levels than the reference, conservation areas and parks.

A number of measures of urbanisation are relevant for debris loads (as noted in Hardesty et al. 2016). Debris levels decrease with distance from rail stations, increase with distance from roads, and are high when roads are particularly concentrated near the survey site. They increase when population is higher near the survey site than in surrounding areas. Debris levels are also signficiantly related to a smooth of population and roads (within a 25km radius). However, these factors have relatively low effect sizes, suggesting they are less important than socio-economic variables, land use, and site type.

Overall the results paint a picture of high debris loads in relatively economically disadvantaged areas, particularly where site types are related to transitory human use (highways, shopping, parking lots; Hardesty et al. 2016). This is particularly true when those site types occur in a context where water courses or other semi-natural areas occur nearby. Together these results paint a picture of two general types of debris sources, littering near transitory locations (such as parking lots) and potentially illegal dumping in natural areas. Both occur more frequently in socio-economically disadvantaged areas. Social context may be important in determining these behaviours, as site types where people are not transitory (i.e. residential) or where there are recognised aesthetic or public use values (beaches, parks) appear to have particularly low levels of debris. Basically, the site types fall nearly into two non-overlapping groups in this respect.

Table 2.1 GAM model parameters for KAB GAM analysis. The estimate column is the coefficient estimated for each model parameter. Positive estimate values indicate that variable is is associated with more debris, negative values indicate that variable is associated with less debris. The standard error is a measure of the uncertainty of the estimate, P values indicate whether or not the association is significant. Values of < 0.05 indicate that the correlation is considered significant, and are denoted with an asterisk (*). The effect size is a measure of how influential each variable is in determining the amount of debris, and the rank is an ordering of the effect sizes, with lower values indicating higher effect sizes.

PARAMETRIC TERMS

	Est.	Std. Error	t value	P value		Median value	Effect size	Rank
Intercept	-15.6746	3.0416	-5.1534	0.0000	*	NA	-15.6746	
State								
NSW	-1.4922	0.3903	-3.8232	0.0001	*	NA	-1.4922	9
NT	27.3216	4.5637	5.9867	0.0000	*	NA	27.3216	1
QLD	-1.6140	0.4489	-3.5955	0.0003	*	NA	-1.6140	7
SA	-2.6262	0.6542	-4.0143	0.0001	*	NA	-2.6262	5
TAS	-1.4773	0.4544	-3.2512	0.0012	*	NA	-1.4773	10
VIC	-3.6883	0.7952	-4.6381	0.0000	*	NA	-3.6883	4
WA	25.1094	3.9522	6.3534	0.0000	*	NA	25.1094	2
Site Type								
Car Park	1.1261	0.0399	28.2452	0.0000	*	NA	1.1261	12
Highway	1.5461	0.0418	36.9446	0.0000	*	NA	1.5461	8
Industrial	0.9567	0.0433	22.1087	0.0000	*	NA	0.9567	14
Recreational	0.3820	0.0433	8.8261	0.0000	*	NA	0.3820	18
Residential	0.1786	0.0395	4.5217	0.0000	*	NA	0.1786	20
Retail Strip	1.2345	0.0440	28.0577	0.0000	*	NA	1.2345	11
Shopping Centre	0.9749	0.0454	21.4499	0.0000	*	NA	0.9749	13
Land Use								
Production natural environments	0.8648	0.1160	7.4567	0.0000	*	NA	0.8648	15
Production dryland agriculture	0.5276	0.0651	8.1039	0.0000	*	NA	0.5276	17
Production irrigated agriculture	0.0339	0.2809	0.1208	0.9038		NA	0.0339	22
Intensive uses	0.2395	0.0417	5.7411	0.0000	*	NA	0.2395	19
Water	0.7154	0.0869	8.2305	0.0000	*	NA	0.7154	16
Eco Resour 50km	0.0158	0.0024	6.5780	0.0000	*	1034.50	16.3722	3
Edu occupa 5km	-0.0023	0.0002	-10.5921	0.0000	*	993.79	-2.3154	7
Roads 5 to 50km resids	-0.0015	0.0005	-2.8468	0.0044	*	-0.09	0.0001	26
Pop 5 to 50km resids	0.0000	0.0000	4.7891	0.0000	*	208.10	0.0003	25
Distance to nearest rail	-0.0165	0.0021	-8.0242	0.0000	*	3.27	-0.0539	22
Distance to nearest road	0.0415	0.0306	1.3547	0.1755		0.17	0.0070	24

SMOOTH TERMS

	Edf	Ref. df	F	p-value	
Lat/Long smooth	19.2659	19.7870	32.1360	0.0000	*
Population 25km	8.4886	8.9160	14.4952	0.0000	*
All roads 25km	8.4331	8.9102	25.3569	0.0000	*
Educ/Econ. Adv residuals	8.4743	8.9182	21.5881	0.0000	*

CUA GAM analysis

The CUA GAM analysis was significantly different from the KAB analysis. First, it only explained 8.2% of the variability in the data. Second, very few predictor variables were significant, even as smooth terms. The two variables with the highest effect size were both socio-economic factors. Economic resource within a 5km buffer was negatively correlated with debris, unlike in the KAB data set. Similarly, education and occupation within a 1km buffer was positively correlated with debris, the opposite trend as seen in the KAB data. The only other parametric term in the model was the area of the survey, with larger surveys finding a slightly smaller amount of debris per unit area. Some of these results are likely due to a site selection bias (see section 3.3 for more details).

Table 2.2. GAM model parameters for CUA GAM model. The estimate column is the coefficient estimated for each model parameter. Positive estimate values indicate that variable is is associated with more debris, negative values indicate that variable is associated with less debris. The standard error is a measure of the uncertainty of the estimate, P values indicate whether or not the association is significant. Values of < 0.05 indicate that the correlation is considered significant, and are denoted with an asterisk (*). The effect size is a measure of how influential each variable is in determining the amount of debris, and the rank is an ordering of the effect sizes, with lower values indicating higher effect sizes.

PARAMETRIC TERMS

	Estimate	Std. Error	P value		Median value	Effect size	Rank
(Intercept)	6.2001	1.5411	0.0001	*	NA	6.2001	
Area_m^2	-4.63E-07	0.0000	0.0000	*	40000	-0.0185	3
Education/occupation 1km	0.0042	0.0017	0.0113	*	981.2056	4.1141	2
Economic resource 5km	-0.0076	0.0026	0.0031	*	999.127	-7.5844	1

2.3 COMPARISON BETWEEN KAB AND CUA ANALYSISES

Results for the KAB and CUA analyses differ significantly from one another. GAM modelling for the two data sets are nearly opposite. One possible cause for this discrepancy is in the methodology utilised in collecting the data, and possible sources of error or bias introduced into the debris measurements. KAB methodology specifies a set area and survey effort, and uses paid (and trained) labour to collect debris data. Surveys are conducted by 2 people, and sites are selected according to a survey design in order to get a representative measure of debris loads on land. The KAB surveys were initially developed to measure the change in litter in the environment in South Australia, after the container deposit scheme was implemented in that state in the late 1970s. The CUA data on the other hand is typical of many clean up efforts, and is produced as a byproduct of clean up efforts by volunteers. The CUA protocol relies on volunteers to nominate sites based on their preferences, and does not specify the area of the survey or the number of surveyors. The first issues that arises with clean up data is the linkage between survey effort and the measured debris density at a site. Since the number of volunteers is not controlled, nor is the area, survey effort per unit area can vary tremendously between surveys. For instance, one could have a few volunteers cleaning an area of thousands of square metres, or hundreds of volunteers cleaning a relatively small area. This lack of control on effort leads to a strong relationship between the number of volunteers per area and the chance that all of the debris in the area will be included in the survey. This effect is exacerbated by the fact that the protocol does not specify a minimum size for the materials collected, which further exacerbates the lack of control on effort as sites with more volunteers are likely to incorporate smaller, and more abundant, debris into their counts. The second major issue that arises in using data from volunteer clean up efforts to measure debris is the control over site selection, and its link to the load of debris at a site. Clean up coordinators choose sites for a variety of reasons, including proximity, attachment, and perceived debris load. This ultimately can result in a strong biases in the data that are difficult to detect, and skew the existing results. A hypothetical example would be a group in a community that is otherwise very clean targeting a site that happens to have high loads due to some local phenomena, such as a spill of rubbish from a truck. In this case the only data from the region suggests that loads are high, while in fact they are not, the clean up group has just targeted a relatively dirty area in their community. This is a key difference with survey methods, such as those used by CSIRO and KAB, which select sites independently of the level of debris at the site, and thus are more representative of ambient levels, instead of biased upward as in the case of clean up data.

These differences appear to be reflected in the data we analysed. Total debris data collected during KAB surveys are between 0 and 3345 items per 1000m^2. The median (i.e. middle) value is 40 items, while the average is 72, indicating that the data are relatively balanced as their average likes fairly close to the middle observation. The CUA vary much more widely by comparison, with loads are distributed between 0 to 134,000 items per 1000m^2. The CUA data also include a much larger fraction of extreme outliers, as can be seen by the increased spread between the median value (i.e. the middle value) of 2.98, and the significantly higher average of 714.20. The source of this difference is unclear. There are at least three possibilities: 1) the difference may come from inaccurate estimations of the area cleaned, 2) from differences in the amount of effort in surveys based on varying numbers of volunteers, or 3) from targeting particularly dirty sites for clean ups. In any event, this large discrepancy between KAB and CUA data likely accounts for the extremely different modelling results we see. Moreover, our inability to distinguish many strong relationships between the CUA data and underlying driving variables suggests that the variability in the CUA data itself is also an issue.

Because of these issues, and the low level of deviance that we can explain in the CUA data from the GAM modelling, we focused the remainder of our analyses on the KAB dataset. However, this is an area which would benefit from further work. In order to determine whether the sampling effort errors are responsible for the differences, we suggest assessing the influence of sampling error on debris measurements could be a useful future direction. Developing a clear understanding of the dynamics around site selection for clean ups could significantly improve our ability to distinguish patterns in the CUA data, and ultimately increase the value of clean up data generally for monitoring debris loads and patterns. This could be undertaken as a future NESP hub activity, and would assist the Department in making use of the many volunteer clean up datasets available across Australia.

3. Understanding pathways through which debris moves into the marine environment, a case study from the Sydney region

To understand how litter moves through the watershed from terrestrial inputs to the marine environment, we selected the Sydney region as a case study. We considered three main factors that can influence the transport of debris; direct deposition through human activity, water transport, and wind transport. We first used the results of the national-scale GAM modelling (Section 2) and built a predictive model of the load of debris at sites in the Sydney region using the KAB dataset. In addition to load at a site we considered various site-based factors such as distance to and amount of transport near a site (including both road and rail networks), as well as population density and socio-economic factors. Based on these predictive models, we then estimated the expected load on a high resolution grid across the Sydney region.

Using this prediction of load across the region, we then turned to evaluating transport. Water transport models were based on digital elevation models (DEMs) and incorporated distance between sites. Wind transport was estimated from Bureau of Meteorology (BOM) wind data. We used the predicted load on the grid locations, overlaid with wind and water transport models, to to determine which factors most strongly influenced debris distribution in the Sydney region. The following sections walk the reader step by step through these analyses.

Key findings

- We predicted debris densities in the Sydney study area with random forest modelling of the Australia-wide KAB dataset in conjunction with a variety of predictor variables.
- We developed models of wind and water transport, and compared the debris levels predicted by these models to the unexplained variation from the GAM and random forest models to determine if transport can explain the remaining variation in the observations.
- Water transport generally had a significant positive correlation with higher than expected debris loads, while wind transport had a significant positive correlation with lower than expected debris loads.

3.1 Definition of the study grid and extraction of predictor variables

The study area for the transport modelling was defined around a single major urban area in Australia. We chose to focus on the greater Sydney area, encompassing portions of 3 major watersheds (Hawkesbury, Georges, and Wollongong Coast) and a number of minor drainages (Figure 3.1). The boundaries of the study area encompass approximately 5,800 square kilometres. We selected the Sydney watershed because there were numerous surveys conducted both on the coast and along various river and road networks.

