ESTIMATING BASELINES AND IDENTIFYING ANOMALIES IN BEACHED BIRD PATTERNS ON THE OUTER COASTS OF WASHINGTON AND OREGON, USA

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Abstract

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The marine ecosystem is a dynamic environment that has been altered globally through direct and indirect human activity. As high trophic predators, seabirds have been used as indicators of marine ecosystem health because their productivity and mortality rates may reflect offshore conditions, particularly when mass mortality events occur. This study created methods to estimate baselines of monthly seabird carcass encounter rates, and statistically identify unusual mortality events (UMEs) at the survey level using beached bird data collected on the outer coasts of Washington and Oregon by the citizen science program, the Coastal Observation and Seabird Survey Team (COASST). We used a generalized additive model (GAM) to estimate beach-specific baselines of carcass encounter rate and an iterative approach to subsequently identify 165 monthly surveys as UMEs (4.49% of all surveys). These anomalous events ranged in encounter rate from 0.667 to 122.5 carcasses km^{-1}; 45.5% of all UMEs had at most 5 carcasses km^{-1} recorded, therefore subsequent analyses were broken down as low encounter rate UMEs (≤5 carcasses km-1), high encounter rate UMEs (<5 carcasses km-1), and mass mortality events (>10 carcasses km-1). Across all regions, UMEs had higher proportions of intact carcasses and carcasses found in the wrack zone of the beach when compared to the baseline, but this signal was inconsistent when comparing carcass proportions in low encounter rate UMEs with those in high encounter rate UMEs. The natural history of prevalent seabirds drove beached bird patterns; in particular, major peaks in the baseline encounter rate pattern were associated with post-breeding mortality of resident breeders (i.e. Common Murres Uria aalge), and winter kill of migratory species (i.e. Northern Fulmars Fulmaris glacialis). Only a third of high encounter rate UMEs aligned with the time and taxon peaks of natural mortality (i.e. "right species, right time" signal). Other UMEs occurred at times of unexpectedly heightened mortality (e.g. atypical spring mortality) and/or involved uncommon species as compared to the entire dataset species distribution. Overall, this study provides methods to estimate statistically estimate baselines and identify UMEs and a set of tools that can be used to characterize them.

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"As long as I've worked with birds, I haven't worked at all" -GB

Introduction

Direct and indirect human activity has altered ecosystem dynamics and species distributions throughout the marine environment (Halpern et al. 2008), including the provocation of some large-scale mortality events (Botsford et al. 1997, Diaz and Rosenberg 2008). One indication of human pressures on marine systems is the increasing magnitude of mass mortality events of marine invertebrates, fishes and birds worldwide (Fey et al. 2015). In the marine environment, seabirds can act as important indicators of the status of ecosystem health (Furness and Camphuysen 1997, Cairns 1988). They are more easily observed and enumerated than their prey (Piatt et al. 2007), and are numerous, particularly in productive coastal waters (Ballance et al. 1997). Unlike many other upper trophic species, marine birds also lend themselves to a wide range of spatially comprehensive sampling via beached bird monitoring (Harris et al. 2006).

Episodic and unexpected mass mortality events of seabirds have been documented in the literature as large numbers of carcasses deposited over a short window of time and space (Bourne 1976, Piatt and Van Pelt 1997). These events, also referred to as "seabird wrecks," have either been linked to mortality sources directly associated with human impacts on the environment (i.e. harmful algal blooms associated with ocean warming, Shumway et al. 2003; oil spills, Hope Jones et al. 1978) or attributed to more non-anthropogenic factors (e.g., severe weather, Underwood and Stowe 1984; food shortage, Baduini et al. 2001). Wrecks recounted in the literature have primarily been events that drew public attention for the sheer number of carcasses encountered on the affected beaches (Bailey and Davenport 1972, Underwood and Stowe 1984). Although the total number of carcasses involved in wrecks are almost always estimated (e.g., Piatt et al. 1990), few are compared to long-term baseline patterns of carcass deposition (e.g. long-term averages, Parrish and Boersma 1995, Harris and Wanless 1996).

Standardized beached bird survey programs are conducted in several regions around the world (Camphuysen and Heubeck 2001, Harris et al. 2006, Wilhelm et al. 2009). Once baseline beaching patterns have been established, survey data can be used to monitor consequences of many human activities, especially those in nearshore systems (e.g., ballast water exchange and subsequent oiling: Wiese and Elmslie 2006, fisheries and subsequent bycatch: Hamel et al. 2009). Long-term studies of carcass beaching patterns have also provided insight into the patterns of “abnormal” stranding events associated with harsh environmental conditions (storm activity: Harris and Wanless 1996; sea ice conditions: Tranquilla et al.2010) and starvation (Ryan et al. 1989, Barrett et al. 2004). If surveys involving heightened carcass encounter rates are associated with anomalous offshore conditions, these events can serve as indicators of poor oceanographic conditions. Therefore, there may be a need to differentiate unusually heightened encounter rate surveys from the baseline pattern of carcass encounter rate. In this paper, we will refer to heightened encounter rate events as unusual mortality events (UMEs, akin to the term used for marine mammal strandings, Litz et al. 2014), and extreme or mass mortality events as wreck events.

Large-scale wrecks involving extremely high carcass numbers are comparably easy to identify as abnormal. However, carcass deposition rate is a continuum, varying seasonally and geographically due to predictable shifts in seabird biodiversity and abundance, at-sea weather and climate forcing, physical forces transporting carcasses to shore (i.e. currents, tides and onshore winds), and combinations of these factors (Bodkin and Jameson 1991, Camphuysen and Heubeck 2001, Parrish et al. 2007). Although specific to system, major modes in the baseline signal can be attributed to post-breeding mortality of both young-of-the-year and adults of resident breeding species (Roletto et al. 2003), and winter mortality of both resident and migratory species via storms and exposure (Harris and Wanless 1996).

A static threshold of carcass count across a region would be insufficient to differentiate UMEs from baseline due to physical and biological differences between beach sites and seasons. For instance, at a beach-specific scale, anomalous carcass counts considered extreme for that location may still be absolutely low at the regional scale. Currently, there is no accepted statistically-based measure of UMEs that would allow differentiation from baseline in terms of the magnitude of beaching. UMEs may also differ from baseline data in characteristics other than carcass encounter rate. Depending on the intensity and duration of the event, the response of predators and scavengers, and the timing and frequency of beached bird surveys, carcasses involved in UME surveys may be different from those found in baseline surveys in their body condition or initial detection location on the beach.

In this study we used a long-term beached bird dataset from the outer coast of Washington and northern Oregon to estimate annual regional patterns and beach-specific baselines of carcass encounter rate as the first step in deriving a statistical classification of an “Unusual Mortality Event” (UME), or any statistically discernable event from a baseline encounter rate pattern. We evaluated whether UMEs differed from the baseline dataset in several independent characteristics, including carcass intactness, location of carcass detection on the beach, and species composition. Finally, we explored the degree to which the spatial and temporal extent of anomalous events was statistically distinct from random. Together, these analyses provide evidence that UMEs that are statistically differentiable from the baseline encounter rate signal actually represent a suite of different anomalously high beaching events, which can only be understood as a function of the natural history and life history of the species in the system, the regional and beach-scale baseline patterns, and independent knowledge of the extent and duration of likely forcing factors.

Methods

Beached bird data were systematically collected by participants of the Coastal Observation and Seabird Survey Team (COASST), a citizen science program of the University of Washington. The COASST program was established in 1998 and has collected data for over 15 years in Washington state, 16 years in Oregon, and 10 years in Alaska and California.

