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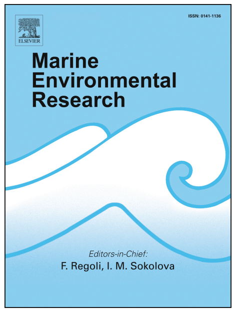

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Factors influencing the detection of beach plastic debris

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ABSTRACT

Marine plastic pollution is a global problem with considerable ecological and economic consequences. Quantifying the amount of plastic in the ocean has been facilitated by surveys of accumulated plastic on beaches, but existing monitoring programmes assume the proportion of plastic detected during beach surveys is constant across time and space. Here we use a multi-observer experiment to assess what proportion of small plastic fragments is missed routinely by observers, and what factors influence the detection probability of different types of plastic. Detection probability across the various types of plastic ranged from 60 - 100%, and varied considerably by observer, observer experience, and biological material present on the beach that could be confused with plastic. Blue fragments had the highest detection probability, while white fragments had the lowest. We recommend long-term monitoring programmes adopt survey designs accounting for imperfect detection or at least assess the proportion of fragments missed by observers.

Keywords: Detection probability; Marine debris; Observer effect; Plastic pollution; Beach clean-up

1. Introduction

Pollution of marine and coastal environments with discarded, lost, and ‘disposable’ plastic items is a rapidly increasing and significant global issue (UNEP, 2014). Plastic pollution has been linked directly to the injury or mortality of an enormous array of marine wildlife (Gall and Thompson, 2015) and incurs large financial costs through lost tourism, the creation of shipping hazards, and clean-up programmes (Barnes et al., 2009; Vegter et al., 2014). Substantial effort has therefore been directed towards monitoring, removing, or preventing plastic from entering the marine environment (Ocean Conservancy, 2015), including a range of national and international programmes (e.g., International Pellet Watch, Australian Marine Debris Initiative) focused on collecting quantitative data on plastic accumulation patterns and associated hazards such as absorbed co-pollutants (Ogata et al., 2009).

Beach surveys implemented by scientists or the general public are an important source of data on the type and provenance of plastic debris on beaches around the world (Ivar do Sul et al., 2011; Lee and Sanders, 2015). Systematic beach surveys or clean-up programmes have been promoted as a tool to provide comparative baseline data on the distribution, abundance, and accumulation of plastic debris (Rees and Pond, 1995; Ribic et al., 2010, 2012). Such systematic programmes can also be used as long-term monitoring tools to document temporal trends in marine plastic pollution (Bravo et al., 2009; Hidalgo-Ruz and Thiel, 2013). However, using the number of plastic items collected by observers along a certain stretch of beach, and comparing these numbers across space and time, rests on the critical assumption that a constant proportion of plastic pieces is detected and recorded. The assumption of perfect detection has been widely criticized in the monitoring of biological populations, and numerous approaches have been developed to account for imperfect detection (Buckland et al., 2008; Kéry and Schaub, 2012; Nichols et al., 2009). For example, counts of mobile birds and lizards depend on the observer, weather, habitat, and several other factors (Alldredge et al., 2007; Kéry et al., 2009; Schmidt et al., 2013), and even counts of sessile plants are generally considered to be less than perfect and vary with substrate and observer experience (Bornand et al., 2014; Burg et al., 2015; Dufrêne et al., 2015). However, such effects have, to our knowledge, not been considered in the majority of beach plastic studies (but see Hidalgo-Ruz and Thiel, 2013). As a consequence, temporal or spatial comparisons of beach plastic accumulation may be biased if certain plastic particles are easier to detect and count at certain sites or during certain times. While large plastic objects (e.g., bottles, buoys, etc.) are likely to be counted with little error, smaller plastic debris is much harder to detect (Baztan et al., 2014; Convey et al., 2002).

Increasing recognition of the hazard posed by small debris to marine wildlife, and expansion of citizen science programmes which contribute debris data over large areas (e.g., National Sampling of Small Plastic Debris programme in Chile and Australian Marine Debris Initiative), has highlighted a growing need for reliable data on micro-plastics (< 5 mm; Hidalgo-Ruz and Thiel, 2013; McDermid and McMullen, 2004). A number of current debris monitoring programmes include micro-plastics (Costa et al., 2010; McDermid and McMullen, 2004; Thompson et al., 2004), which are counted manually on beaches. Floatation (where sediment is placed in water, buoyant plastics rise to the surface and more dense debris is then sorted in the sediment) can be effective for some types of plastic polymers, but still relies on manual sorting for a portion of debris which is both time consuming and prone to errors (Nuelle et al., 2014). Approaches to account for imperfect detection, therefore, may be useful to ensure that data from beach survey programmes are comparable across space and time.