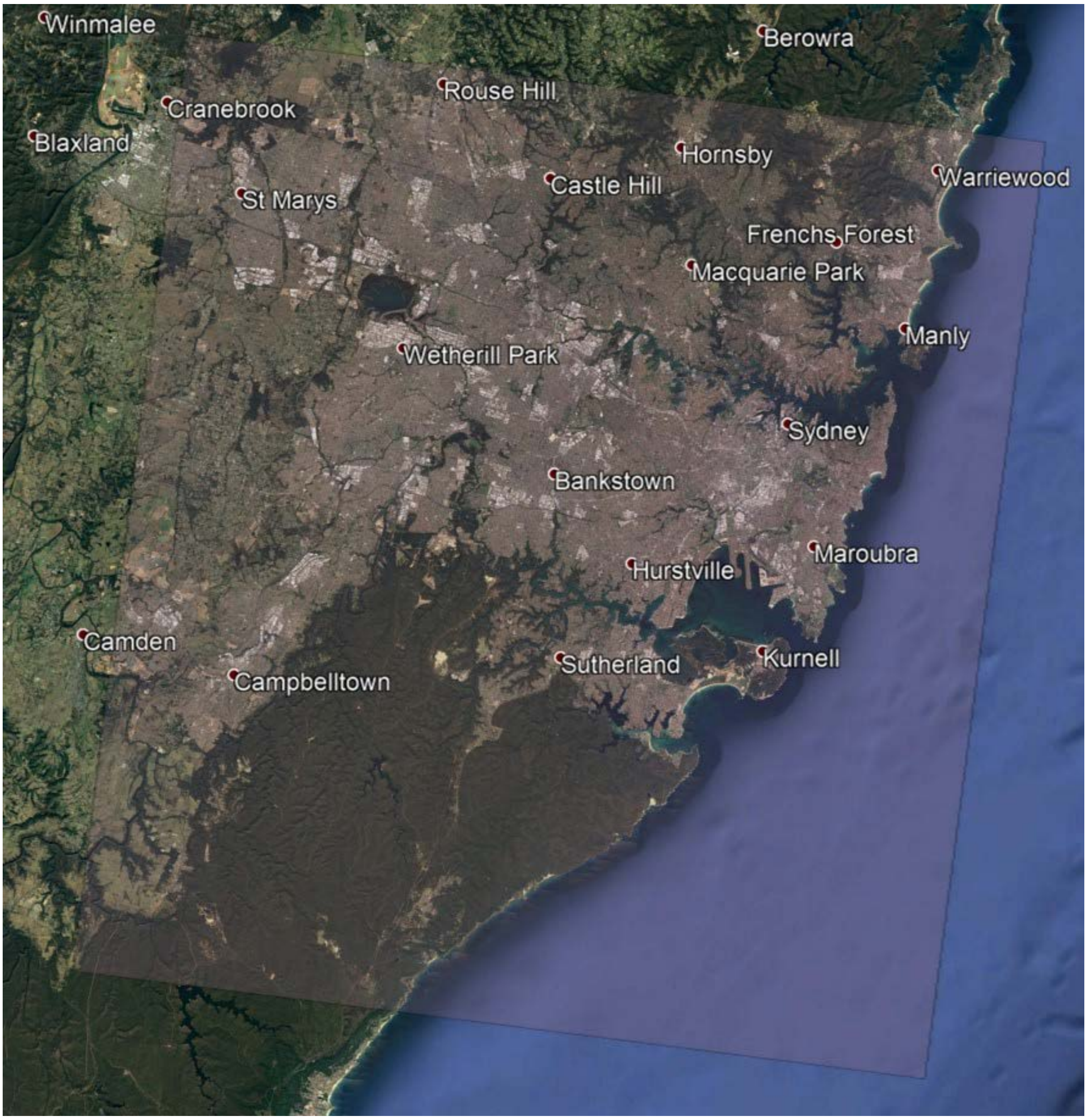

Figure 3.1. Watershed study area, Sydney, NSW.

To determine variable values and forcing functions for transport across the landscape we created a 300m x 300m grid over the study area. We calculated the centre-point of each grid cell and used this point to extract the variable data using the same methodology outlined in Appendix C. The same grid centre points were used as locations in the calculation of surface water flows and wind velocities.

3.2 WIND TRANSPORT MODEL

We modelled transport by wind using the downwind velocity between sites at each pair of points on the 300m grid. We obtained daily wind speed and direction from The Bureau of Meteorology (BOM), binned into speed and direction classes, for each of the 53 weather stations across the Sydney watershed area (Figure 3.2).

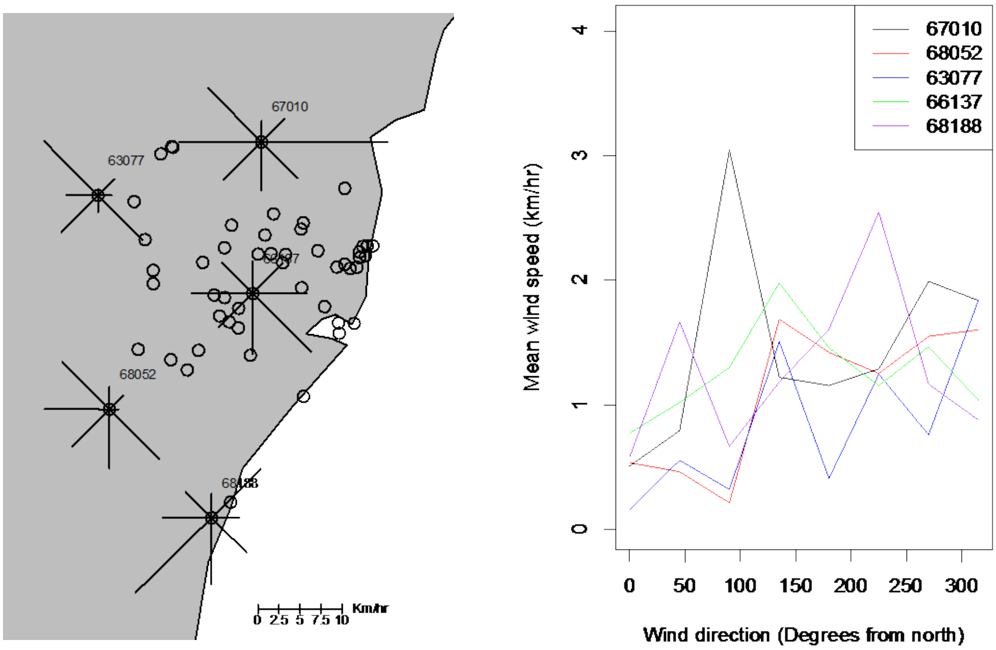

Figure 3.2. Weather stations and wind patterns in the Sydney area. The left panel shows the mean wind velocities by direction, calculated across all of the daily records for five weather stations. Stations not used in the analysis are shown as open circles, without rays for wind speed and direction. The right panel shows the relationship between wind speed and direction for each of the stations.

Based on previous experience with modelling wind fields in Brisbane, we found that while stations were correlated with respect to wind speed and direction, this local correlation varied significantly across sites. We explored using a statistical model of the wind field based on the stations in a region; however, we found it difficult to produce accurate predictions for unmeasured sites. Based on extensive exploration, we concluded that using the mean wind direction and speed across a region provided reasonable predictions for sites, without the complexity of developing a full physical model.

We based our analysis for the Sydney region on these insights, using the overall mean velocity for each compass quadrant across the five stations as our measure of wind speed and velocity for the analysis. We found that wind speeds were generally correlated across stations in the Sydney region (Figure 3.3). The strength of this correlation does vary across the year, with some periods such as late spring being strongly correlated, while others such as mid-winter show more variation across sites.

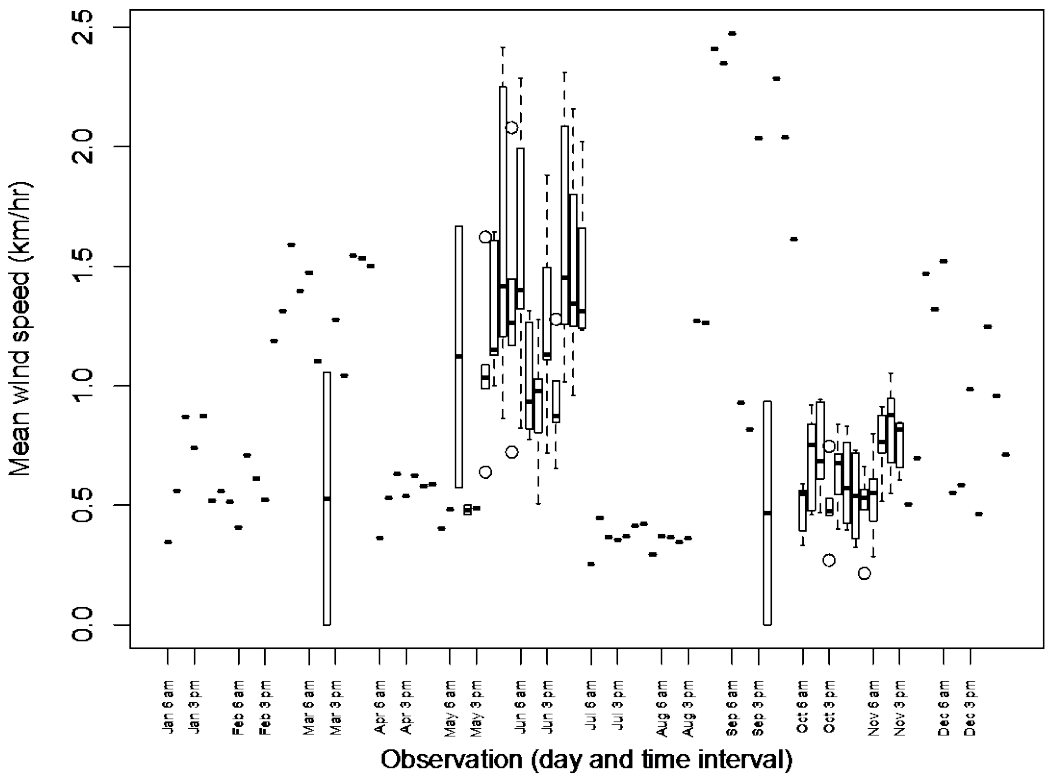

Figure 3.3. The distribution of wind speeds across five weather stations in the Sydney area. The data are binned into 3 hour blocks on each day, thus wind speeds are the average over each 3 hour period. Some data are missing from the weather stations, therefore some sampling periods are represented by a single observation, while others have up to five observations, one for each station. Bars show the central 50% of the observations, with dotted lines showing the full range.

Tto assess the influence of wind in transporting debris at sites on the Sydney grid, we calculated the downwind speed vector between source locations and sink locations on the grid, for every grid observation.

We also calculated the great circle (i.e. following the curvature of the earth) distance between each pair of locations. Due to the very large volume of data, we chose a single year during which we had relatively complete observations to estimate the distribution of velocity and direction. We then took the mean of the daily downwind speed across the year as a measure of transport.

We used this process to estimate two data sets, one providing the downwind velocity from every point on the 300m grid to each point where we had data on debris load, and a second providing the inverse, the downwind velocities from each location with data to all of the grid points in the Sydney region. The first data set gives a measure of wind transport to the survey points from all possible sources, the second a measure of the locations that might receive debris from the survey sites where it was measured.

3.3 WATER TRANSPORT MODEL

Topography is an important variable controlling water flow direction and speed. For the purpose of modelling the influence of water transport on debris, the water transport potential was determined from the landscape surrounding the survey points. A flow accumulation map was created from lidar measurements of global land surface heights (Geoscience Australia, 2015). A LiDAR derived DEM is available for approximately 245,000 square kilometres of Australia. The LiDAR model represents a National 5 metre (bare earth) DEM which has been derived from some 236 individual LiDAR surveys between 2001 and 2015. These surveys cover Australia's populated coastal zones; floodplain surveys within the Murray Darling Basin, and individual surveys of major and minor population centres. The source datasets have been captured to standards that are consistent with the Australian ICSM LiDAR Acquisition Specifications.