All participants are trained in person by COASST staff in a 5-hour session conducted in their community. Trained participants are encouraged to survey monthly in pairs or teams, excepting regions where winter conditions prevent year-round data collection (e.g., portions of Alaska and the north outer coast of Washington). Survey beaches have set start and turn-around points and are variable in length depending on local geomorphology and participant choice. A survey consists of a single pass search from the water's edge to the leading edge of beach vegetation, where the search pattern is dependent on beach width and team size. For each carcass encountered, species were identified using morphological (foot type), morphometric (tarsus, culmen, and wing chord measurements) and plumage characters using a dichotomous key to beached birds (Hass and Parrish 2013). Following carcass identification, all carcasses were uniquely tagged and photographed. Data on carcass location and carcass condition are also recorded. Location is categorized into one of three zones: surf (defined as the water line to the change in beach inclination, often indicated by the presence of macroalgae and other flotsam), wrack (demarcated by successive tide lines of flotsam), or high (the portion of the beach above the wrack zone to the start of vegetation and typified by bare substrate and/or driftwood). Condition includes a bimodal measure of intactness (yes or no), where fully intact birds have all body parts and no incisions. Following each survey, data sheets and photographs are sent to COASST staff for species verification and archiving.

We subdivided the coastline into three regions, two in Washington and one in Oregon, to account for differences in geomorphology, persistent oceanographic features, and seasonal shift in breeding phenology of locally abundant species (e.g., Common Murres *Uria aalge;* Manuwal et al. 2001). We selected 34 survey beaches with the longest sampling records from all COASST beaches on the outer-coast of Washington ($n_{northern}$=15 beaches; $n_{southern}$=11 beaches) and northern Oregon (n=8 beaches; Figure 1). Our study was restricted to data collected from January 2003 through December 2013 to account for standardization in the data collection protocol. The selected beaches had data for at least 50% of all months within our temporal window. To prevent selective oversampling, we only used data from the first survey for beaches surveyed more than once within a month.

For each region, observed carcass counts were used to model unique baseline patterns of carcass encounter rate (carcasses observed standardized to per kilometer) at the regional scale. We accounted for local variability in UMEs due to live bird densities and physical forces influencing carcass deposition, persistence and detection by fitting the regional scale baseline encounter rate magnitudes for each beach (Van Pelt and Piatt 1995, O'Hara and Morgan 2006). Generalized additive models (GAMs, Hastie and Tibshirani 1990) were fitted using the package "mcgv" in R version 3.1.2 (Wood 2004, R Core Development Team 2013) as:

$$N_{ij} \sim offset(\log(L_i)) + s\left(Month_j\right) + Beach_i \qquad (1)$$

where N_{ij} is the observed number of birds on the *i*th beach in the *j*th month, and L_i is the length of the *i*th beach in kilometers. The term $s(Month)$ is a smoother relating mean bird densities to month of year, thereby accounting for phenology of species and climate. The term $Beach$ estimates the baseline of each beach with a magnitude relative to other beaches within the region. The offset component adjusts the expected carcass count by the beach-specific survey distance. To account for over-dispersed count data within each month, GAMs were fitted using the negative binomial family (Thurston et al. 2000), and the variance was estimated by the model. we used this basic model structure in three different methods to explore the validity of categorizing each survey as a UME: an iterative approach which serially deleted UME events from the sample set, and two more validation measures: cross validation (Browne 2000), and jackknife sampling (Efron and Gong 1983).

We predicted beach-specific baseline patterns that identified and excluded anomalous events by applying an iterative approach. The initial fitted GAM that included all survey data resulted in a baseline prediction influenced by the anomalously heightened encounter rate surveys included in the dataset. To estimate baseline patterns omitting these anomalous events, we identified and removed from the dataset any survey that exceeded the 99th percentile of the null negative binomial distribution, where the GAM prediction for each beach and month served as the mean of the negative binomial null distribution. These removed surveys were noted as UMEs, and all remaining surveys were considered part of the baseline pattern. The GAM was re-fitted to estimate a new baseline omitting UME events. A single threshold to identify UME events was insufficient due to the spatiotemporal variation in normal carcass encounter rate patterns. To account for variability that may have resulted from localized environmental or physical forces, the process of identifying and removing UMEs was repeated until the number of UMEs identified reached a minimum across all iterations. By removing UMEs with each repetition, the baseline correspondingly decreases and may ultimately become uninformative, identifying heightened encounter rate baseline surveys as UME events. This procedure resulted in two datasets: baseline surveys and UME surveys.

We employed two more approaches to identify UMEs with the same underlying GAM model: cross validation and jackknife sampling. These methods used different subsets of the original dataset to identify UME surveys independent of the GAM baseline estimation. In the cross validation approach, each beach-month-year was randomly assigned to a “training” set or “test” set. The GAM was applied to the training set as above to create the null distribution, and data points from the test set exceeding the 99th percentile of the null distribution were categorized as UMEs. we repeated the random assignment and UME identification process 10,000 times with 90% of all data assigned to the training set, and 20,000 times with 95% of all data assigned to training set. Surveys were classified as anomalies if they were identified as UME in at least one repetition. In the jackknife sampling approach, a single beach-month-year observation was removed from the entire dataset and the GAM baseline was created with the remaining data. Each beach-month-year observation was evaluated as being a UME or not using the same identification technique as above.

All three methods identified overlapping sets of UME events, with ~48-53% concurrence (Table 1). The iterative procedure identified the highest number of UMEs, approximately twice as many as the more conservative procedures. Iterations were discontinued at the fourth iteration for northern and southern Washington, where the minimum number of UMEs per iteration was identified (Figure 2). All UMEs not captured by the cross validation and jackknifing methods were discovered in secondary to quaternary iterations (Table 1); however the range of encounter rate for UMEs identified by cross validation and jackknifing methods (0.91-122.5 carcasses per kilometer) were similar to that of UMEs identified by the iterative approach (0.67-122.5

carcasses per kilometer). The iterative approach identified more lower encounter rate UMEs than the other two methods, but this also identified more UMEs with an encounter rate of 10 carcasses per kilometer or more than the cross validation (n=12 more UMEs) and jackknifing method (n=16 more UMEs). We chose to use the iterative results in all subsequent analyses because this approach effectively identified a baseline devoid of anomalous events. The relevance of low encounter rate events must be considered when comparing UMEs to the baseline signal and to higher encounter rate events. Although they may be statistically identified as abnormal, they may only be identified as UMEs because of baselines lowered by the iterative procedure.

Using the classification output from the iterative GAM procedure (i.e. UME, baseline), we explored whether carcasses involved in baseline and UME surveys were different in where they were initially found, or their body condition. We tested our hypotheses using Chi-square tests of homogeneity, including multiple pairwise post-hoc tests as needed (Cox and Key 1993). Our hypotheses are based on the assumption that the classification of a “UME” is a function of the surveyor capturing an anomalously heightened encounter rate as it is happening. *Carcass location* - Wave and tidal action influence carcass persistence and location on a beach, and may quickly rearrange freshly deposited material up the beach (Burger 1992). Therefore, carcasses found within the surf zone may indicate very recent deposition (e.g., within the tidal cycle). If UME events are partly due to surveys occurring immediately after deposition events, then we hypothesized that UME events would have relatively more carcasses found in the surf zone. *Carcass condition* - The presence of intact carcasses may indicate a sudden increase in deposition because carcasses are quickly scavenged in many locations (e.g., within 24 hours, Unalaska Island, Byrd et al. 2009). In other locations, scavengers may become satiated or disinterested (Fowler and Flint 1997), leaving a higher proportion of carcasses untouched for subsequent discovery by surveyors. we hypothesized that UMEs would have relatively more intact carcasses due to the combination of increased deposition, coincidence of that deposition with the survey, and the potential for scavenger satiation.