Here we used recent statistical advances for the monitoring of wildlife populations (Dénes et al., 2015; Kéry and Schaub, 2012) to examine whether the detection of plastic debris on beaches can, and should, be accounted for. We investigated which type of plastic debris had a probability of detection substantially less than 100%, and explored the relative importance of observer heterogeneity, beach substrate, and plastic visibility, on the detection probability of plastic items varying in size and colour. This assessment provides a first estimate as to what proportion of plastic is missed routinely in beach survey programmes, and provides guidance on the design of future monitoring programmes to account for variable detection probabilities of different types and colours of plastic.

2. Methods

2.1. Data collection

A confounding issue for the interpretation of plastic found on beaches is how much was washed ashore and how much was deposited locally by people. To avoid this issue and ensure that all encountered plastic was washed ashore from the sea, we conducted our study on one of the remotest islands of the world, far from anthropogenic debris sources.

Henderson Island (24º20 S, 128º19 W), one of four islands belonging to the Pitcairn Island group, is an uninhabited island in the South Pacific Ocean. The island is surrounded by a fringing limestone reef with open sandy beaches on the north, east, and north-western shorelines. Over a two-day period in July 2015, thirty-three 50 × 50 cm quadrats were centred along the high tide line of the northern beach, which has a pale coral sand substrate with white coral pebbles and small amounts of black biological debris (Fig. 1). Five observers visually inspected each quadrat independently for two minutes, recording the number and colour of specific plastic items present. Observers were not allowed to touch or re-arrange anything in a quadrat to maintain identical conditions among observers, and the entire trial was completed within 1.5 hours before tidal action could alter the abundance of plastic in each quadrat.

Micro-plastic items are increasingly the focus of pollution monitoring programmes (Costa et al., 2010; McDermid and McMullen, 2004; Thompson et al., 2004). We therefore focused on five different types of plastic items ranging in size from 2.5 to 60 mm, representing a range of plastic items that are very easy or very difficult to detect given the substrate of the beach in our study area. We chose white, black, and blue fragments of all sizes to represent items that contrast little, moderately, and strongly with the beach substrate, respectively. In addition, we counted black and white resin pellets ('nurdles'; average 2.7 mm diameter), as these tiny but readily identifiable items are considered a priority in many beach clean-up and monitoring programmes (e.g., International Pellet Watch; Ogata et al., 2009).

The detection of plastic particles on a beach can depend on multiple factors, such as the experience of the observer, visibility, or other objects that can be confused with or obscure plastic particles. We therefore recorded the observer identity and the order in which the 33 quadrats were examined by each observer to account for improvements or deterioration of detection over time. We further estimated cloud cover to the nearest 10% for each 2 min interval during which observers counted plastic to account for differences in detectability of plastic particles in bright sunlight and in cloudy conditions. Lastly, we estimated the cover of pale-coloured coral rubble and dark-coloured biological debris (e.g., dried algae, seeds, charcoal, and leaves) for each quadrat to the nearest 5% to account for substrate effects on the detectability of plastic.

After all observers had recorded the abundance of all types of plastic in each of the 33 quadrats independently, we carefully removed the top layer of sediment (ca. 3-5 mm) in each quadrat to determine the true abundance of plastic items, ensuring that only surface plastics but no buried items were collected. For each quadrat, we placed the sediment in a bucket of sea water following methods outlined by Hidalgo-Ruz et al. (2012), allowing low-density plastic items to be collected and sorted once they had floated to the surface (Imhof et al., 2012). We then examined the sediment for any high-density plastics that may have settled to the bottom, and added the two components to yield the total number of plastic present in each quadrat.

2.2. Statistical analysis

Our main goal was to estimate the number of five different types of plastic particles in 33 sampling quadrats from a series of independent counts conducted by five different observers. We then compared those estimates to the true number of particles retrieved from each quadrat to assess whether a multiple observer design could provide an accurate statistical estimate of the amount of plastic. Finally, we examined which of several factors affected the probability of detection for the five different types of plastic in our study.