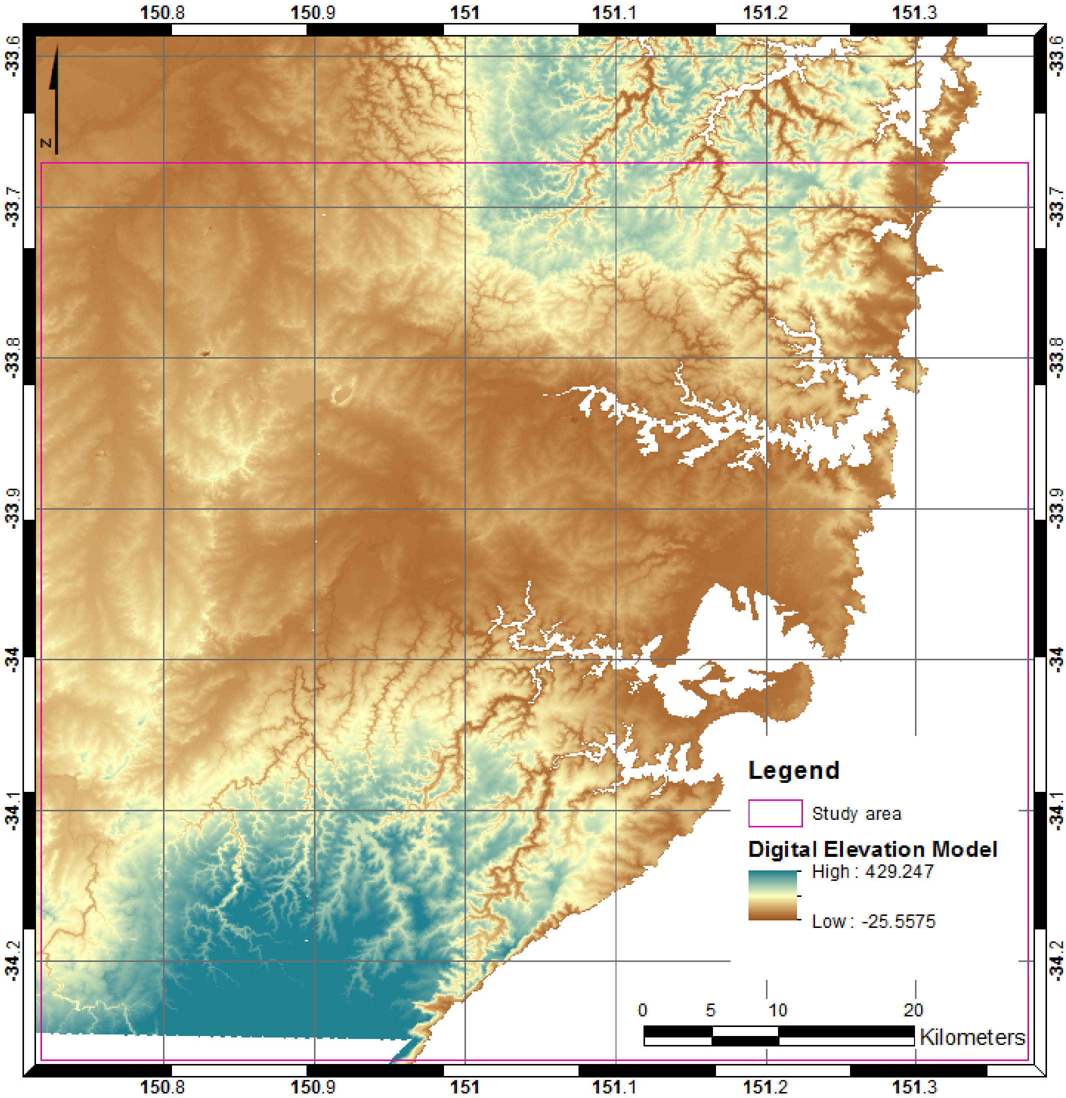

Figure 3.4. Digital Elevation Model (DEM) of Australia derived from LiDAR 25 Metre GridShuttle Radar Topographic Mission (SRTM) DEM-S digital elevation model (DEM) showing topographical elevation above sea level in metres.

The accumulated flow (Figure 3.5) is based on the number of cells flowing into each cell in a downstream trajectory. We calculated the transport of water from any location on the landscape to the survey locations within the Sydney watershed.

Additionally we modelled water transport by determining the elevation of each cell on the grid, which watershed it fell in, and the total flow accumulation at that point from all upstream locations. We then calculated several different measurements incorporating the number of uphill cells, the predicted amount of debris in the uphill cells, and the distance between uphill cells to the survey points. These calculations formed the basis of our water transport models.

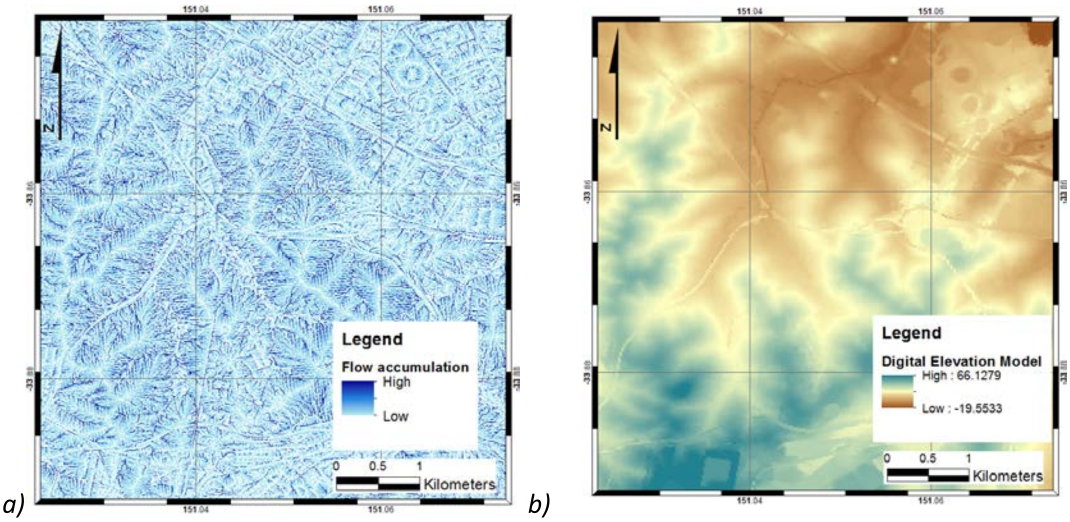

Figure 3.5 a) Flow accumulation and b) underlying digital elevation model in metres

3.4 MODELLING TRANSPORT OF DEBRIS BY WIND AND WATER

In our grid encompassing the Sydney region, there were 30,402 grid cells, and 1743 KAB surveys at 109 different sites.

Our analysis entailed three separate steps. First we predicted the amount of debris found at each cell in the region, based on random forest modelling of the full Australia-wide KAB data set with predictor variables. Next we used the transport models for wind and water (sections 3.2 and 3.3) to predict the amount of transport by wind and water from every cell of the grid to every cell where we had transect data. Finally we compared the density of debris measured in each survey to the density predicted by wind transport and water transport models.

3.4.1 MODELLING DEBRIS LOAD IN KAB DATASETS

We used both datasets to individually model the relationship between the total amount of debris and a suite of predictor variables. We used random forest models to develop a predictive model for the total amount of debris at a site, separately for each dataset. Random forest models are an excellent tool for exploration of large complex datasets, and are well suited to making predictions based on sampling data. Essentially random forests fit a large number of conditional inference trees to samples drawn from the original data set, drawn with replacement (bootstrapping). The conditional inference tree models use predictor variables to split the observations on the variable being modelled into sub-groups which are very similar. The idea is to choose a value of one of the predictor variables, for instance distance to the nearest road, which if used to split the observations gives two groups with similar values. So, in this case distance to road might be split at 100 metres, giving a set of load observations that are high (and near roads) and low (and far from roads). The process then repeats for each subgroup, with the algorithm examining all of the possible variables to find the one and its value that best split each of the subgroups from the previous step. This process continues to split the data further down the "branches" until it cannot find a significant difference within a data subset. These models allow for a very complex structure, taking into account multiple variables and their interactions to explain the pattern in the data. The random forest function in the R package party was used to implement conditional inference trees for our analysis. We used the Australia-wide KAB dataset of surveys at 983 different sites to create our prediction model, which we then fit to the Sydney area to make predictions. We removed 16 surveys from the analysis, due to the lack of complete set of predictor variables from these sites. We therefore analysed 15,678 surveys from 982 different locations. The ctree function does not require data to be normally distributed, so we used the total number of debris items per 1000m2 area, as reported by the KAB surveyors.

The random forest models incorporated all predictor variables for each buffer size; population, socio-economic variables, distance to nearest rail, sum of all roads, distance to nearest road. As in Hardesty et al. (2016), we incorporated measures of the differences in urbanisation and population density close to the site (within 5 km) from those within 50 km around the site. We used the residuals of the relationship between the length of road within 5km of the survey location and 50km of the survey location, and similarly, the residuals of the relationship between the population within 5km of the survey location and 50km of the survey location. By using the residuals we are able to remove any issues with the correlation between the 5km and 50km values, allowing us to distinguish between areas where there is urbanisation both locally and regionally, locally only, regionally only, and neither locally nor regionally.

3.4.2 PREDICTING DEBRIS LOADS ON A GRID ACROSS THE SYDNEY REGION

We used the random forest model of the KAB dataset to predict debris values at each cell of the Sydney grid (Figure 3.6). As a comparison, we depict an amalgamation of all of the KAB litter data collected within the Sydney region, corrected for area but uncorrected for factors such as population or socio-economic status (Figure 3.7). It is interesting to note that although there are several individual surveys that found large quantities of debris on the shorelines, modelling results indicate that many of the highest concentrations of debris are predicted to be in upland areas, based on predicted debris loads in the Sydney region even for areas where litter surveys were not conducted (Figure 3.6).

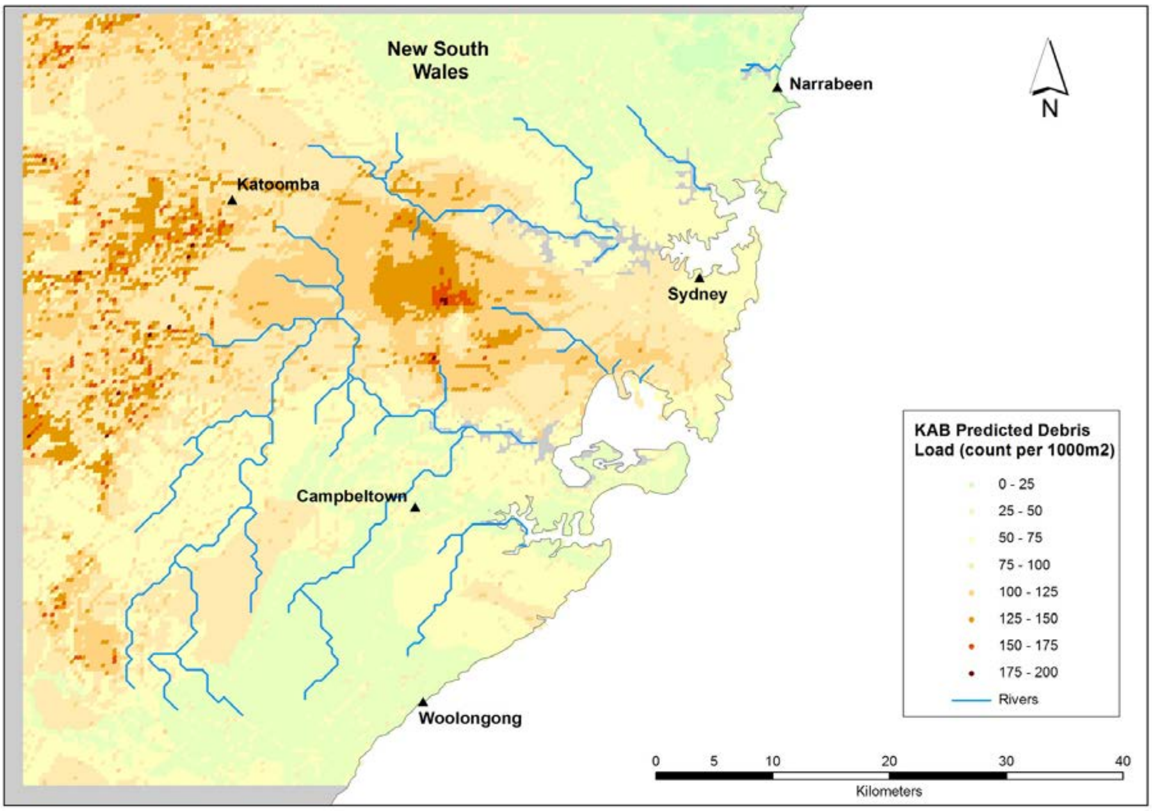

Figure 3.6. Predicted debris loads (shown as counts of items per 1000m²) in the Sydney region, based on models using the Keep Australia Beautiful data from the region. Note that relatively lower counts of debris are predicted to reach the ocean than are present in inland areas directly west of Sydney.