UMEs have been documented to involve a continuum of species composition from species-specific (i.e. Common Murres in the Irish sea, Bourne 1976; Short-tailed Shearwaters *Puffinus tenuirostris* in Alaska, Baduini et al. 2001) to speciose (i.e. 16 species associated with a harmful algal bloom in Monterey Bay, California, Jessup et al. 2009). To understand whether species composition patterns are UME-specific, we explored species composition of all surveys, as well as only those surveys categorized as UME events, using Principal Coordinate Analyses (PCoA, Legendre and Gallagher 2001). Only carcasses identified to species were included in these analyses, including those identified as large immature gulls. These carcasses were not identified further to species but comprise a vast majority of the overall COASST data (7.2% of all COASST data, 2000-2016, www.coasst.org). To compare surveys based on relative proportions of the species recorded, we restricted the analysis to surveys with a minimum of five carcasses (n=939 surveys across all regions) and applied a logarithmic transformation to species abundance data to reduce the influence of extremely abundant species. We created a Bray-Curtis distance matrix to calculate linear distances that quantified the similarity in species composition among surveys (Bray and Curtis 1957). The PCoA algorithm ordinates the surveys using the distance matrix to explain as much of the dataset variation as possible (Gower 1966). Variable (e.g. species) loadings, plotted as eigenvectors, indicate which species exert a significant influence on the similarities across survey observations, where the length of the eigenvector indicates the degree of influence (Cadima and Jolliffe 1995).

UMEs have been documented over a wide range of spatial extent, from single locations (akin to one-to-few contiguous survey beaches in the COASST dataset; e.g. UME of Common Murres on the Alaska peninsula, Bailey and Davenport 1972) to extents reaching regional scales and beyond (e.g., UME of auks from Scotland to England, Underwood and Stowe 1984). We tested for spatial connectivity amongst UMEs identified at the survey (i.e. beach*month) level by creating contiguous chains of UMEs through space (i.e. a survey beach immediately north or south of an identified UME) or time (i.e. a month immediately before or after; Figure 3). For each identified UME survey, we systematically searched all contiguous beach*month combinations, linking all adjacent UMEs into clusters. Thus, a cluster could be composed of a single beach*month, or a series of beach*months stretching over one to several beaches and one to several months. For all clusters, we counted the spatial links across contiguous beaches. For instance, a cluster spread over two beaches and occurring in the same month would have a link count of one; whereas a UME occurring on the same beach over two months would have a link count of zero. To understand the degree to which UMEs were clustered across space, we created cluster-specific nulls by randomly sorting all beach*month UME surveys within the temporal window specific to the month(s) they occurred in (i.e., number of contiguous months over which the cluster occurred), and extended across all 34 beaches. We then recalculated spatial link counts. To evaluate the degree of dispersion across space, we calculated the number of clusters observed within three-month moving windows. Three-month windows allowed the potential of observing clusters that are linked across time and space that may not be captured if counting clusters within a single month. We created probability distributions for the number of spatial links and clusters created by random chance after 1000 resorting permutations. Figure 3 portrays a single version of these techniques assessing spatial aggregation and dispersion, specific to a seven month temporal window and assuming complete spatial coverage (i.e., no missed surveys). We evaluated the percentage of times the observed spatial links and number of clusters occurred by random chance. The lower the percentage, the more likely the observed event was spatially aggregated or over-dispersed in space.

Results

Over the 3,673 surveys performed by COASST volunteers, carcass encounter rate varied widely both geographically and seasonally; however, average encounter rate was consistently highest in the fall (i.e. September, October, and November) across all three regions (Figure 4, Table 2). The relative count of UME events also varied by region and season, and with no consistent signal. Winter was the only season that did not have a peak in relative UMEs for any region.

UMEs also ranged widely in encounter rate, from 122.5 carcasses per kilometer (196 carcasses, September 2009 in northern Washington) down to only 0.667 carcasses per kilometer (1 carcass, 7 surveys in southern Washington), reflecting the methodological approach of identifying UMEs as a function of the regional monthly baseline adapted to beach (Figure 5). In fact, 45.5% of all identified UMEs recorded five carcasses per kilometer or less (n=75 UMEs; 98.7% in the Washington regions). These events were identified on beaches with a month-specific baseline signal of ≤2 carcasses per km (n=12 beaches with low encounter rate UME events). Despite their frequency in the UME dataset, carcasses recorded in low encounter rate UME events (n=249 carcasses) comprised only 9.64% of the total carcass count across all UMEs. Low encounter rate events also tended to be isolated in time and space (i.e. occurred in one month with no other UMEs identified in adjacent beaches), accounting for 59% of all 83 isolated UME events (n=49 UMEs).

To explore whether our definition of UME events using encounter rate could be supported by data on the carcasses involved, we examined whether other characteristics assorted statistically according to “UME” versus “baseline” surveys. We focused on characteristics collected at the carcass scale, including location relative to the waterline and intactness; and at the survey scale, including species composition. We hypothesized that UME events may have higher proportions of carcasses found in the surf zone (i.e. the wetted area demarcating the extent of the last tide) and more fully intact carcasses relative to baseline surveys. When carcasses of all UME events were grouped together, UMEs had a significantly higher proportion of intact carcasses relative to baseline surveys across all regions (Table 3). Carcass location was also significantly different between UME and baseline surveys, albeit not as we initially hypothesized. Across the entire dataset, UME surveys had significantly more carcasses recorded in the wrack zone (i.e. area demarcated by successive tide lines of flotsam) than baseline surveys for all regions. Contrary to our hypothesis, there were consistently fewer carcasses observed in the surf zone for UME events in all regions. When ranges of encounter rate baseline and UME events were assessed separately (i.e. low encounter rate UMEs: ≤5 carcasses per kilometer, high encounter rate UMEs: >5 carcasses per kilometer, and mass mortality events: >10 carcasses per kilometer), there were no consistent wrack or intact signals across regions (Table 4). In northern Washington, we found a strong signal of higher proportions of fully intact carcasses and carcasses found in the surf zone in high encounter rate UME events. This signal supports our initial hypotheses because this region included the two highest encounter rate events observed in this data set (46.5 and 122.5 carcasses per km). These events likely drove the significance in these signals because of the influx of many carcasses beaching all at once and continuously.

To explore the species composition of baseline and UME surveys, we conducted Principal Coordinate Analyses (PCoA). We restricted these analyses to surveys with at least five carcasses identified to species to accurately portray species communities for each survey, decreasing our sample sizes to 707 baseline surveys and 104 UME surveys. When baseline and UMEs were ordinated together, 10.5% of the variation in species composition across baseline and UME surveys was explained in the first two axes, and 13.4% of the variation was explained in the first three axes of the ordination (Figure 6). Common Murres (r^2=0.74) and Northern Fulmars *Fulmarus glacialis* (r^2=0.72) dominated the first axis (7.1% explained variation). The second axis (3.3% explained variation) was defined by murres and fulmars versus other species, predominantly large immature gulls *Larus spp.* (r^2=0.55; Figure 6). The third axis (2.9% explained variation) was driven by large immature gulls (r^2=0.61), Rhinoceros Auklets *Cerorhinca monocerata* (r^2=0.50), and Common Murres (r^2= 0.24). Using the Kolmogorov-Smirnov test (Young 1977), we tested whether there was a difference in the frequency distributions of baseline and UME points across each of the first three PCoA axes. Of these, only a significant difference was detected for the third axis, suggesting that UMEs had fewer gulls and more Rhinoceros Auklets than baseline surveys (D=0.219, p=0.0003, Figure 7).

Because baseline surveys comprised the vast majority of the total dataset in our initial ordination (87.2%), we conducted secondary PCoAs solely focused on UME events. We restricted the dataset to carcasses identified to species, including large immature gulls (Figure 8). When confined to UMEs only, the ordination explained more than twice the variation of the previous PCoA (e.g., Figure 6). The first two axes explained 27.3% of the variation, and the third axis added 7.4%, suggesting that UMEs were consistently more species-specific than baseline surveys. As in the larger baseline-inclusive PCoA, the first axis (16% of the variation in the dataset) was heavily influenced by Common Murres (r^2=0.60) and Northern Fulmars (r^2=0.81).