Our analysis was guided by recent analytical developments in the wildlife literature that allows the estimation of detection probability and abundance from repeated counts (Chandler and King, 2011; Kéry, 2008; Kéry et al., 2005; Royle and Nichols, 2003; Royle et al., 2005). Because the same observer is unlikely to provide independent counts of the same static objects in a quadrat, we used the five independent counts provided by different observers as repeat counts of the same quadrat.

We estimated plastic abundance and detection probability using binomial mixture models (Kéry et al., 2005; Royle and Nichols, 2003; Royle et al., 2005). These models use the repeated observations for a given sampling quadrat to separately estimate the probability to detect plastic particles and the number of plastic particles in this quadrat. Briefly, these models consist of two components which link the state of interest (abundance of plastic) and the observation process (detection probability) in a hierarchical fashion:

$N_i \sim$ Poisson (λ) 1. State process that describes the abundance at site i

$y_{i,j} \mid N_i \sim$ Binomial (N_i,, p) 2. Observation process that describes the abundance at site i

where y_{ij} is the number of plastic items observed at site i during count j with detection probability p given the true number of plastic items present N_i at site i. The abundance component is modelled as a random Poisson process and estimates the number of plastic particles present (Kéry et al., 2005; Kéry and Schaub, 2012; Royle and Nichols, 2003). The observation model component is conditional on the number of plastic particles estimated in each sampling quadrat, and estimates the probability of detection based on repeated counts at a given site using binomial trials for each plastic item. Two critical assumptions for these models are that the population is closed over the period during which the repeat surveys are conducted, and that no false positive detections occur. Because we conducted all repeat counts of our sampling quadrats on the same day within a 90 min interval, no plastic particles were added or lost by tidal action between counts by different observers and the closure assumption was fully met. We tested the assumption of no false positive observations by comparing observations to sieved abundances prior to fitting models.

We fit binomial mixture models in R 3.1.3 (R Development Core Team, 2014) using the function ‘pcount’ in R package ‘unmarked’ (Fiske and Chandler, 2011) with ‘sampling quadrat’ as categorical site covariate affecting abundance. We then extracted the mean estimated abundance for each sampling quadrat from estimated coefficients and compared the mean and 95% confidence interval of the estimated abundance to the true abundance of plastic determined by sediment extraction to quantify the degree of bias of the models.

To examine which factors affected the probability to detect different types of plastic, we used an information theoretic approach and constructed 12 plausible candidate models explaining the variation in plastic count data. We first constructed a null model that assumed that detection was constant across space, time, and different observers. We then constructed a model that assumed that detection of plastic was affected by the beach substrate, namely the percent cover of coral rubble and biological debris. The remaining ten models all considered that detection probability varied either among the five observers or whether observers had previous experience in collecting plastic debris from beaches. Eight of these 10 models additionally accounted for variability in detection with the percent cover of coral rubble, the cover of biological debris, the percent cloud cover, and the temporal sequence of counts as a measure of observer fatigue (i.e., reduced vigilance) or increasing experience. We ranked all 12 models using Akaike's Information Criterion (AIC; Burnham and Anderson, 2002), and provide mean parameter estimates with standard errors for those detection parameters that received the greatest support from our data. All data and the R code used to obtain the results have been deposited at https://github.com/steffenoppel/plastic.

3. Results

Across the 33 quadrats, observers counted between 0-5 blue fragments, 0-7 black fragments, 0-23 white fragments, 0-4 black pellets, and 0-7 white pellets per quadrat. True abundance of plastic particles obtained from sediment extraction resulted in 0-6 blue fragments, 0-3 black fragments, 0-34 white fragments, 0-4 black pellets, and 0-9 white pellets per quadrat. Summed across all plastic particles, each observer recorded only 67.3 – 81.3% of the plastic particles that were actually retrieved from the sampling quadrats, and raw detection probabilities ranged from 60 – 100% across each observer and types of plastic (Table 1).

Black fragments were the only type of plastic easily confused with other particles on the beach, which led to highly variable detection and a high incidence of false positive detections. Of the 33 sampling quadrats, only 8 contained any black plastic fragments, but observers recorded black fragments in 30 quadrats. Each observer recorded non-existing black fragments in at least four quadrats, and overall 48 counts (29%) of black fragments contained false positive observations. We therefore did not estimate abundance of black fragments with binomial mixture models because a key assumption was violated. For white fragments, white pellets, and black pellets, <10% of observations contained false positives, for blue fragments 17% of observations contained false positive detections.