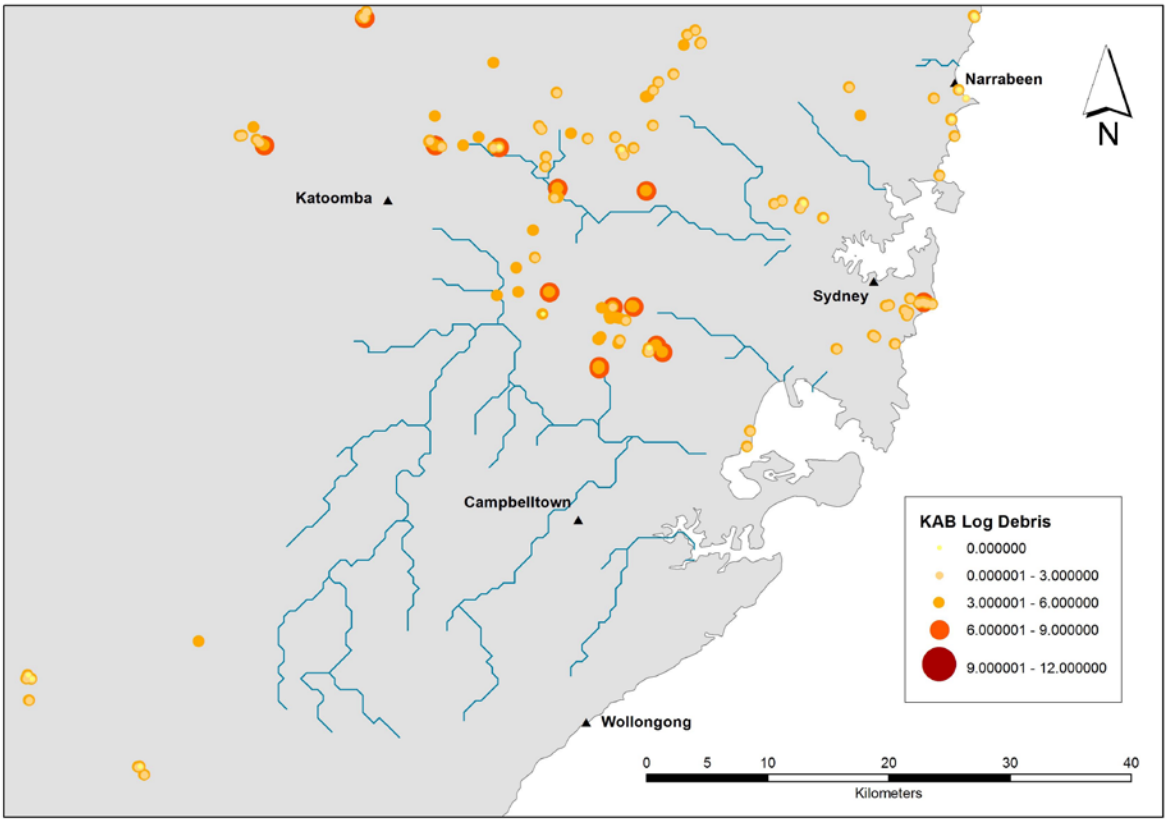

Figure 3.7. Litter and debris densities in the Sydney watershed region based on surveys conducted by KAB. Data are shown on a log 10 scale with darker, larger circles depicting areas of higher debris loads.

3.4.3 Evaluating Transport by Wind and Water

We next assessed the potential contribution of both wind and water transport. We had a number of hypotheses as to how wind and water transport would be related to the debris load at the 109 KAB survey sites (1743 total transects) within the Sydney region.

H0: Debris is deposited in place and does not move, therefore there will be no correlation between the predicted transport to a site (by wind or water) and the amount of debris at that site.

H1: The total number of grid cells that are upwind (or uphill) from a given grid cell will be positively correlated with the amount of debris at that site. In other words, the more potential input locations, the greater the total amount of debris at a given site.

H2: Debris will increase relative to the number of upwind or uphill grid cells, but the total amount of debris will be inversely proportional to the distance from each upwind (or uphill) site. So if a cell is upwind but far away, it will contribute less debris than a cell that is upwind but close.

H3: Debris inputs will be proportional to the sum of the magnitude of the wind or water flow from upwind (or uphill) grid cells.

H4: Debris inputs will be scaled by the total amount of debris predicted to be found in each source grid cell (upwind or uphill) in either an absolute sense or a proportional sense and may also include an effect of distance between sites.

We used the wind and water transport models to create predictions for each of the survey sites based on our hypotheses, and then tested the correlations between the predicted debris loads based on the hypotheses, and the residuals from the tree models as well as the GAM models (section 3). Residuals of a model are a measure of the remaining variability in the data after model predictions are made. Areas with positive residuals have more debris than than we would expect at a site given its characteristics, and areas with negative residuals have less debris than expected.

Positive residuals, therefore, may indicate debris sink cells, and thus transport mechanisms may explain why there is more debris than site characteristics would indicate. Negative residuals, on the other hand, could indicate debris source cells, as the debris loads are lower than expected, which may be a result of loads being transported away by wind or water.

The transport mechanisms we have modelled here represent an abstraction of the full mechanistic process. They do not take into account characteristics of the debris, such as size or shape, or characteristics of the landscape, such as land cover or surface roughness which would influence transport by wind and water. Therefore we would expect that their predictive function is relative only, and would not provide an estimate of the absolute amount of debris. We therefore compare predicted values using the the Spearman rank correlation test, which compares the rank order of items, and not their absolute values. This test is useful here, because although we can predict where the debris might travel with wind and water, it is much more difficult to predict how much debris will move, or how far it will move. The rank test, therefore, is independent of the actual magnitude of the debris, and compares the relative rank order of debris at different survey sites (Hardesty et al. 2016).

We tested the predictions against the two residuals measurements. The results are summarised in Table 3.1 below.

Looking at the GAM model residuals, the strongest correlations were with the number of uphill sites. More uphill cells (and greater water transport) correlates with increased levels of debris. Scaling the number of uphill cells by the amount of debris in uphill sites increased the strength of the correlation and yielded the highest correlation measurement of all transport mechanisms. Adding in the distance to uphill sites slightly reduced the strength of the correlation, but all uphill site analyses were significantly correlated with GAM residuals. The flow accumulation models, however, did not correlate with residuals.

The third strongest correlation was between upwind sites and observed debris. However, the correlation was negative; the more upwind sites, the less observed debris. This could be due to high wind transporting debris away from the site. Adding in additional explanatory factors, such as the proportional amount of wind from each upwind cell, the volume of debris in upwind sites or the distance between source cells and sink cells made the correlation less negative, but still significant for all of the wind models.

These results suggests that both upwind and uphill sites above a survey site do explain additional variation in the data, on top of that explained by direct deposition at a site based on the site characteristics.

None of the tree residuals were significantly correlated with transport mechanisms. Maximum likelihood models are inherently complex, and while the design of random forest models is such that they are theoretically unlikely to overfit (Breiman, 2001), in practice there are instances where overfitting can occur, such as in data sets with more factors than observations (Strobl et al., 2009). Any overfitting of the random forest models would reduce residual variation, and thus be less likely to show patterns with respect to transport mechanisms.

Additionally, both random forest and GAM models will both try to account for any pattern in the data, including that due to (unobserved) transport (Hardesty et al. 2016). For instance, site type is an important variable in the model. Watercourses are the second highest of all the site types in terms of debris loads in the GAM models. Thus, the model is potentially already capturing water transport to some extent, via estimating that creeks and rivers are expected to have high loads. As discussed in Hardesty et al. 2016 from analyses based on the Brisbane region, it is important to note that this is not to say the model includes transport by water explicitly, it just recognises that if a site is in a creek it is expected to have higher loads. Thus, if a site is in reality affected by transport of debris from other sites to the site, it still may not have a very strong pattern in its residuals as the statistical models have already captured some amount of that pattern. In this context the residual for the hypothetical creek site would be expected to be zero, and thus even though it is likely to be strongly affected by water transport processes, that would not show up as strongly in the residuals from either the GAM or the tree models. It would be possible to address this complexity in a more in-depth analysis. This could be pursued as a future extension to the transport analysis here.

Table 3.1. KAB correlation test results. The rho value is the strength of the correlation, on a scale of -1 to 1, and the p value is the measure of significance. P-values of <0.05 are considered to be a significantly correlated.

	rho	p	
Tree residuals			
Upwind sites	0.0421	0.0792	
Total wind, no deb	0.0231	0.3360	
Total wind, with debris	0.0420	0.0798	
Proportional wind with debris	0.0043	0.8571	
Wind by distance, no deb	0.0336	0.1610	
Wind dist pos only, no deb	0.0028	0.9079	
Upwind prop to distance with deb	-0.0167	0.4861	
Uphill sites	-0.0328	0.1707	
Uphill sites times debris	-0.0320	0.1824	
Number of uphill cells proportional to distance	-0.0395	0.0992	
flow accumulation	-0.0138	0.5635	
GAM residuals			
Upwind sites	-0.201	0.000	*
Total wind, no deb	-0.170	0.000	*
Total wind, with debris	-0.201	0.000	*
Proportional wind with debris	-0.192	0.000	*
Wind by distance, no deb	-0.193	0.000	*
Wind dist pos only, no deb	-0.104	0.000	*
Upwind prop to distance with deb	-0.075	0.002	*
Uphill sites	0.209	0.000	*
Uphill sites times debris	0.215	0.000	*
Number of uphill cells proportional to distance	0.197	0.000	*
flow accumulation	-0.043	0.071	

4. An analysis of policies and practices aiming to reduce debris inputs to the marine environment

We utlilised patterns emerging from the CSIRO transect data taken around the Australian coastline to investigate patterns of plastic in the environment with respect to local, regional and state level policies to address plastic marine debris. We compiled information on council waste management, including budgets, infrastructure investments, policies and regulations, and local programs. We compared these measures against the unexplained variation in local coastal debris densities, based on a statistical model of debris densities along the coastline using the CSIRO transect survey data (Hardesty et al. 2016).

Based on the surveys, we compiled a list of 21 possible measures that might be applied to address debris in a local council area, ranging from state level regulations down to community actions. We conducted single factor regressions to compare the presence or absence of a measure in a council with the level of debris on the coastline in that region, across the 40 councils included in our survey. Therefore, estimates with a positive sign indicate that a policy would be associated with a higher level of debris in surveys, while estimates with a negative sign indicate that the policy would be associated with lower levels of debris. Lower levels of debris in this context suggest that the policy in question is effective in reducing loads. In Table 4.1 we present the estimate for each of the single factor models, the p values which measure the statistical significance (by convention, a p value < 0.05 is considered to be significant statistically), and the AIC value (Aikake's Information Criteria). AIC can be considered a measure of the relative quality of each model as compared to the others. Lower values indicate a better fit model.

We found that some policies were associated with differences in coastal debris levels. For instance, education programs were associated with a significant reduction in marine debris levels on council coastlines (Figure 4.1). In general, most programs were associated with some level of reduction in debris levels, as indicated by their negative coefficent. However, in general these programs did not generate decisive reductions in debris levels, as indicated by the absence of a significant relationship between the policy and the level of coastal debris. However, it does appear that debris levels are higher where the are no policies present (Table 7, Null) in comparison with those where there is some policy effort to address debris. It may be that while most policies may not make major impacts alone, they indicate an increased level of attention in the community overall, which is generally associated with lower debris levels.

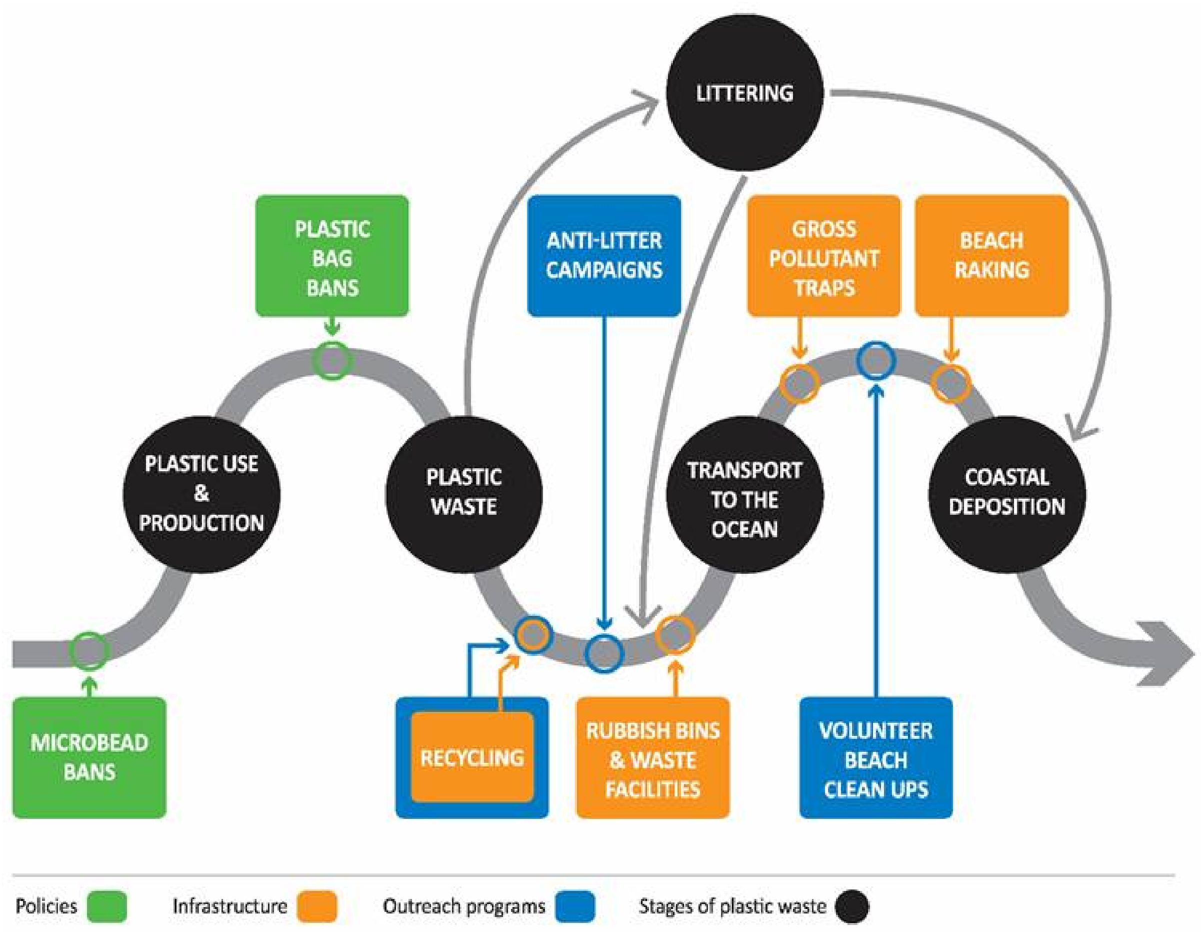

Figure 4.1 The type and point of waste abatement interventions along the plastic waste pathway. Thin arrows indicate the point of intervention, shapes indicate the type of intervention and large arrows indicate the pathway flow.