To explore temporal patterns, we visually coded the data according to month (Figure 8). In the Pacific Northwest, Common Murres regularly experience heightened mortality during the post-breeding season from May to October (Manuwal et al. 2010). We found that the majority of UMEs from August to October were predominantly murres (69.3% of 49 COMU events in August-October). Within this system, Northern Fulmars migrate south from breeding colonies in Alaska to the coasts of Washington and Oregon to overwinter, and have been observed to remain in the area as long as through March (Hatch et al. 2010). In our dataset, the majority of UME events involving fulmars were observed from October to April (66.7%, n=30 total NOFU UMEs). The second axis (11.3% of the variation) separated murres and fulmars as a group from the true puffins: Rhinoceros Auklet *Cerorhinca monocerata* (r^2=0.87), Tufted Puffins *Fratercula cirrhata* (r^2=0.50), and Horned Puffins *Fratercula corniculata* (r^2=0.33). These UMEs occurred in the early to mid-spring when these species are typically migrating north to breed (Wilson and Manuwal 1986). The third axis was driven by the presence of Rhinoceros Auklets (r^2=0.70), Surf Scoters *Melanitta perspicillata* (r^2=0.60), Tufted Puffins (r^2=0.48), White-winged Scoters *Melanitta deglandi* (r^2=0.47), and Northern Fulmars (r^2=0.31, Figure 9). The Surf and White-winged Scoter eigenvectors corresponded with a series of UME points that occurred in September and October of 2009.

Overall, the vast majority of UMEs were not spatially aggregated or over-dispersed in space. The spatial analysis resulted in 111 clusters, where 50.3% (n=83 UMEs) were isolates, occurring on a single month and beach. Only one cluster of UME surveys observed across seven beaches (i.e. 6 links, over 2 months) was more concentrated in space than predicted by chance (i.e. never occurred within the 1000 permutations, Figure 10, Table 5). This cluster corresponds to the scoter UME that occurred in September-October 2009 as a result of a bloom of the dinoflagellate *Akashiwo sanguinea* (Phillips et al. 2011). The two clusters that were identified as significantly concentrated under the spatial aggregation analysis (p=0.01-0.05) both involved three beaches and occurred over 3 months. These events documented contiguous UMEs that moved northwards each month. The other four clusters that occurred in 6 to 10% of the random permutations represented UMEs that occurred across two beaches, with varying temporal windows. The contrasting condition to aggregated UMEs was a spatially dispersed UME represented by a series of 20 UME events detected in January through March 2012. Although many UMEs were recorded in this temporal window, the spatial dispersion of these events was observed by random chance in 30.5% of the 1000 permutations. In fact, most potentially dispersed events were observed by random chance (n=10 temporal windows with ≥10 UME events identified across 34 beaches, p=0.12-0.98). The cluster counting method identified the particularly clustered UMEs as occurring outside of random chance (Table 4).

Discussion

Worldwide, beached bird patterns are primarily driven by the natural history and phenology of common species in the system (Camphuysen et al. 1999, Roletto et al. 2003) and our study supported this pattern (Figure 4; Figure 5; Figure 7). Two modes were observed in long-term baseline encounter rate patterns, particularly in southern Washington and northern Oregon. The first mode occurred in September, which can be attributed to post-breeding mortality of Common Murres. The second mode, that was less prominent in northern Washington, was in November when Northern Fulmars arrive in the area to begin overwintering. Many high encounter rate UMEs in this study were exaggerations of these modes (17.8% of

UMEs with >5 carcasses per km were observed in September and November). In particular, 34 UME events were characterized by increased mortality of adult and young-of-the-year Common Murres during the post-breeding season (Manuwal et al. 2001), followed by increase of Northern Fulmar carcasses in the late fall/early winter, after these birds have migrated to their overwintering areas (Hatch 2010). The preponderance of "right species, right time" UMEs indicate that UMEs may be predictable in time and species involved because they align with the phenology of predominant species in a system. Camphuysen et al. (1999) noted that the life histories of certain seabirds make them susceptible to expiring and beaching at certain times of the year. This includes, but is not limited to, migratory species being exposed to severe winter weather in overwintering areas, post-breeding mortality of local breeders and first-year fledglings, and compounding factors that may impact birds in particular areas (i.e. combinations of severe wind activity and food shortages, Camphuysen et al. 2002, Tranquilla et al. 2010). Species and groups of species may also experience differential vulnerability to certain causes of UMEs such as oil spills and harmful algal blooms, dependent on their exposure, molt timing and foraging behavior among other characteristics (King and Sanger 1979).

However, we also discovered anomalously high encounter rate events that did not fit these natural and life history-driven patterns. In particular, our analysis also highlighted common species deposited in higher than expected numbers during unexpected times of year, as well as uncommon species deposited in extreme UME events during phenologically appropriate times of year. For common birds, expiring and beaching during the spring would be unexpected, because typically conditions are opportune to support adult survival and, ultimately, breeding behavior (Erikstad et al. 1998). For uncommon species that are typically observed in the environment as live bird assemblages, depositing on beaches in larger numbers than expected for known (i.e. oil spill, Greenwood et al. 1971) or unknown reasons (Ryan et al. 1989) would be considered UMEs of the "wrong species, right time." Common species beaching at heightened numbers at the "wrong" time may indicate system-wide ecosystem stress, as was the case in 2005, when anomalous die-offs of Rhinoceros Auklets and other species followed a delay in upwelling and resulting change in prey availability off the coast of Monterey Bay, California (Parrish et al. 2007). In two separate years (2006 and 2012), UMEs consisting primarily of true puffins (i.e. Rhinoceros Auklets, Horned and Tufted Puffins) were observed from March to April (n=19 UMEs). Although these three species are typically observed in Washington and Oregon in the spring (Wilson and Manuwal 1986, Piatt and Kitaysky 2002), they comprised only 1.8% of all carcasses recorded in March and April on average. However, in March and April of 2006 and 2012, these three species comprised 67.0% of the carcasses observed in high encounter rate surveys (>5 carcasses per km, n=4 surveys). We also observed UMEs of Common Murres in May and June of 2005 and 2012 (n=7), and of Northern Fulmars in April and May in 2008 (n=5). Overall, the "right species, wrong time" pattern constituted just under a third (29.8%) of all identified UMEs (n=31), and 13.3% of all high encounter rate wrecks (i.e. >5 carcasses per km, n=12).

The "wrong species, right time" pattern was the weakest in terms of number of high encounter rate wreck events (only five such beach*months, or 5.6% of the total number of UMEs with >5 carcasses per km), but one of the strongest in terms of intensity (16.4 to 122.5 carcasses/km observed). An anomalous cluster of UMEs consisting predominantly of scoters (*Melanitta spp.*) was observed along the Washington coast in September and October 2009. Scoters are rarely observed in COASST surveys (3.37% of all carcasses, N=59,065 carcasses, www.coasst.org), and are observed in the fall when migrating birds arrive from breeding habitats in the boreal north (De La Cruz et al. 2009). During the 2009 event, up to 180 Surf *Melanitta perspicillata* and White-winged Scoter *Melanitta deglandi* carcasses were found on a single beach (three orders of magnitude above normal for this taxon group). Five surveys were recorded as high encounter rate wrecks (>5 carcasses per km) and scoters comprised 65.8-92.3% of all carcasses found within these surveys. High encounter rate events that are spatially aggregated may imply a local forcing factor, or a single mortality source wholly restricted within the spatial extent of the study system, such as the *Akashiwo sanguinea* harmful algal bloom of 2009 (Phillips et al. 2011).

In addition to ease of detection through statistical methods, high encounter rate events had emergent signals that differentiated them from both baseline surveys and low encounter rate UMEs. For northern Washington, we found that high encounter rate wreck events consistently had more intact carcasses and carcasses in the surf zone relative to baseline surveys (Table 4). This signal may be unique to this region because it contained the overall highest encounter rate UME events (September 2009, up to 122.5 carcasses per km observed). During this event, hundreds of birds were impacted by the harmful algal bloom and many carcasses may have been washing ashore continuously during the survey period, lending to heightened proportions of intact carcasses and carcasses found in the surf zone. In both northern Washington and Oregon, there was a consistent signal of carcasses found in the wrack zone despite the number of carcasses involved (≤5 to >10 carcasses per km). This may indicate that UMEs in general had higher proportions of carcasses that were found in the latest tide more so than in baseline surveys, potentially signaling simultaneous deposition. Higher proportions of intact carcasses and carcasses in the wrack zone were consistently observed in UME surveys across all regions when all of the data were included (Table 3).