Despite the mild violation of a core assumption, binomial mixture models generally retrieved an accurate estimate of the true abundance of plastic from the repeated count data (Fig. 2). True abundance values were within the 95% confidence interval of the estimated abundance for 94% of quadrats for blue fragments, 91% for black and white pellets, and 82% for white fragments. The models indicated that the detection probability of plastic was highly variable among the different types and colours (Table 1). Blue plastic fragments were detected most accurately by all observers (Fig. 2), with estimated detection probabilities approaching 1 even for inexperienced observers (Table 1). Estimated detection probability of white fragments was below 50% even for experienced observers (Table 1). Detection of the small pellets was extremely variable among observers, but overall the probability to detect white or black pellets was slightly higher than the detection probability for white fragments (Table 1).

The factors affecting detection probability varied across the four different types of plastic we modelled. Blue fragments were easily detected by all observers, and there was model selection uncertainty (Table 2) with ambiguous support for either detection to vary by observer (Table 1), or increase with experience ($\beta = 0.353 \pm 0.379$, z = 0.93, $p = 0.35$), or decrease with the amount of biological debris ($\beta = -0.740 \pm 0.332$, z = -2.23, $p = 0.03$). By contrast, white fragments were difficult to detect given the pale sandy background and the presence of natural rubble, and the best supported model indicated that detection probability increased with experience ($\beta = 0.304 \pm 0.094$, z = 3.25, $p < 0.001$) and decreased with increasing cover of white coral rubble ($\beta = -0.295 \pm 0.071$, z = -4.18, $p < 0.001$). For the much smaller pellets, observer experience received little support from the data, and detection probability was better explained by differences amongst individual observers independent of their previous experience (Table 2). For white pellets, there was overwhelming support for observer differences and decreasing detection probability over time as observers showed signs of decreasing vigilance ($\beta = -0.396 \pm 0.118$, z = -3.36, $p < 0.001$). Detection probability of black pellets also varied by observer and appeared to increase with more biological debris ($\beta = 0.543 \pm 0.344$, z = 1.58, $p = 0.11$; Table 2).

4. Discussion

Counts of plastic on beaches are useful for monitoring the quantity of plastic in the marine environment, but spatial and temporal comparisons assume that the proportion of plastic counted by observers is constant across space and time. We identified and quantified three common sources of error that may lead to highly variable counts of plastic on beaches, namely imperfect detection, misidentification, and misclassification. We have shown that even experienced observers generally detect less than 100% of all plastic particles, and that detection probability is extremely variable among types and colours of plastic, and among different observers. These sources of variation may confound any spatial or temporal comparison of plastic counted on beaches, and may lead to biased or erroneous conclusions about the accumulation of plastic in the marine environment.

Imperfect detection of plastic debris can potentially be accounted for using repeat surveys and binomial mixture models to estimate the true abundance of plastic. Such data could be easily generated by at least 3-10 independent repeat counts from at least 25-50 distinct sites. While these approaches require a more stringent monitoring design and greater monitoring effort, the statistical framework is applied increasingly to large-scale citizen science datasets (Isaac et al., 2014; Tulloch et al., 2013; van Strien et al., 2013) and we envision that results from beach surveys could be analysed in a similar fashion to account for the imperfect detection of plastic. Alternatively, more efficient monitoring designs that use the time to detection to estimate detection probability have proven useful in botanical surveys and may reduce the number of observers required for robust monitoring (Bornand et al., 2014). However, an important consideration for the design of such surveys is the interval between repeat surveys and between surveys that are used to estimate changes over time: the abundance of plastic on a beach is a function of accumulation over time, hence the interval between sampling events will influence the abundance of plastic that is collected (Moreira et al., 2016; Ryan et al., 2014; Smith and Markic, 2013).

Existing beach surveys and clean-up programmes that do not account for imperfect detection underestimate the amount of plastic on beaches. For these existing datasets, or for monitoring programmes where designs or analyses accounting for imperfect detection are logistically impractical, the true amount of plastic could be coarsely extrapolated by using the detection probabilities estimated here. Based on detection probabilities calculated from sediment extraction and estimated from models, we suggest that the true amount of white fragments can be 1.3-9.5× higher than raw counts, 1.0-1.4× higher for blue fragments, 1.2-5.7× higher for white pellets, and 1.0-4.9× higher for black pellets. These correction factors apply however only for plastic visible on the surface, and do not account for the invisible plastic buried in the sediment (Kusui and Noda, 2003; Williams and Tudor, 2001). In addition, these factors are likely to vary among different beaches, and we strongly recommend that long-term monitoring programmes assess the amount of plastic missed by observers and develop correction factors for the local conditions on each target beach if no robust monitoring approaches are feasible. Despite their limitations, correction factors have proven beneficial in ecological studies (Eagles-Smith et al., 2008; Johnson, 2008).