Table 4.1. Coefficients for single factor regression analyses of debris reduction measures. The estimate column is the coefficient estimated for each model parameter. Positive estimate values indicate that program is associated with more debris, negative values indicate that program is associated with less debris. P values indicate whether or not the association is significant. Values of < 0.05 indicate that the correlation is considered significant, and are denoted with an asterisk (*). The AIC is a relative measure of the quality of the model. Lower values are associated with better models.

Type of Outreach Program	Estimate	Pr (>|t|)	AIC
Education	-7.615	0.006 **	542.527
Clean Up Australia	6.719	0.012 *	543.682
Litter Prevention	6.715	0.055	548.148
Illegal Dumping	-5.394	0.062	546.415
General Clean up	-4.544	0.128	527.129
Home Composting	-4.384	0.246	507.484
Reduce, Reuse, Recycle	-4.299	0.131	554.670
Plastic Recycling	-4.117	0.228	507.374
Worm Farming at Home	-4.089	0.415	508.196
National Recycling Week	-4.064	0.195	527.769
Love Food, Hate Waste	-3.837	0.225	548.559
Packaging	-3.423	0.447	508.290
Electronic Waste	-2.981	0.056	594.037
Plastic Bags Ban	-2.806	0.309	528.458
REDcycle	-2.805	0.705	508.739
Recycling	-2.805	0.705	508.740
Chemical Waste	-2.506	0.129	588.484
Null (No programs)	1.832	0.032 *	911.109
Keep Australia Beautiful	-1.406	0.682	508.713
Other Outreach programs	-1.014	0.301	616.783
Get it Sorted	0.484	0.940	508.882
Bin your Butts	0.484	0.940	508.882

Interestingly, we found a significant positive assocation between litter prevention or coastal clean up programs and debris, suggesting that these programs are associated with higher levels of coastal debris. This somewhat odd result is likely driven by selection of relatively dirty sites for prevention activities and clean ups. While this is sensible from a direct action and community engagement perspecitve, it does point to an issue of bias in using clean up data for monitoring debris. Data from clean ups likely overestimates coastal debris loads (Hardesty et al. 2017) , and changes in site selection over time may lead to false estimates of trends or hotspots. Significant care must be used in treating clean up data as a source of monitoring information.

During the emerging priority project we were unable to obtain actual dollar value cost information on the local policies listed in Table 4.1. However, we have obtained ethics approval conduct a follow up survey with councils. In this additional survey, we will ask questions about estimated costs of policies to interviewees. We anticipate moving forward with follow-up surveys over the next year, and will report on those findings in the NESP follow-up project.

5. National land-based, coastal, and at-sea floating debris hotspots

Below, we present a series of national hotspot maps. First, we present a national hotspot map for land-based debris from CSIRO coastal debris surveys, Keep Australia National and Keep South Australia Beautiful data, and Clean Up Australia data. We then show the results of a simple geographic model applied to the three national data sets, as well as a subset of TBF data. (Figures 5.2 – 5.5). Finally, the at-sea distribution of floating plastic litter based on CSIRO surveys is shown in Figure 5.6.

One strong pattern emerging from the national hotspot map amalgamating raw debris counts from the national land-based datasets that we accessed (CUA, CSIRO, KAB) (Figure 5.1, adapted from Hardesty et al., 2016) is that a large proportion of the surveys have been completed near capital cities and the capital cities have a number of surveys with high concentrations of debris. This map presents the raw data corrected for area only, and does not take into account any other factors, including the local human population density, site characteristics, or socio-economic factors.

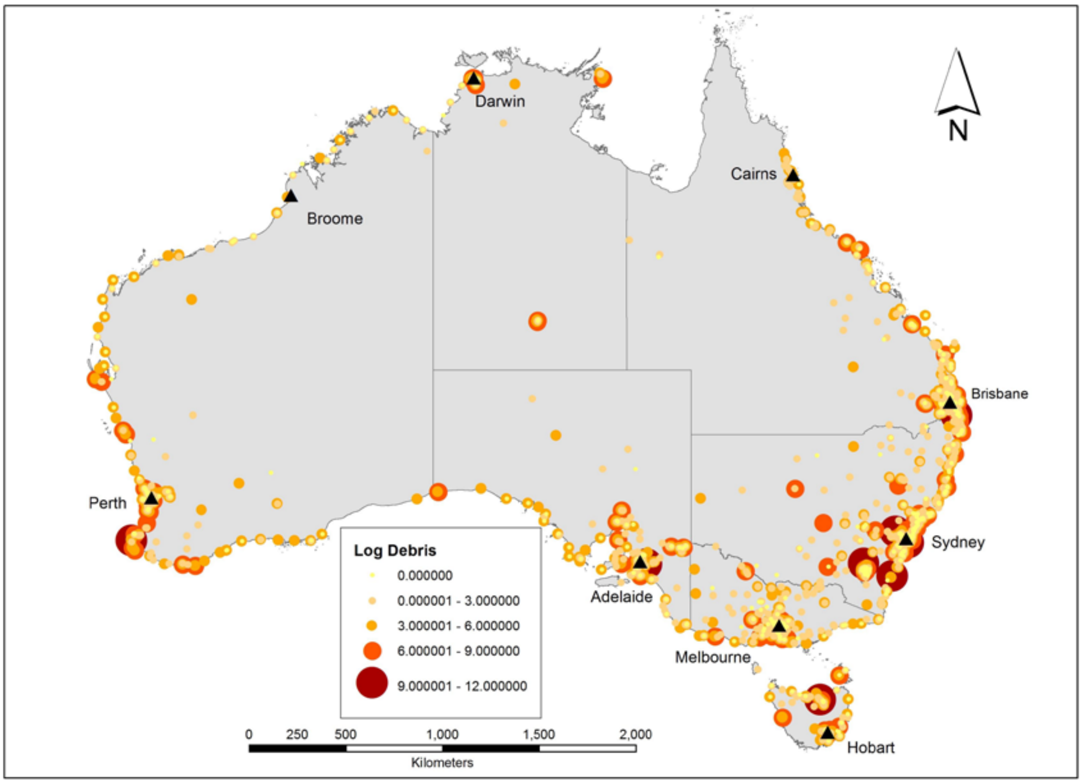

Figure 5.1. Map of debris hotspots based on all survey data from CUA, CSIRO, and KAB. Data has been corrected for area searched and effort (number of volunteers). Note higher debris loads in urban cities around Australia's coastline. Survey methods are dissimilar among organizations, but this provides a general depiction of relative debris. (adapted from Hardesty et al., 2016)

To take a closer look at some of the differences between the data collected by the various sampling programs, we created a simple model incorporating only the raw data (corrected for area and effort) and the latitude and longitude of each study. This is one step up in complexity from the raw data points themselves. The model gives an idea of the geographic distribution of debris found by each survey method, but still does not incorporate driving variables, such as the socio-economic or site characteristics (Figure 5.2, Figure 5.3, and Figure 5.4). TBF data was provided for analysis for the Sydney region only, so it is presented on a different geographic scale from the other three data sets (Figure 5.5). Note that the data are reported as the natural log of modelled debris amounts, and that the range varies between the four figures. This range variability provides an indication of the differences between surveys. Of the national-scale surveys, CSIRO has the highest range of values (Figure 5.2). The range in CSIRO data is due in part to a sampling regime that incorporates sites far from urban centres (which may have fewer debris items), and in part to survey methodology which counts pieces of debris as small as 1mm in length. In areas where fragmented debris is prevalent, this methodology will yield higher numbers of items per survey. The only other survey method with higher maximum values is in the TBF data. This may may be a result of employing a methodology which specifies debris as small as 5mm in length (compared to much larger debris collected by CUA and KAB) plus the fact that many volunteer groups who contribute their data to the AMDI database have a specific focus on cleaning up 'dirty' areas.

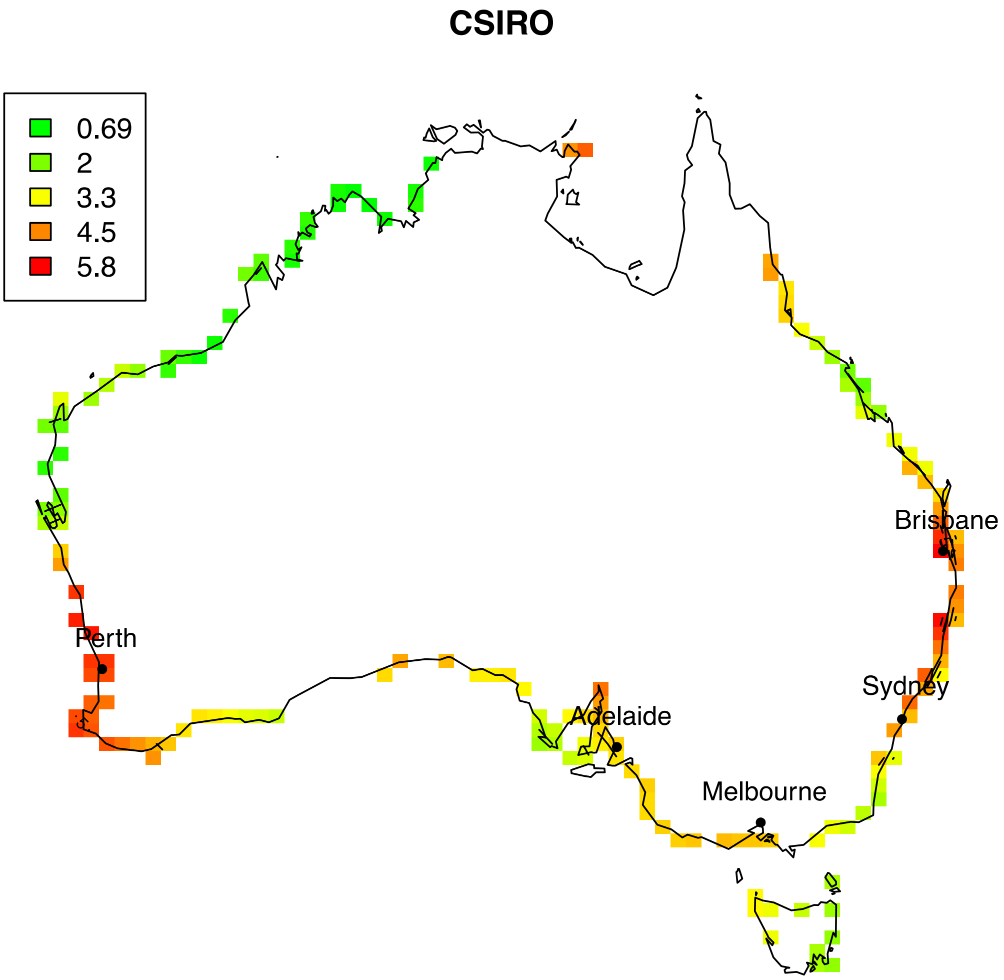

Figure 5.2 Relative debris density on Australia's coastline based on CSIRO national coastal debris survey data (2011-2016). Surveys were carried out following a stratified random sampling approximately 100 km apart, with minimum of three (maximum of six) transects per site. Green indicates less debris, with red indicating highest debris counts recorded.

Hotspot areas in CSIRO data include capital cities, in particular Brisbane and Perth, as well as a coastal location in the Northern Territory (Figure 5.2). KAB surveys, which are clustered almost exclusively in urban centres (Figure 5.3) find Darwin as the city with the highest debris loading, though Brisbane, Sydney, Melbourne, and Perth also have areas of high debris.