The fourth pattern revealed in our analysis consisted of low encounter rate events which, while statistically detectable, would likely not draw public or resource management attention due to their low carcass count and dispersion across the study area. In total, 45.5% of anomalous events could be characterized as low UMEs (≤5 carcasses per km). The vast majority of these low UMEs were identified in sequential iterations (78.7%), but still exhibited characteristics unique to UME events (i.e. heightened proportion of carcasses in the wrack zone, Table 4). Monitoring the frequency of these types of anomalous events is essential to evaluate whether the baseline of carcass encounter rate is increasing and/or if there are particular years with higher than expected deposition across multiple sites. In particular, low encounter rate highly dispersed UMEs may be the result of a geographically expansive forcing factor such as a strong El Niño (Hodder and Graybill 1985), or prolonged storm conditions (Underwood and Stowe 1984). If the baseline for carcass encounter rate is indeed increasing, low encounter rate events would be numerous and pervasive in more recent years, a pattern that did not emerge in this study. Future research with a longer term dataset can be conducted to explore characteristics of low encounter rate UMEs to evaluate whether they are indeed providing insight to unusual mortality patterns or are a result of the statistical method.

Mass mortality events garner public and scientific attention (Fey et al. 2015) in part because they are particularly catastrophic and often affiliated with a specific causality. However, we found that more than 45.5% of statistically anomalous events in our study system are low encounter rate UMEs that were often dispersed single events that would not necessarily draw attention to particular stressors or a changing ecosystem. Our study provides methods to create regionally-specific seasonal patterns that inform beach-specific baselines, and further permits the exploration of those intensity signals in taxonomic, spatial and temporal dimensions. In summary, we find that anomalous events can, and should, be characterized in many ways.

Our study revealed that baselines can have unique seasonal patterns on a regional- and site-specific scale. Since they are not static, many years must be incorporated to create reliable baselines because they can be influenced by oceanographic conditions (i.e. El Nino and Pacific Decadal Oscillation; Dayton et al. 1998, Edwards et al. 2010), and interannual variability in seabird population dynamics (Bertram et al. 2001). Baselines provide context to define normality, monitor changes, and assess impact of certain stressors on the environment. They are necessary to reliably assess the influence of anthropogenic impact on marine ecosystems in the face of a changing environment.

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Figures

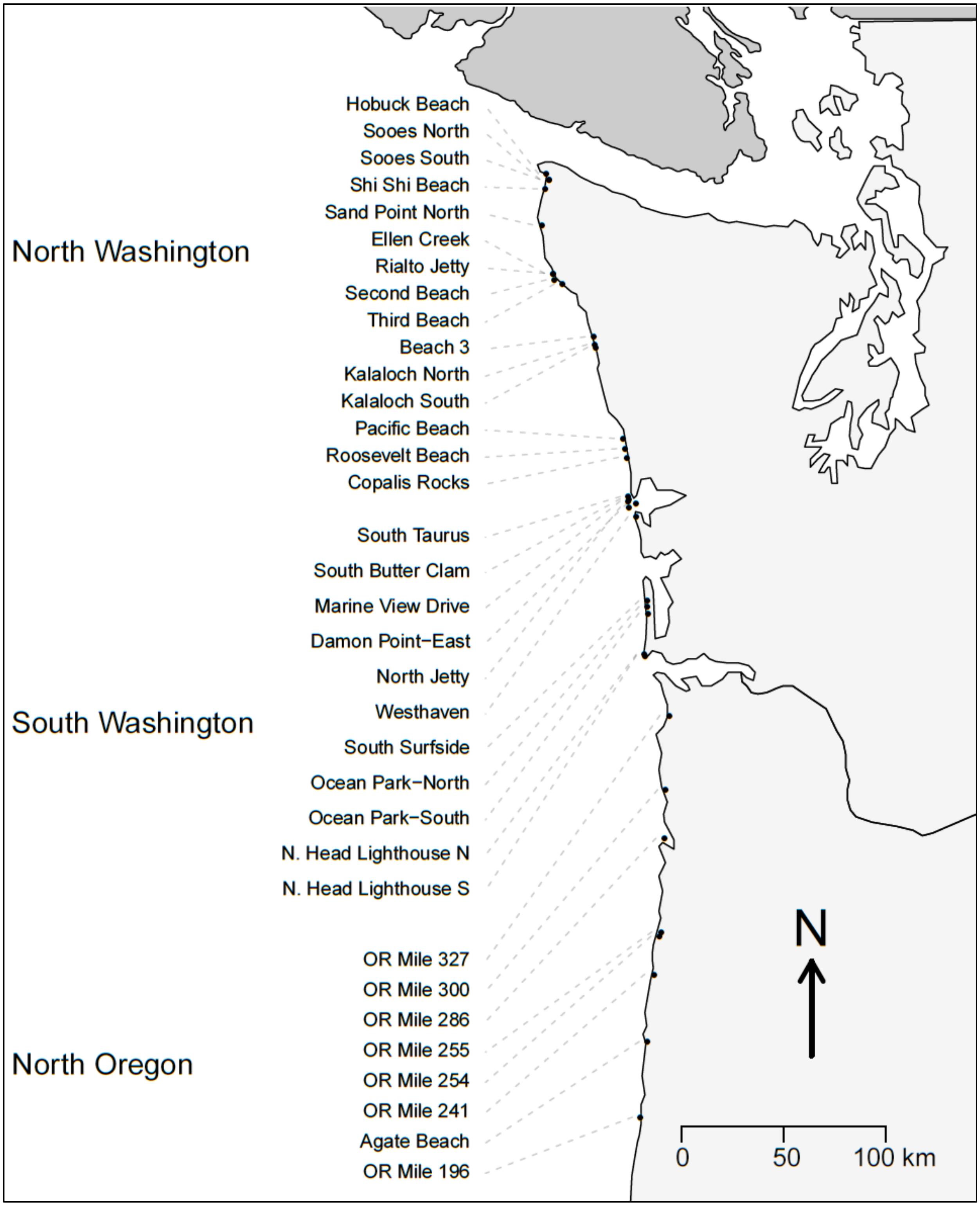

Fig. 1. Beach locations of sites selected for this study along the outer coasts of Washington and Oregon