The most important variable that affected detection probability of plastic debris across the different types of plastic that we investigated was the identity of the observer. For some items, in our case white fragments, observer experience could adequately control for variation among observers, whereas for smaller pellets and black fragments experience alone was a poor predictor of observer performance. In addition to the observer effect, fatigue played an important role in the detection of white pellets, where detection probability decreased towards the end of the trial. Observer effects and experience are well known to influence surveys of animal (Alldredge et al., 2007; Diefenbach et al., 2003; Gale et al., 2009) and plant populations (Ahrends et al., 2011; Burg et al., 2015; Dufrêne et al., 2015), and we recommend that observer heterogeneity is considered routinely in the analysis of beach plastic monitoring studies.

Besides imperfect detection, the second major source of error was misidentification. Some observers in our experiment counted more plastic fragments than were actually present in a given quadrat, and this pattern was most prominent for black fragments, and to a much lesser extent for black pellets. False positive detections likely occurred due to confusing natural debris, for example clam shell fragments, charcoal, leaves, or coral items with similar white or black plastic fragments or pellets. While the non-detection of plastic particles that are actually present can be accounted for using the binomial mixture models that we have employed, most current abundance estimation methods assume that no false positive detections occur in the data (Dénes et al., 2015). Although there are some approaches that correct for false positive detections in applications dealing with binary detection / non-detection data (McClintock et al., 2010; Miller et al., 2013; Royle and Link, 2006), we are not aware of techniques that control for false positive detections in abundance estimates (Dénes et al., 2015). False positive detections will lead to an over-estimation of the actual abundance of plastic, and a concomitant underestimation of the detection probabilities (Table 1). Although both our abundance and detection probability estimates were slightly affected by the occurrence of false positive detections, we believe that this problem may be less severe in actual beach surveys than in our experiment: to maintain equal detection opportunities in our experiment the observers were not allowed to touch any fragments, as this could have altered the detection probability for subsequent observers. Biological compounds and plastic fragments are generally easy to distinguish by their texture and weight, and practical beach survey applications may therefore suffer from far less false positive detections than our artificial experiment. Where possible, polymer identification techniques, such as Fourier transform infrared spectroscopy (FTIR) should be adopted (Mecozzi et al., in press).

One approach to overcome difficulties with observer heterogeneity and imperfect detection in long-term monitoring programmes of plastic pollution could be to choose to monitor plastic items with very high detection probability which may offer the most reliable data without the need to control for observer differences and imperfect detection. In our experiment only blue fragments were detected reliably and almost perfectly by all observers, most likely because blue fragments contrasted strongly with the beach sediment colour and all natural compounds encountered on the beach (Fig. 1). Easily detectable blue fragments could therefore serve as an indicator that is less affected by imperfect detection. The adoption of a single candidate indicator would however require further studies that estimate the correlations between the abundance of blue plastic fragments and other plastic items (Ribic, 1998).

While focussing on one particular type and colour of plastic may help control for detection probability, such an approach will introduce the risk of misclassification. In our experiment blue fragments had the second-highest proportion of false positive detections despite the generally very accurate counts. Observers likely detected and correctly identified plastic pieces that had different hues of blue and erroneously classified them as blue (e.g. bluish green, purple). Therefore, deciding on the type and colour of plastic that will enable unambiguous classification and spatiotemporal comparisons without the need to control for variable and imperfect detection is likely very challenging: dark volcanic sediments, coarser biological debris of various colours, and other natural debris will likely lead to locally diverse conditions that affect the detection probability of different types of plastic in different ways.

5. Conclusions

In summary, we recommend that the highly variable and inconsistent detection probability of different plastic types and colours is considered for any spatial or temporal comparisons of plastic surveys along beaches. Estimates of the total amount of plastic on beaches need to be corrected for imperfect detection, and we provided a range of possible correction factors for various types of plastic. Future monitoring programmes should consider appropriate survey designs with multiple observers or recording the time-to-detection to control for imperfect and variable detection.