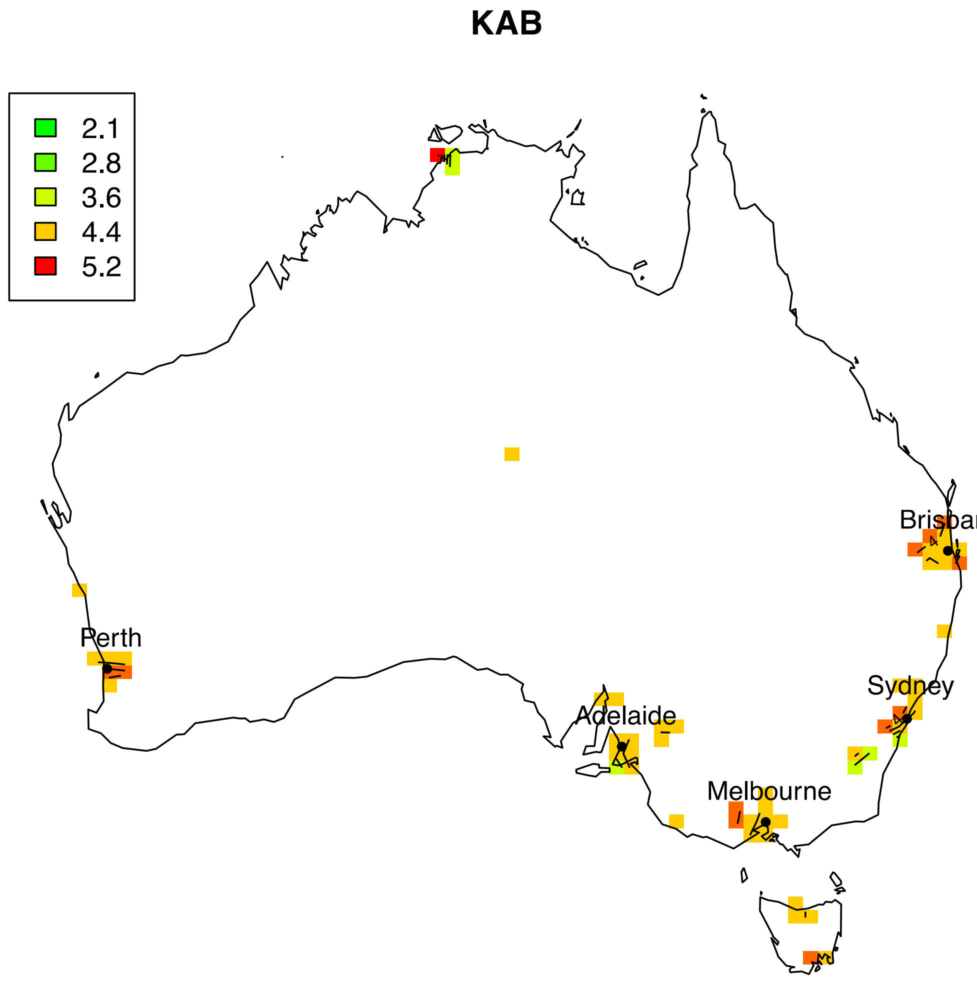

Figure 5.3. Relative debris density in Australia based on National Keep Australia Beautiful and Keep South Australia Beautiful (2007-2015) data. Surveys were conducted along highways, in parks, on beaches and in developed areas. Green indicates less debris, with red indicating highest debris counts recorded.

The CUA data (Figure 5.4) are collected over a much broader area, and include rural areas as well as urban centres. Here we see a very different pattern from the CSIRO data, with hotspots predominantly in Darwin and coastal Northern Territory, but also along remote areas of the northwest-facing Western Australia coastline. One possible explanation for this variability is the site selection biases discussed in Section 3.3. CSIRO surveys are conducted at randomly selected spots at intervals along the coast, while CUA clean ups are selected by volunteers and may be biased towards areas of high debris accumulation. Along the northwest coast there are a number of very remote communities which often do not have adequate access to waste management facilities. Clean ups in this type of community would certainly be likely to yield above average amounts of debris. In this instance, the relatively small number of surveys in the NW coast, and the presence of a couple of surveys with very large amounts of debris has likely driven the higher debris levels predicted in Western Australia. As previously discussed, one of the important next steps is to develop methods for modelling clean up data that account for some of these biases. In the short term, however, it is worth nothing that the modelling results presented here have not accounted for these biases, and as such, provide a very different picture from the results of designed surveys.

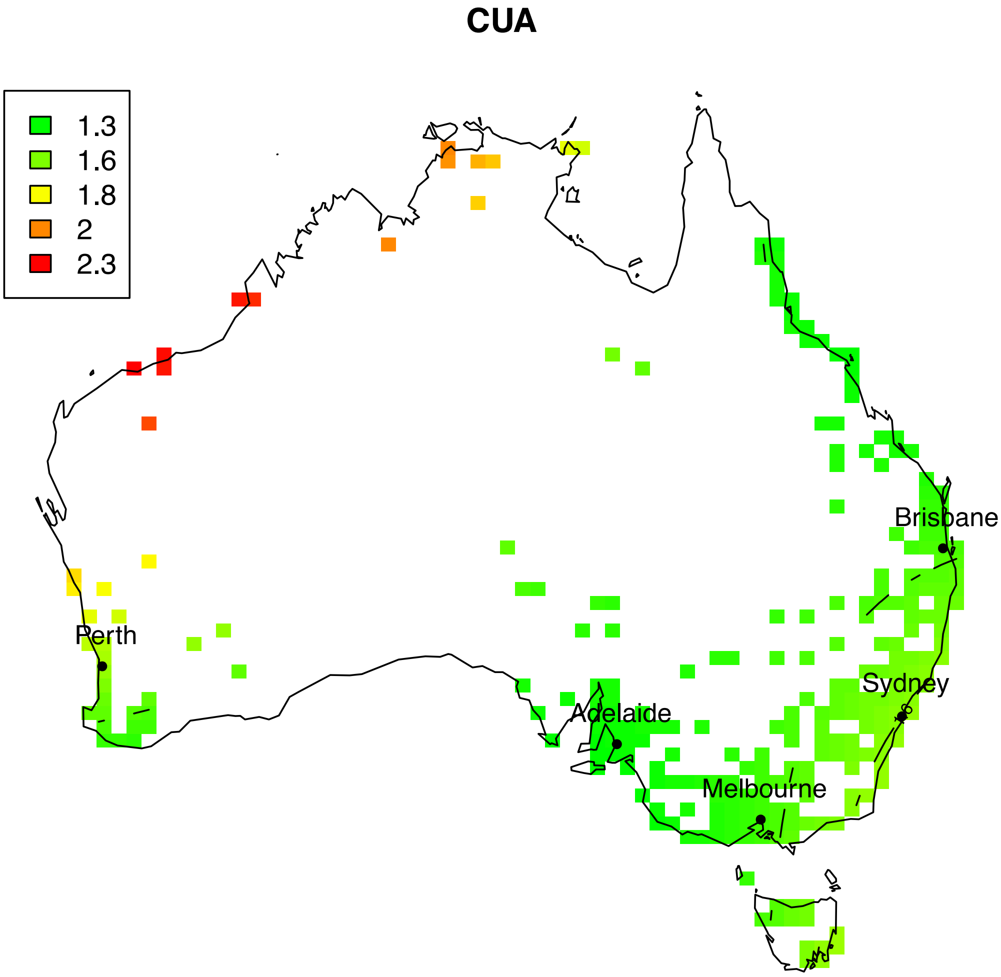

Figure 5.4 Relative debris density in Australia based on Clean Up Australia(2007-2015) data. Green indicates less debris, with red indicating highest debris counts recorded.

The data we analysed from TBF is only in the Sydney region, so note that this analysis is at a different scale than analyses from other data sources. For comparison we present a "raw data" hotspot map for TBF data. This means that the data are corrected for area and effort only (but not for socio-economic, population density or other factors). Note that the higest levels of debris modelled are found in the Botany Bay region.

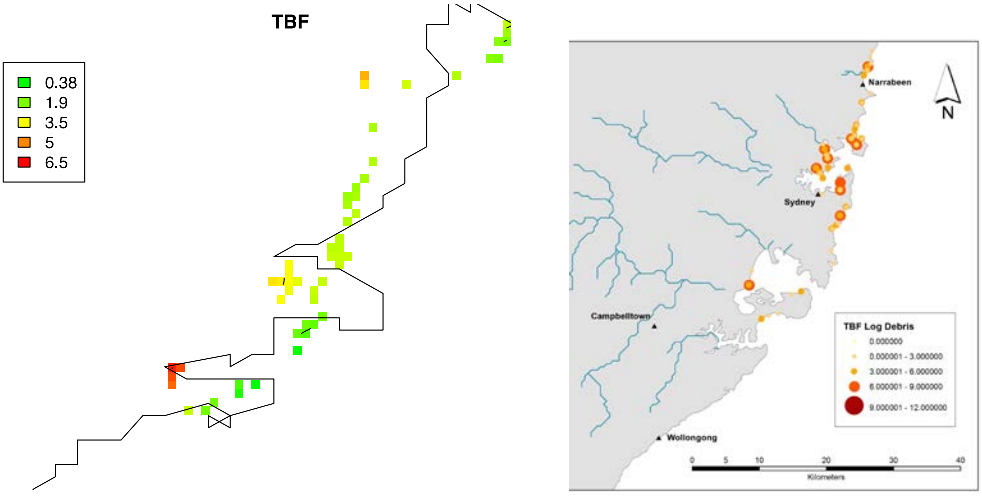

Figure 5.5. a) Hotspot map of TBF data corrected for area, effort, and modelled with a lat/long smooth. b) comparison map of TBF data corrected only for area and effort.

Finally, we present results from at-sea surveys around Australia. Each data point represents a separate station along the coast, where 3 trawl samples of approximately 15 minutes each were conducted. Debris densities at sea roughly mirror the CSIRO coastal survey data, with higher densities found along the east coast. However, there is much more variability at sea, and unlike in the land-based surveys, the highest levels are not associated with capital cities. Because the ocean systems are more dynamic than on land, debris is considerably more mobile and can travel great distances from source locations.

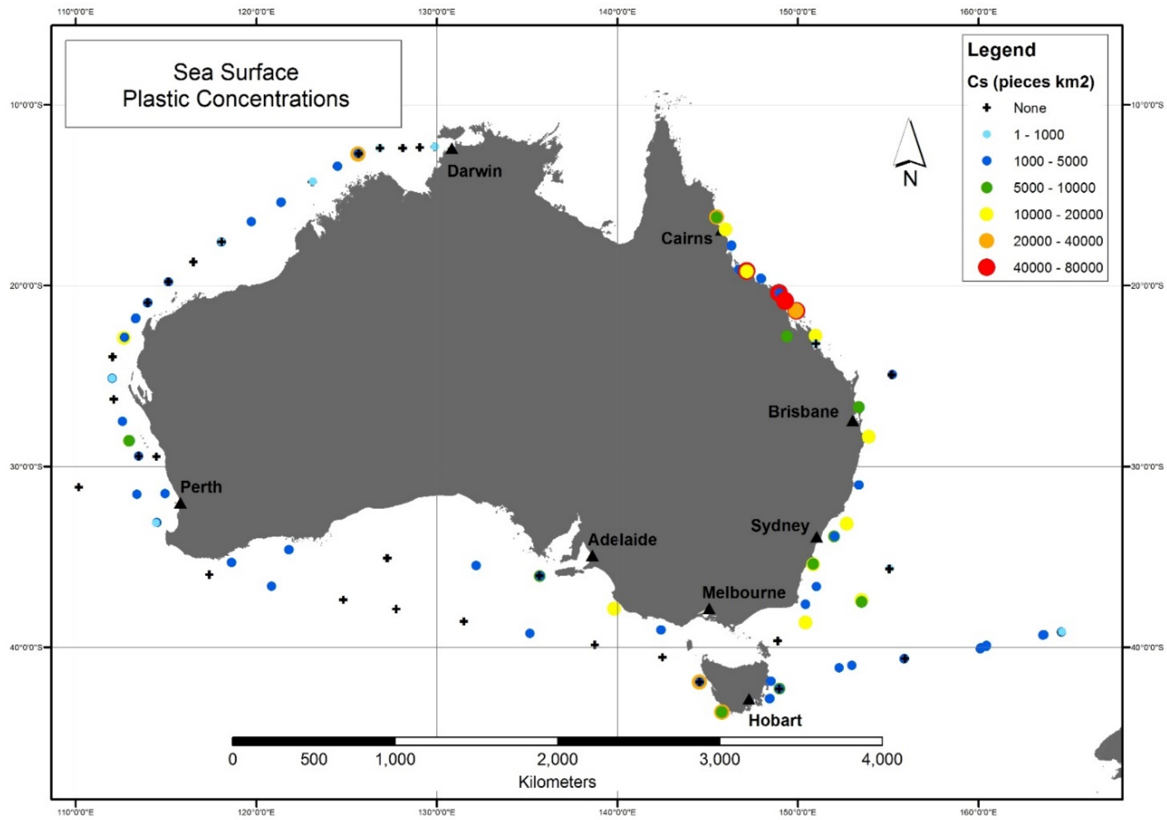

Figure 5.6 Debris densities for at-sea floating plastics based on CSIRO conducted surveys on board CSIRO and AIMS research vessels (2012-2016). Data are based on three approximately 15 minute trawls per 'station'. Counts are reported in pieces per square kilometre.