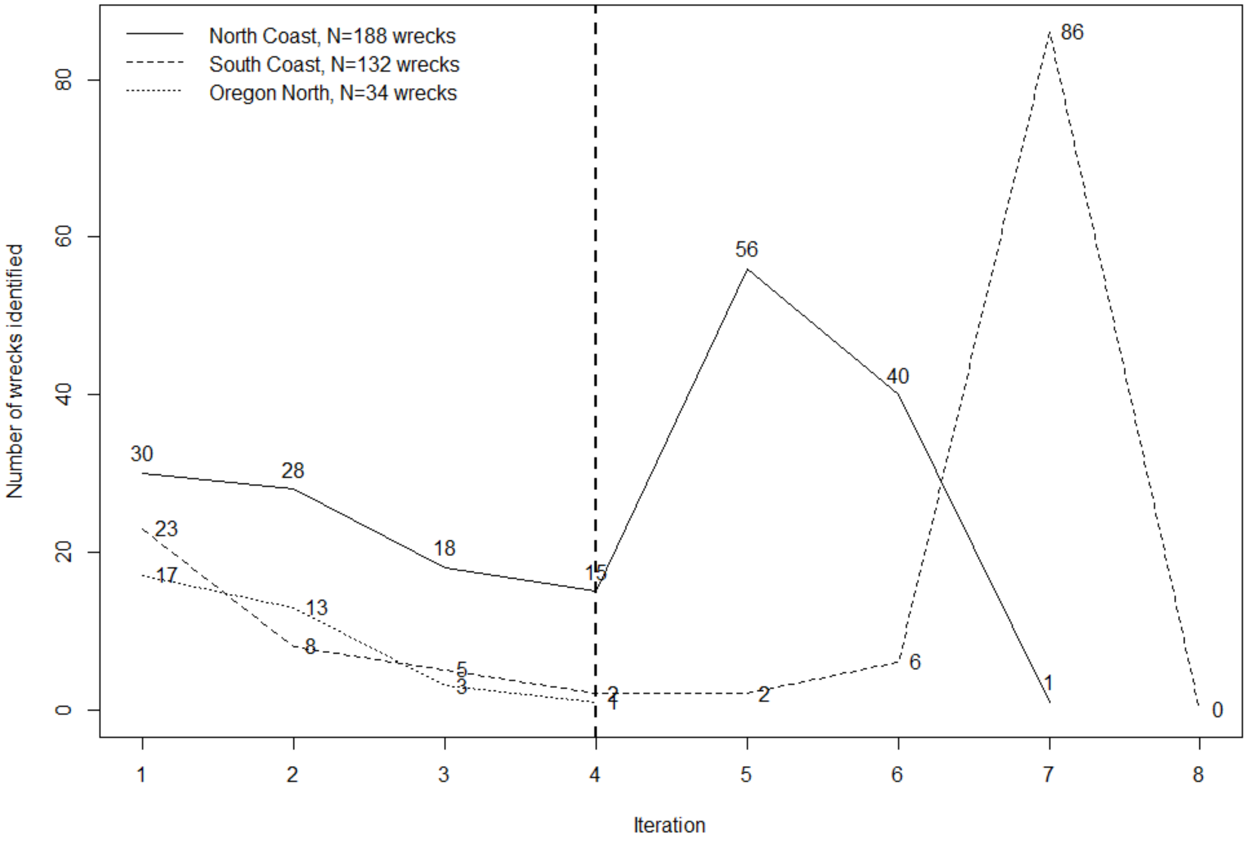

Fig. 2. Number of UMEs identified in each iteration of the iterative procedure. The threshold to discontinue the iterative process was established at the iteration with the minimum number of UMEs identified.

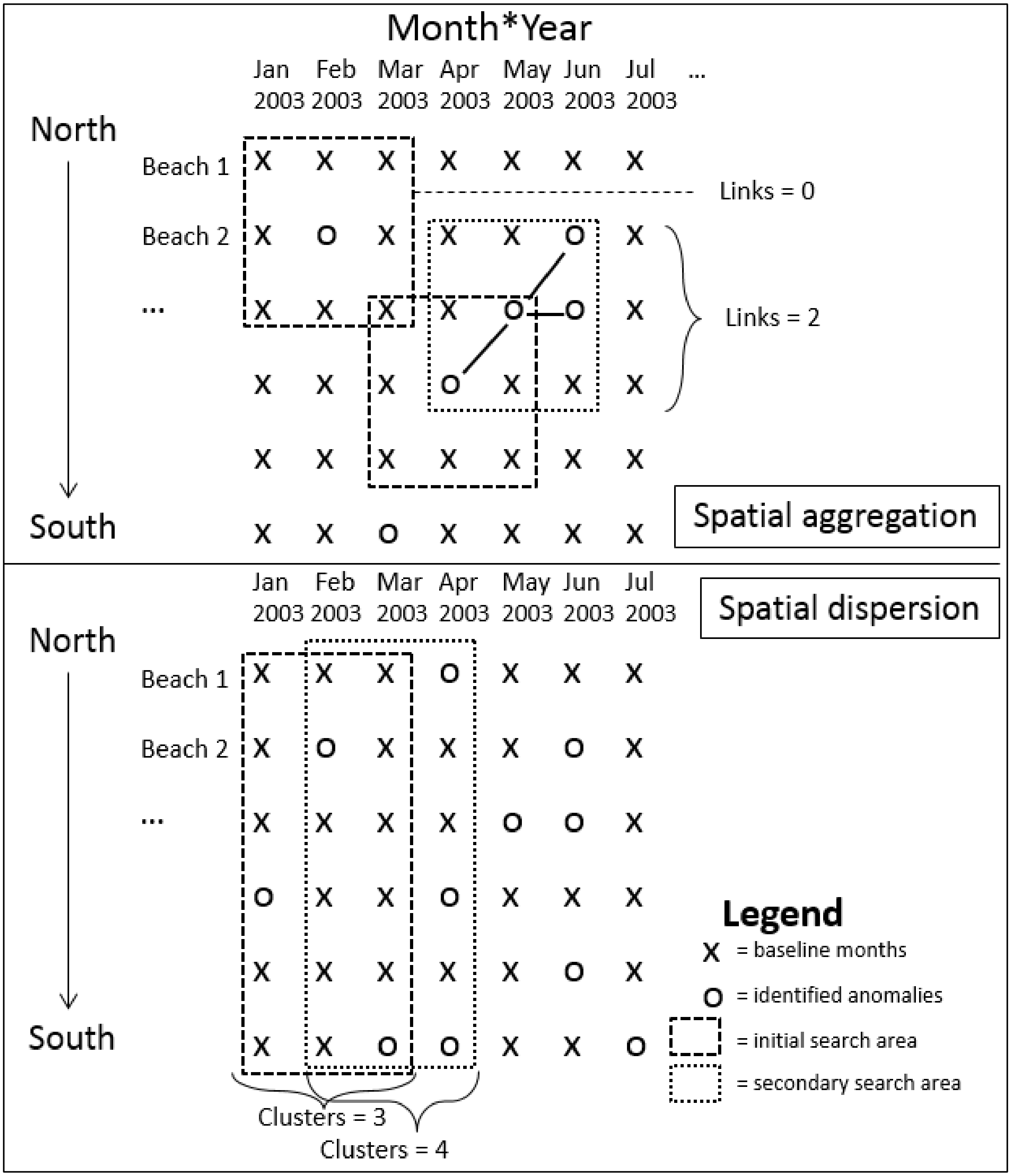

Fig. 3. Schematic of spatial linkage and cluster counting procedure. Anomalous events are considered linked if another anomaly was identified adjacent in time (i.e. previous or following month) or space (i.e. beach north or south of original location). For spatial linkage, the search window shifts to center on the newly identified anomaly to link others until no more adjacent anomalies are identified. Clusters were counted based on moving three-month windows. Anomalies outside of the window were not considered in cluster creation.

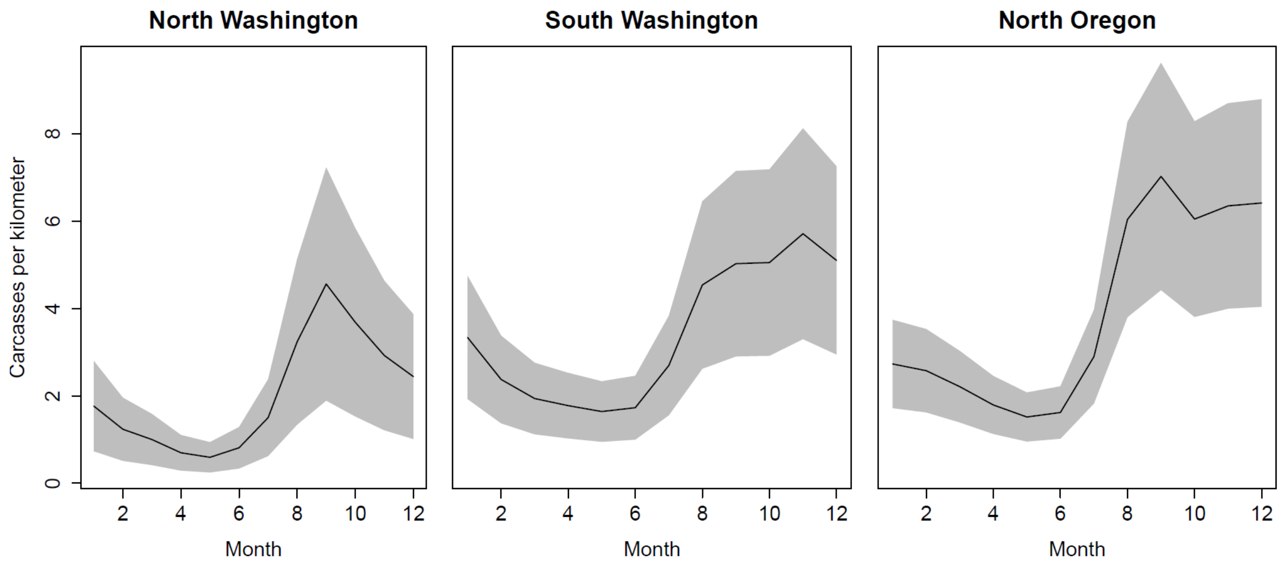

Fig. 4. Estimated monthly baselines and associated 95% confidence intervals for each region. These are the final baselines after the fourth iteration of UME identification process for all three regions.