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Table 1

True (sieved) and estimated detection probabilities (mean, and 95% confidence intervals) for five different types of plastic counted by five different observers with or without previous plastic detection experience in 33 50 × 50 cm quadrats on a pale sandy beach on Henderson Island, South Pacific in July 2015. Raw probabilities were based on sieved abundances, estimates were based on binomial mixture models.

Type	Colour	Observer	Previous experience	True detection probability	Estimated detection probability		
					Mean	Lower 95% CI	Upper 95% CI
Fragment	Black	A	no	0.833	model assumptions violated		
		B	yes	1.000			
		C	yes	0.974			
		D	no	0.897			
		E	no	0.974			
	Blue	A	no	0.947	0.902	0.764	0.946
		B	yes	0.947	0.904	0.759	0.953
		C	yes	0.965	0.901	0.755	0.951
		D	no	0.902	0.865	0.704	0.926
		E	no	0.934	0.857	0.695	0.920
	White	A	no	0.663	0.178	0.105	0.288
		B	yes	0.797	0.226	0.136	0.353
		C	yes	0.777	0.226	0.136	0.353
		D	no	0.639	0.179	0.106	0.289
		E	no	0.685	0.179	0.106	0.290

Pellets	Black	A	no	0.980	0.826	0.525	0.932
		B	yes	0.859	0.763	0.435	0.895
		C	yes	0.952	0.826	0.522	0.933
		D	no	1.000	0.805	0.494	0.919
		E	no	0.795	0.543	0.200	0.746
	White	A	no	0.626	0.445	0.325	0.572
		B	yes	0.759	0.556	0.423	0.681
		C	yes	0.872	0.648	0.485	0.782
		D	no	0.847	0.725	0.568	0.840
		E	no	0.602	0.271	0.176	0.389

Table 2

Model selection table examining effects influencing the detection probability for five different types of plastic counted by five different observers on a pale sandy beach on Henderson Island, South Pacific in July 2015. Factors included observer experience, proportion of substrate covered by pale-coloured coral rubble or dark-coloured biological debris, visibility (sun or shade), and observer fatigue (see Methods for details). k: the number of parameters, AIC: Akaike's Information Criterion, ΔAIC: difference in AIC values from the best-fitting model (lowest AIC value), ωAIC: Aikaike weight.

Type	Colour	model	*k*	AIC	ΔAIC	ωAIC
Fragment	White	experience+coral rubble	36	723.93	0.00	0.89
		observer+coral rubble	39	729.05	5.12	0.07
		experience+fatigue	36	732.01	8.08	0.02
		experience	35	732.74	8.81	0.01
		experience+biol.debris	36	734.55	10.63	0.00
		experience+visibility	36	734.67	10.74	0.00
		biol.debris+coral rubble	36	734.95	11.02	0.00
		observer+fatigue	39	736.60	12.67	0.00
		Observer	38	737.87	13.94	0.00
		observer+biol.debris	39	739.68	15.76	0.00
		observer+visibility	39	739.78	15.85	0.00
		null	34	741.67	17.74	0.00
	Blue	experience+biol.debris	36	283.61	0.00	0.36
		observer+biol.debris	39	283.82	0.21	0.32
		biol.debris+coral rubble	36	284.43	0.82	0.24

		experience+visibility	36	289.43	5.82	0.02
		observer+visibility	39	290.10	6.49	0.01
		null	34	290.24	6.63	0.01
		experience	35	291.32	7.71	0.01
		Observer	38	291.54	7.93	0.01
		experience+fatigue	36	291.69	8.09	0.01
		observer+fatigue	39	292.16	8.55	0.00
		experience+coral rubble	36	293.28	9.68	0.00
		observer+coral rubble	39	293.50	9.89	0.00
Pellets	White	observer+fatigue	39	407.39	0.00	0.98
		observer+biol.debris	39	417.10	9.70	0.01
		Observer	38	417.72	10.33	0.01
		observer+coral rubble	39	419.34	11.95	0.00
		observer+visibility	39	419.57	12.18	0.00
		experience+fatigue	36	435.95	28.55	0.00
		experience	35	439.55	32.16	0.00
		experience+biol.debris	36	439.71	32.32	0.00
		experience+visibility	36	440.90	33.50	0.00
		experience+coral rubble	36	441.07	33.68	0.00
		null	34	443.18	35.79	0.00
		biol.debris+coral rubble	36	444.66	37.27	0.00
	Black	observer+biol.debris	39	245.59	0.00	0.35
		Observer	38	246.12	0.53	0.27
		observer+fatigue	39	247.70	2.11	0.12