6. Recommendations

6.1 Evaluating Sources of Existing Data

There are a number of existing sources of data on plastic pollution in the terrestrial and marine environment in Australia. These include at least three formal large scale surveys and a number of volunteer clean up based datasets. We explored the largest of these datasets in this Emerging Priorities project, and were able to draw significant information from the formal survey datasets. We were unable to distinguish substantial patterns in the clean up dataset we worked with. However, in other cases, such as the International Coastal Cleanup dataset, we have found significant patterns and been able to provide policy relevant recommendations based on the data (Hardesty et al. 2017). It may be possible with further evaluation to identify the underlying issues causing bias in volunteer datasets like that collected by CUA, and develop analytical methods to remove those issues to facilitate extracting policy relevant information from those datasets. Key priorities would be: 1) understanding the dynamics of site selection and developing methods to correct the bias it introduces, and 2) developing improved methods for correcting for sampling effort in modelling volunteer clean up data.

6.2 Deepening Understanding of Key Driving Variables for Debris Loads and Transport

We found strong and significant relationships between debris loads and key driving variables such as land use, site type, socio-economics, population and infrastructure. These relationships are useful in understanding total loads at the landscape level and identifying key intervention points. For instance, these models can be used to identify high risk areas that might warrant increased surveillance or could be targets for policy interventions. Our finding that sites with lower levels of transience and higher aesthetic value have low loads suggests that changing the context for people in a location with high debris levels might reduce littering and dumping behaviour. An example might be the installation of a green belt and picnic bench in a parking lot that historically has high littering rates.

In this project we conducted a preliminary analysis of debris transport in the Sydney region, based on analysis of existing data. This preliminary analysis suggests that both wind and water transport play a significant role in moving debris at an urban watershed scale. It would be possible to improve this analysis significantly, extending the models to be more mechanistic and incorporating additional aspects such as the plume moving outward from water bodies in the urban area, and its connection to the load offshore and along the surrounding coast. This analysis could point to key intervention points, where additional infrastructure or programs could be efficient investments.

6.3 Providing Guidance for Marine Debris Monitoring

Our analysis of the CUA and KAB data, and the difference in our capacity to distinguish patterns and driving variables between the two datasets, points to some key issues involved in monitoring debris at a national scale in Australia and elsewhere. Reliance on volunteer-collected data can result in misleading patterns, or potentially no capacity to distinguish patterns at all. While volunteer data can be useful for monitoring debris, developing a clear understanding of the purposes behind data collection, the methodologies employed to collect, record, and ensure data quality for each program, and key factors driving bias and potential error in the data is essential if it is to be used as an indicator for marine debris distribution, amounts, and change over time. The Department currently has no formal policy on how marine debris will be monitored in Australia, despite the need to report against the Threat Abatement Plan, the requirement for State of Environment Reporting, and the need for data to underpin environmental assessments and the management of Australia's marine parks and reserves. A key role for the Department, in the context of its policy advice via the Threat Abatement Plan, would be to develop and promote design principles for marine debris programs, either those conducted by volunteer clean up groups, scientific bodies, industry bodies, or non-government organizations. There is currently an international effort to harmonize data collection methods, and develop guidance that can be used by organizations interested in monitoring marine debris. The department could play a key role in translating this process to an Australian context by developing local guidance for marine debris monitoring targets, survey designs, and reporting standards. This guidance could form a future basis for the department in awarding funds in programs such as Caring for Country and the National Environmental Science Program, and could form the basis for programs designed by other bodies in Australia.

Overall, we suggest the following as key priorities:

1) developing a national mapping tool, based on these predictive models, for estimating areas of high and low debris loads that can be used in targeting; and

2) refining models of key drivers, and connecting them to possible interventions to reduce littering and dumping.

We also recommend:

1) refining the exploratory analysis of transport, to improve its accuracy and move to a quantiative basis for modelling load movements;

2) connecting transport modelling to existing dynamic data such as litter traps and harbour cleaning programs to improve its fit and quality;

3) connecting transport modelling to infrastructure in trial urban regions to understand the relationship between infrastructure and debris loads; and

4) applying (3) above to identify new or additional sites for carrying out waste-reduction interventions.

6.4 Extending Policy Analysis

This project identified a number of local and state government policies that were correlated with reduced coastal debris loads. This research could be extended to incorporate program cost, allowing evaluation of the return on investment for local and regional bodies in implementing programs to address marine debris. There is substantial variation among local, regional, and state governments in policies to address marine debris. Providing a national picture of programs that are effective in reducing debris could substantially improve the condition of the marine environment across Australia, through increased focus on particularly effective strategies by local governments. Key recommendations in this area are 1) extension of the preliminary analysis to identify the policies that result in the biggest reduction in marine debris loads, 2) collection and evaluation of cost data to determine return on investment in policies, 3) collection of information on changes in policies and debris loads in the 5 years since the data presented in this report was collected to evaluate policy innovation and resulting changes in environmental performance.

6.5 Improving Hotspot Analysis and Incorporating Into Department Data Resources

We presented a preliminary analysis and maps of debris hotspots. The CSIRO coastal and offshore and KAB data sets tell a relatively coherent story of high loads in urban areas, and in selected areas like the GBR. However, key missing features are a coherent picture of debris loads away from urban centres in terrestrial areas and a mechanistic link between the data sets that can provide an overall picture of the density of debris across the Australian continent and marine estate. Through an improved analysis of the available terrestrial data, such as the CUA clean up data, and oceanographic models of transport, it is likely possible to build a more complete picture of debris across the Australian region. A key priority in this context would be to develop estimates of loads across all locations in the region, incorportating a measure of uncertainty, and in a format that can be incorporated into the Department's data infrastructure such as through the the Environmental Resources Information Network or the Atlas of Living Australia. This would allow decision-makers and others in the Department to access synoptic, up to date, and simple information on debris loads that could readily be incorporated into decision-making and reporting.

6.6 Aligning Debris Hotspots with Key Ecological Features

There is currently no assessment of impacts of marine debris to Matters of National Environmental Signficance, including: marine parks, Ramsar wetlands, Heritage areas, key ecological features, listed species and marine ecosystems for Australia. While there have been large scale studies for some species, such as turtles and seabirds, and risk modelling in some regions such as the Gulf of Carpenteria, a coherent review and a national analysis remains lacking. Addressing this issue would be a key advance in both understanding priorities for the Threat Abatement Plan moving forward, and providing feedback on the threat to decision-makers and stakeholders. Recommendations in this area include: 1) developing a literature review of known studies of marine debris impacts on species in or relevant to Australia, 2) down- or up-scaling existing pressure layers and spatial risk assessments to a national scale to allow mapping of areas of high and low impact.

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APPENDIX A. PROJECT OUTPUTS

Assessing the effectiveness of waste management in reducing the levels of plastics entering Australia's marine environment. This written report and plain English summary for this Emerging Priorities project is intended to be a high-level document that synthesises existing knowledge on the relationship between debris in the marine environment and litter data from nearby sites, and the pathways through which litter moves into the marine environment.

Maps showing leakage points and litter or debris concentrations (e.g. hotspots) are also provided.

1. A written report and plain English summary for use by state, territory and local governments, which:
    a. Synthesises existing knowledge on the relationship between debris in the marine environment and litter data from nearby sites, the types of litter and the pathways through which litter moves into the marine environment.
    b. Summarises existing coastal debris/litter survey methodologies with discussion of applications of each.
2. A list of activities and programs associated with plastic waste reduction (including facilities, policies and outreach).
3. A publically accessible analysis and summary of different survey methods aiming to reduce debris inputs to the marine environment.
    a. A relative ranking of activities and programs regarding their effectiveness in reducing plastic waste in the marine environment (see table 4.1).
4. Conclusions on where marine debris hot spots are in Australia's marine environment and effective mitigation strategies.
5. Recommendations on where more information (such as scientific, policy, infrastructure, community engagement) is required to obtain a better understanding of the problem and possible solutions. This may include identifying knowledge gaps and needs for further analysis.

APPENDIX B. DATA

While the analyses reported on here are novel, some of the data sets (Appendix B) and predictor variables (Appendix C) were originally compiled for a previous analysis conducted for the Australian Packaging Convention (Hardesty et al., 2016). A detailed description of the data and predictor variables is available in that report, and for reference, is summarised here. Note that there were some minor differences in covariate processing between this report and the original work.

Site debris survey data has been collected by a number of different organisations. For this study, four sources of consistent site surveys were assessed, though not all data were used in all analyses (Table B.1) This section of the report will cover details on the survey characteristics.

Table B.1 Survey grouping for analysis. Note: Keep Australia Beautiful counts are for combined national and South Australian sites.

Data source	Description
Clean Up Australia (CUA)	National annual public clean ups
CSIRO transect	National 100 km transect method coastal surveys
Keep Australia Beautiful (KAB) including KESAB	National representative debris counts and public clean ups
Tangaroa Blue Foundation (TBF)	Data from clean-ups provided from community groups collated for the Sydney region (see appendix D for list of community groups)

Data was constrained to include sites that were surveyed from 2007 onwards. The decision to limit the time period of records was made to enable the most accurate covariate data collection. The entire set of survey data consists of 18,730 records across all four data sources. This includes 3577 site locations with some sites being surveyed at multiple times. KAB surveys make up the majority of data, with an average of 16 surveys at different times per site.

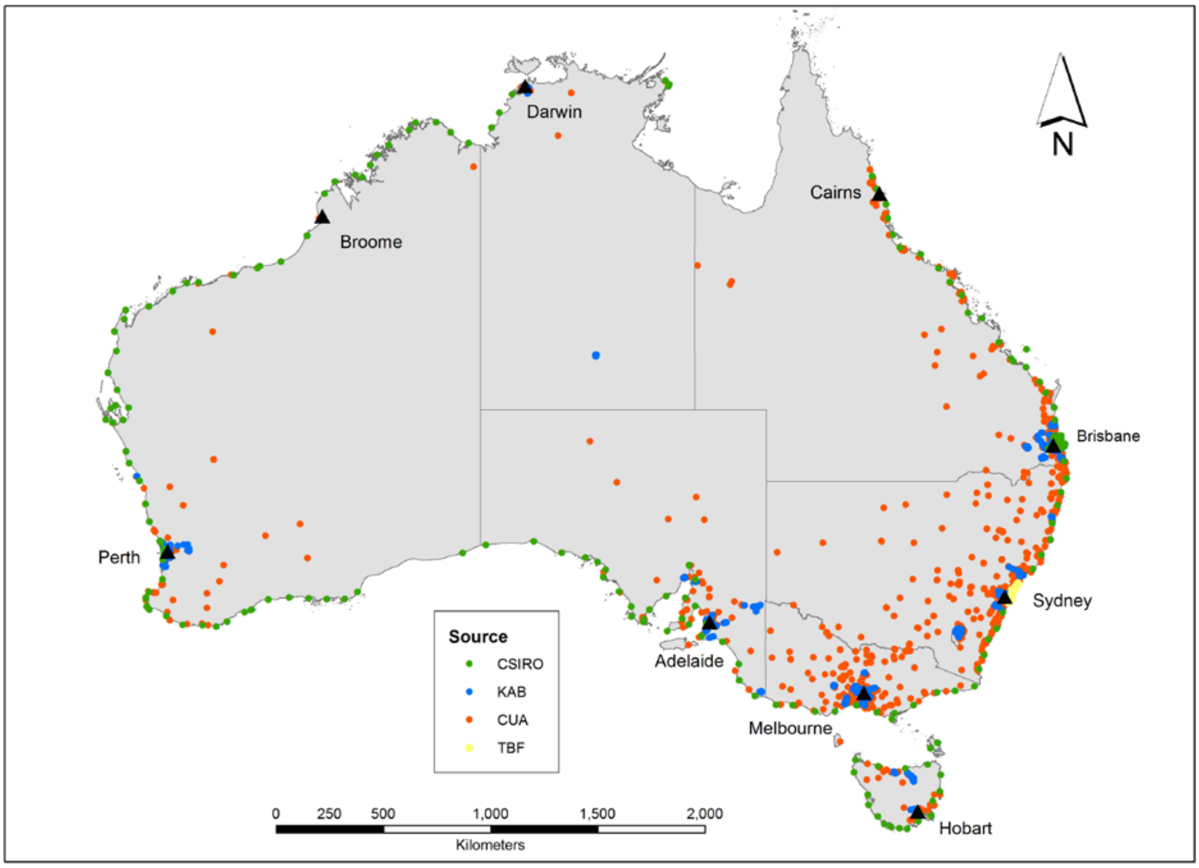

Figure B.1 Map of CUA (orange circles), CSIRO (green circles), KAB (blue circles), and data from Sydney region provided by TBF (yellow circles) survey sites between 2007 and 2017 for data provided by each organization for inclusion in analysis. Note that this represents the 74 sites provided by TBF, rather than the 2400+ datasets they hold.Adapted from Hardesty et al. (2016).