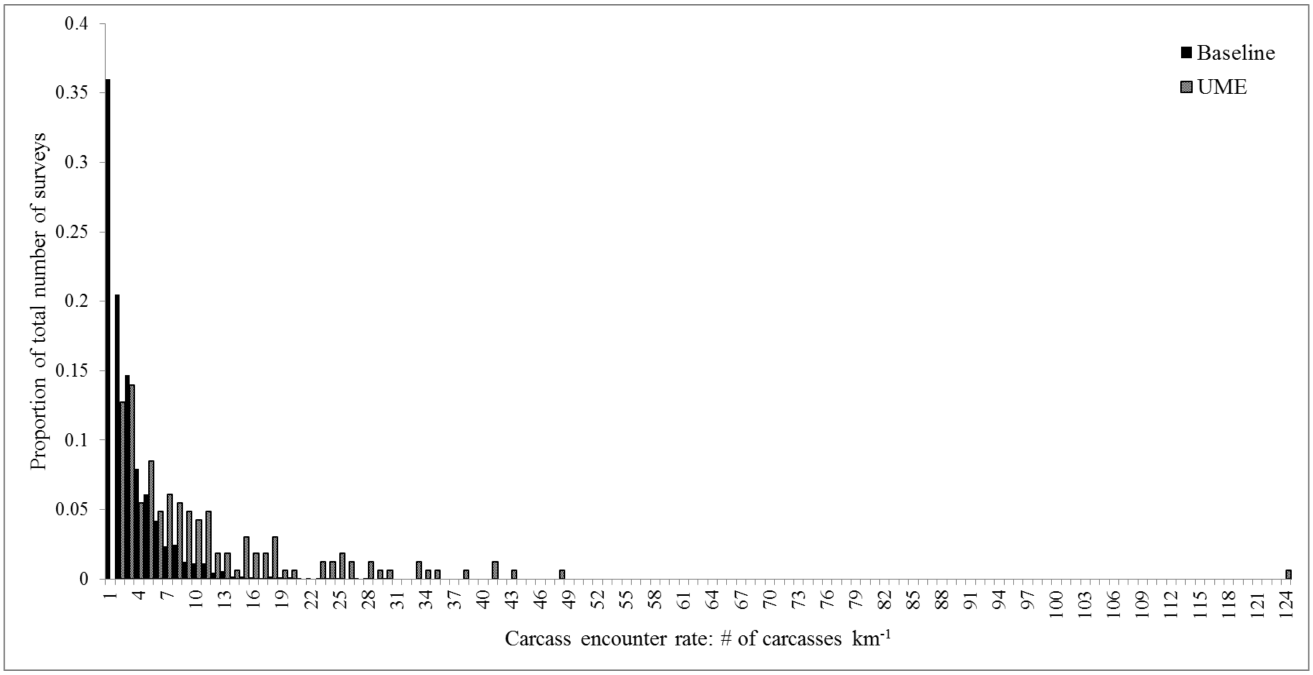

Fig. 5. Proportions of surveys with each carcass encounter rate value (rounded to the nearest integer). Dark bars represent the number of baseline surveys out of the total count of baseline surveys and shaded bars represent the proportion of UME surveys out of all UME surveys.

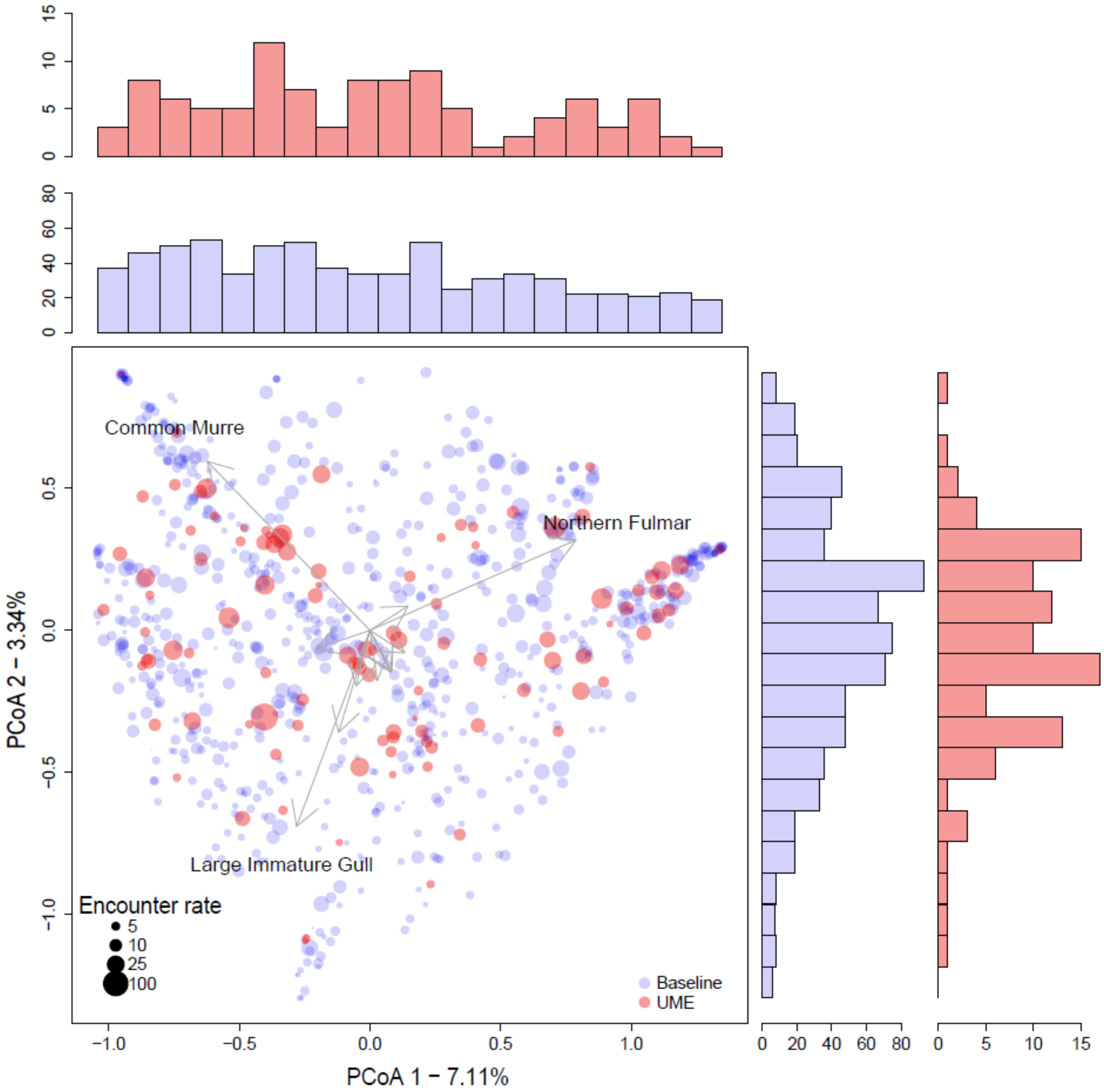

Fig. 6. Principal coordinate analysis of species composition of UME (n=104) and baseline (n=707) surveys with at least 5 carcasses observed. Significant species loadings at the alpha level of 0.001 are portrayed.