	observer+visibility	39	247.90	2.30	0.11
	observer+coral rubble	39	248.07	2.48	0.10
	null	34	252.30	6.71	0.01
	experience+biol.debris	36	252.57	6.98	0.01
	experience	35	252.95	7.36	0.01
	biol.debris+coral rubble	36	253.69	8.10	0.01
	experience+visibility	36	254.85	9.26	0.00
	experience+coral rubble	36	254.91	9.32	0.00
	experience+fatigue	36	254.95	9.36	0.00

Fig. 1. A 50 × 50 cm quadrat located along the high tide line of North Beach, Henderson Island, in July 2015. Observers were given 2 minutes to visually estimate the total number of white, black, and blue plastic fragments, and white and black plastic pellets. The percent cover of pale-coloured coral rubble and darker biological material was included in the analysis.

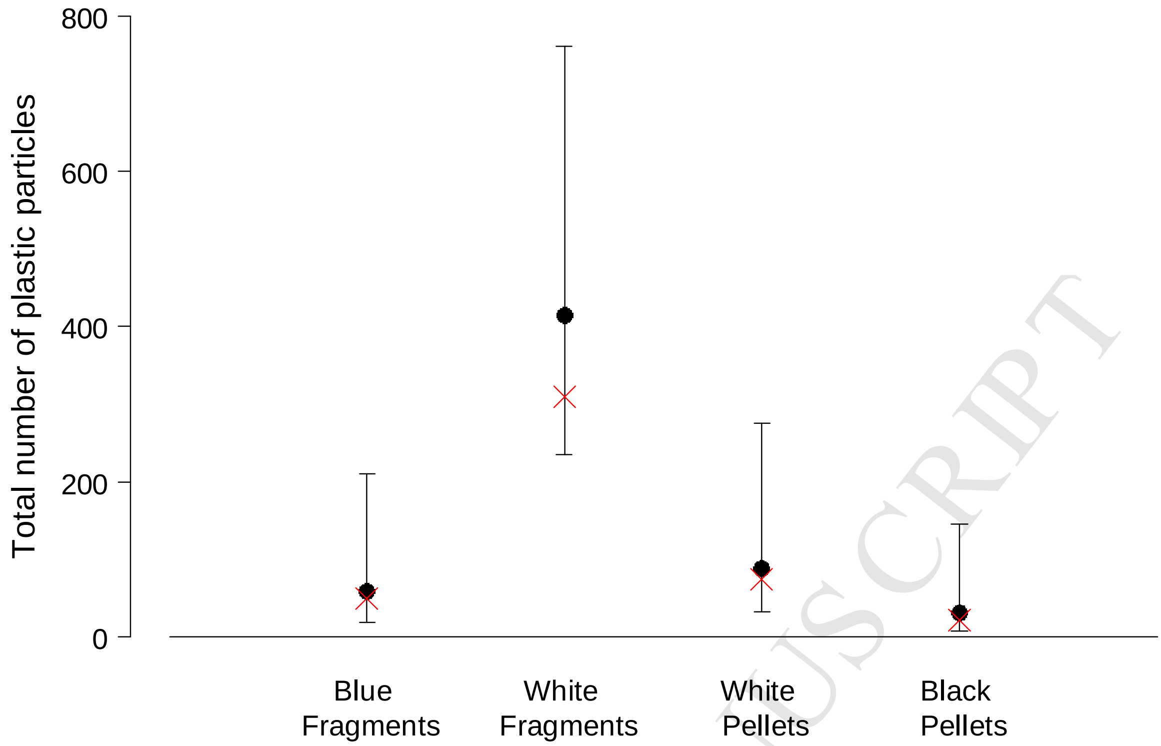

Fig. 2. Total number (± 95% confidence intervals) of plastic fragments and pellets in 33 different 50 × 50 cm quadrats estimated with a binomial mixture model from repeated count data provided by five observers. Red crosses indicate true abundance determined by collecting all plastic items within each quadrat (see Methods).

Highlights

- Detection probability for beach plastic debris varies from 60 - 100%
- Detection rates varied considerably by observer and with observer experience
- Detection rates were also influenced by biological material present on the beach
- Blue fragments had the highest detection probability and could function as an ‘indicator species’