CLEAN UP AUSTRALIA DATA

Clean up Australia (CUA) is an annual event where the public are encouraged to complete debris clean ups. Locational organisers are provided with equipment (gloves, rubbish bags, etc.) and survey forms. Surveys collect details such as the location of the clean up, the area targeted for the clean up, how many people are in attendance and detailed debris categorisation. The information is used by CUA to generate annual reports detailing debris concentrations. Typically, a community group will organise one or more clean ups in their area. Every site is surveyed on the same day each year. Location identification information in the surveys was used to generate a Geospatial Information System (GIS) dataset. Every effort was made to accurately locate the site of the clean up. Sites within 20 meters of one another in subsequent years were assumed to be the same location. Those surveys that did not have sufficient location information were removed from the data used in the analysis. Also removed were surveys with incomplete or inconsistent records. For example, no assumptions were made about the intended value (number) of items when the answer supplied for a count of a certain type of debris was entered as ‘Many’ or ‘Lots’. Only data from 2007 to 2015 were used in analyses (Table B.2).

Table B.2 Count of site surveys provided by CUA and the final number of sites assessed in the analysis over the years of interest.

Year	Sites provided	Sites used
2007	1203	249
2008	1058	226
2009	2870	316
2010	691 (pre cleaned by CUA)	103
2011	2660	244
2012	453 (pre cleaned by CUA)	148
2013	1238	245
2014	540	241
2015	668	172

CSIRO staff cleaned and verified data collected in CUA surveys. This reduced the number of surveys used in analyses, as per Table B.2. The number of sites was reduced in part because not all CUA data included location information (e.g. latitude/longitudes or descriptions that would enable staff to pinpoint locations in geographic space).

CSIRO SURVEYS

CSIRO staff have conducted marine debris surveys at over 202 sites around the coast of Australia, including Tasmania (Figure B.1). At each coastal site, staff carried out 3 to 6 transect surveys, resulting in 668 records used in analyses. The coastal surveys started at Cape Tribulation in far north Queensland and were conducted clockwise around the coast approximately every 100km to Darwin. In instances where staff did not have access at 100km from the last site, staff used the nearest access point to the coast. Conducting the surveys in this manner resulted in both heavily used and rarely used coastal areas being sampled. Site information was collected at the point surveyors accessed the beach. This included information related to weather, time of day, number of people on the beach, and the location of the access point.

For more detailed information about the survey methodology used, see Hardesty et al. (2014) and Hardesty et al. (*2017*).

KEEP AUSTRALIA BEAUTIFUL DATA

Keep Australia Beautiful and Keep South Australia Beautiful (hereafter referred to as KAB collectively) provided their survey data from 2005 to 2015. Only data onwards from 2007 was considered for this analysis. This decision was made because of the large changes in the method of data collection and recording prior to and after 2007. Textual and photographic information was provided for each site location. This was used to build a GIS dataset for analysis purposes. Every effort was made to correctly identify the location of surveys. KAB surveys occur at representative anonymous sites nationally several times a year. Between 2007 and 2015 sites were surveyed on average 16 times. The anonymity of the site location allows for an unbiased sample of debris type and volume. From this data, KAB produces an annual report. CSIRO staff cleaned and verified data collected in KAB surveys. Furthermore, CSIRO staff then amalgamated data from the 84 categories used by KAB into 21 categories for comparison with CSIRO collected data surveys and methodology.

TANGAROA BLUE FOUNDATION DATA

Tangaroa Blue Foundation (TBF) provided survey data collected in the Sydney region from 2009 – 2017. The entire datset comprised a total of 423 surveys ranging from 2009-2017. We subset the data to include only those that reported survey area and time, so that we could accurately correct for area and effort. We also removed data points with fewer than 10 items, because in these surveys the data have not all been collated; only a single item or selected items have been recorded. After removing these surveys, we analysed a total of 380 surveys.

DATA SUMMARY

In order to compare data from different survey methodologies, we corrected the count data for area and effort (number of volunteers), and calculated summary statistics on the count data. Here we compare the summary statistics for surveys Australia-wide. Note that TBF data are not included as we do not have national scale data.

Table B.3 Summary statistics of Australia-wide data sets.

Data source	Mean (items per 1000m2)	Median	Range (min-max)	Mean:Median
CSIRO	115.626	20.135	0 – 4750	5.74
KAB	35.84	20	0 – 1672.50	1.79
CUA	78.019	0.178	0 – 8950	438.3

To compare TBF data, we compiled similar summary statistics for the Sydney region alone. Note that CSIRO data is not included in this table as there were only 3 surveys in the Sydney watershed area.

Table B.4 Summary statistics for surveys in the Sydney region

Data source	Mean (items per 1000m2)	Median	Range (min-max)	Mean: median
TBF	130.065	7.990	0.061 – 5000	16.28
KAB	39.97	26	0 - 511	1.54
CUA	96.086	0.254	0 - 8950	378.27

One item of note is the comparison between mean and median values. When mean values are significantly higher than the median values, this indicates the presence of outlier data points. One way to compare the data sets is to assess the ratio of mean to median values. Here we see that CUA data have a consistently high ratio, which points to some of the site selection biases that we have addressed in Section 3.3.

APPENDIX C. SITE PREDICTOR VARIABLES

For each of the data points, a suite of information about the site and its attributes were collected. In some cases a single distance to features was calculated (e.g. distance to nearest roads), but in most cases predictor variables were collected at a range of distances from the survey point. Covariate segments are concentric circles with a radius of a given distance (1km, 5km, 10km, 25km and 50km) from the survey sites. This allows for an analysis of the distance at which site characteristics have an influence on debris type and volume.

ROADS

The data used in this analysis is the GEODATA TOPO 250K Series 3 Topographic Data (Geoscience Australia, 2006) dataset. The distance to the nearest road was used as a proxy for the potential number of people accessing sites (accessibility). To do this, we determined the distance in kilometres to the nearest road. Sites were further characterised by the total length of different road types (dual carriageway, principal road, secondary road, minor road, and track) within the covariate sample segments.

LAND COVER

Land cover was classified by the Catchment Scale Land Use of Australia (CLUM) dataset developed by the Department of Agriculture, Fisheries and Forestry (DAFF, 2015). Land use is classified according to the Australian Land Use and Management (ALUM) Classification version 7. CLUM is compiled from vector land use datasets collected as part of the state and territory mapping programs through the Australian Collaborative Land Use and Management Program (ACLUMP). Catchment scale land use data was produced by combining land tenure and other types of land use information, fine-scale satellite data and information collected in the field. CLUM is the most recent national land cover product. The ALUM classification defines land cover in three tiers of classifications consistently across Australia at a spatial resolution of 50 meters.

The land use identifier that correlated to all three tiers of categories was captured at each site location. The changes in version of CLUM do not necessarily reflect land use change. CLUM is constantly updated using better techniques and more accurate data. For this reason only the latest (most accurate) land use is captured for each site regardless of the time that the survey occurred.

RAILWAYS

The rail data used for this analysis was the GEODATA TOPO 250K Series 3 Topographic Data (Geoscience Australia, 2006) dataset. As a proxy for determining the accessibility and presence of people on each site we looked at the proximity to railway stations. For this we collected the distance in kilometres to the closest railway station from each survey site.

POPULATION DENSITY DATA

Population census data was evaluated for each of the covariate segments for each survey site. The highest spatial and temporal resolution data available for this task is the Australian Bureau of Statistics (ABS) Statistical Area 2 (SA2) Estimated Residential Population (ERP) (ABS, 2016). The geography of this data is according to the 2011 edition of the Australian Statistical Geography Standard (ASGS2011a). ERP is the official estimate of the Australian population, which links people to a place of usual residence within Australia. Usual residence within Australia refers to that address at which the person has lived or intends to live for six months or more in a given reference year. To enable the comparison of regional populations over time, historical population estimates based on consistent updated geographic boundaries are prepared for this dataset. The dataset sampled for this study was for the year 2011 to coincide with available socio-economic data(see below section on Socio-Economic Indexes for Areas). There are 2214 SA2 regions covering the whole of Australia without gaps or overlaps. The ASGS2011's SA2 geographic sampling areas are not the highest possible resolution data available from the ABS, however the ERP at this spatial resolution is high enough to estimate the surrounding population at survey location accurately.

Total values were estimated for each site at each sampling distance by summing the percentage area of the SA2 covered by the segment, multiplied by the ERP value for that SA2.

SOCIO-ECONOMIC INDEXES FOR AREA (SEIF)

The Socio-Economic Indexes for Areas (SEIFA) contains four summary measures from Australian Census data. The summary measures are represented as relative indices for every statistical area in Australia. Each index summarises a different aspect of the socio-economic conditions of people living in an area. They each summarise a different set of social and economic information. The indexes take into account a range of factors in determining socio-economic conditions. SEIF data from 2011 (ABS, 2011b) were used in this analysis as they are the most recently available socio-economic indices published.

The four indices are:

i. The Index of Relative Socio-economic Disadvantage

The Index of Relative Socio-economic Disadvantage summarises variables that indicate relative disadvantage. The index is designed to focus on disadvantage only. A low score on this index indicates a high proportion of relatively disadvantaged people in an area. We cannot conclude that an area with a very high score has a large proportion of relatively advantaged ('well off') people, as there are no variables in the index to indicate this. We can only conclude that such an area has a relatively low incidence of disadvantage.

ii. The Index of Relative Socio-economic Advantage and Disadvantage

The Index of Relative Socio-economic Advantage and Disadvantage summarises variables that indicate either relative advantage or disadvantage. This index can be used to measure socio-economic wellbeing in a continuum, from the most disadvantaged areas to the most advantaged areas.

An area with a high score on this index has a relatively high incidence of advantage and a relatively low incidence of disadvantage. Due to the differences in scope between this index and the Index of Relative

Disadvantage, the scores of some areas can vary significantly between the two indexes. For example, consider a large area that has parts containing relatively disadvantaged people, and other parts containing relatively advantaged people. This area may have a low Index of Relative

Disadvantage, due to its pockets of disadvantage. However, the Index of Relative Advantage and Disadvantage may be moderate, or even above average, because the pockets of advantage may offset the pockets of disadvantage.

iii. The Index of Economic Resources

The Index of Economic Resources summarises variables relating to the financial aspects of relative socio-economic advantage and disadvantage. These include indicators of high and low income, as well as variables that correlate with high or low wealth. Areas with higher scores have relatively greater access to economic resources than areas with lower scores.

iv. The Index of Education and Occupation

The Index of Education and Occupation summarises variables relating exclusively to education, employment and occupation. This index focuses on the skills of the people in an area, both formal qualifications and the skills required to perform different occupations.

A low score indicates that an area has a high proportion of people without qualifications, without jobs, and/or with low skilled jobs. A high score indicates many people with high qualifications and/or highly skilled jobs.

Census districts with very low populations, or high levels of non-response to certain Census questions, were excluded from the analysis. Mean SEIF indices were calculated for each sample segment and these were used to derive the SEIF index for the date the survey occurred based on a linear model.

APPENDIX D. TANGAROA BLUE FOUNDATION CONTRIBUTORS

Adobe Systems Pty Ltd

Australian Maritime Safety Authority (AMSA)

Australian Seabird Rescue

Bank of America

Blue Tongue Brewery

Brisbane Waters Secondary College, Woy Woy Campus, Support Unit

Central Coast Marine Discovery Centre

Central Environment Network

Combined Hunter Underwater Group (CHUG)

Contiki

Dive Centre Manly

Eco Divers

Ecotreasures

Freshwater Surf Lifesaving Club

Friends of Avoca

Gosford State High School

Graham Johnston Training Services

Hemingways Manly

HNCMA Foreshore Cleanup Programme

In Hearts Wake Band

Jarvis Bay Schools

Johnson Ohana Charitable Foundation

Lendlease

MacMasters Beach SLSC

Manly Sea Life Sanctuary

Manly Surf Lifesaving Club Nippers

Merrill Lynch International Australia Limited

Mosman Community

Narrabeen Learn 2 Swim

Northern Beaches Clean Up Crew

Ocean & Coastal Care Initiatives (OCCI)

Ocean Conservancy

Phoenix Drinks

Redlands Independent School

Responsible Runners NSW
Responsible Runners QLD
Sea Life Trust
Sea Shepherd NSW
Seaside Scavenge
Shark in a Bus
SO Manly
St Brigids Catholic College, Lake Munmorah
St Leonards NSW
SUPExplore
Surfrider Foundation Australia NSW
Sustainable Organisations of Manly
Take 2 Ltd
Take 3
Tangaroa Blue Foundation
Taronga Zoo Project Insitu
The Coast Christian School
The Seaside Scavenge
Tuggerah Lakes Secondary College - Tumbi Umbi Campus
Two Hands
Umina Surf Live Saving Club
Underwater Research Group of New South Wales
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