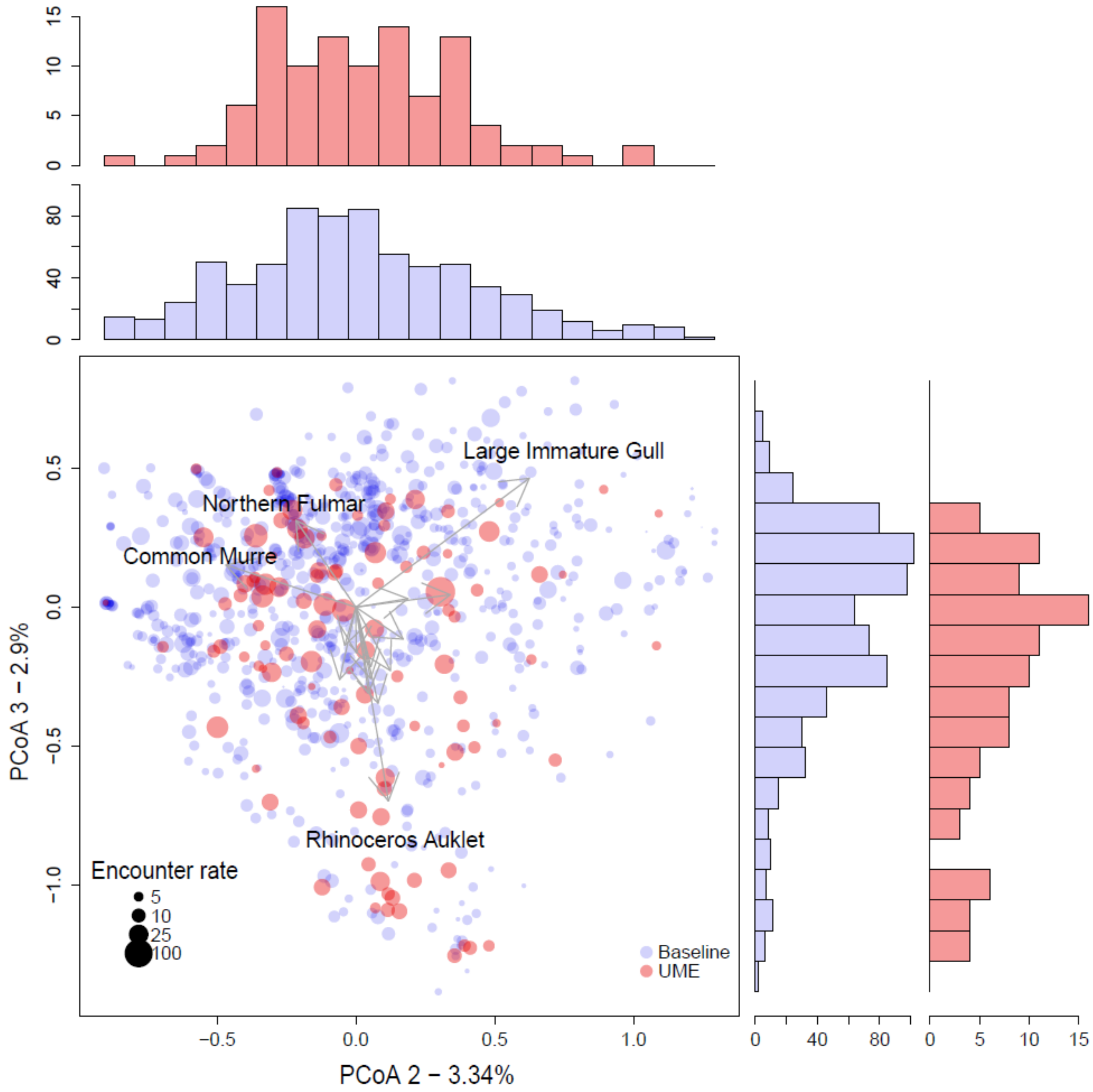

Fig. 7. Second and third PCoA axes of species composition for baseline and UME surveys. A significant difference in distributions was detected for baseline and UME surveys along the third axis. Significant species loadings at the alpha level of 0.001 are portrayed.

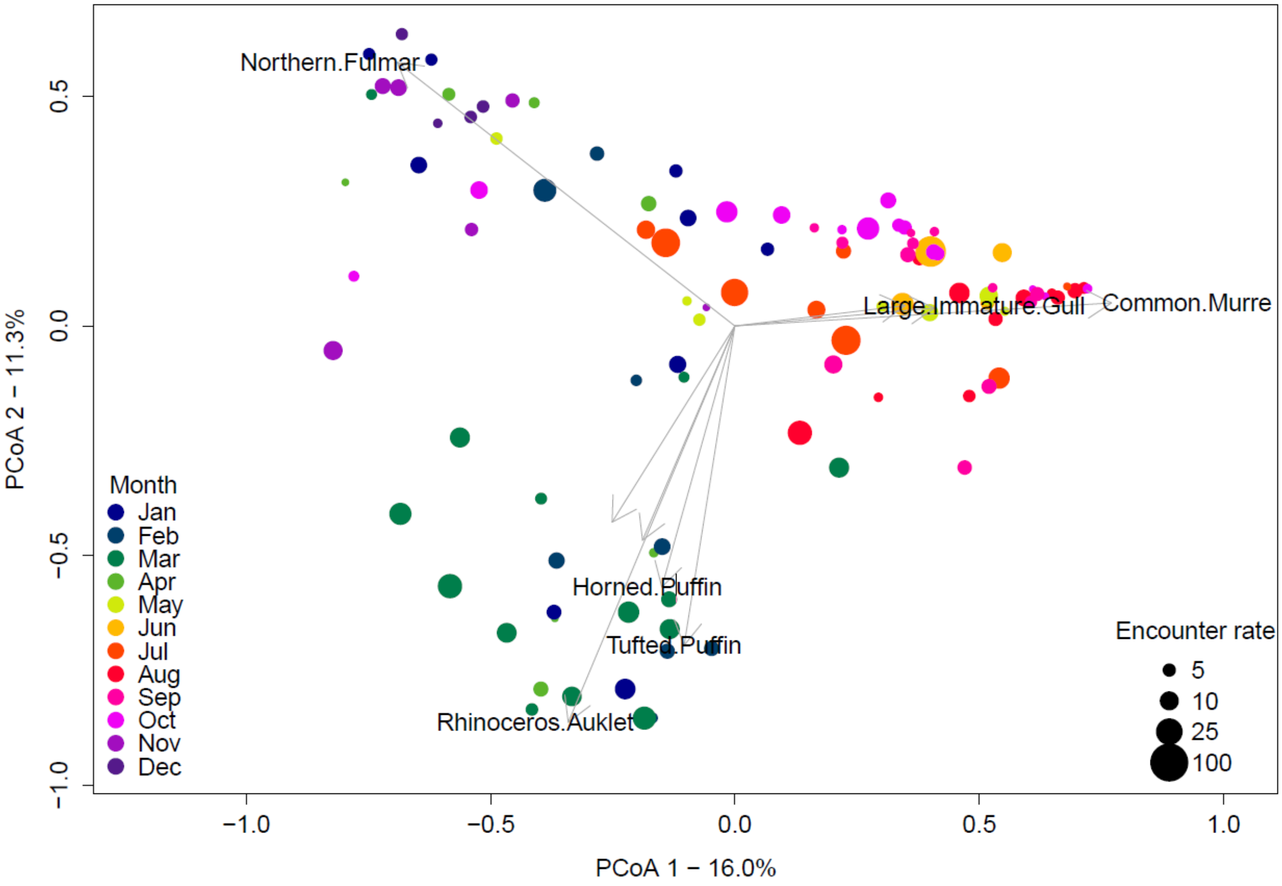

Fig. 8. PCoA ordination of species composition of surveys identified as UMEs with at least 5 carcasses observed (n=104), color coded by month. Significant species loadings at the alpha level of 0.001 are portrayed.

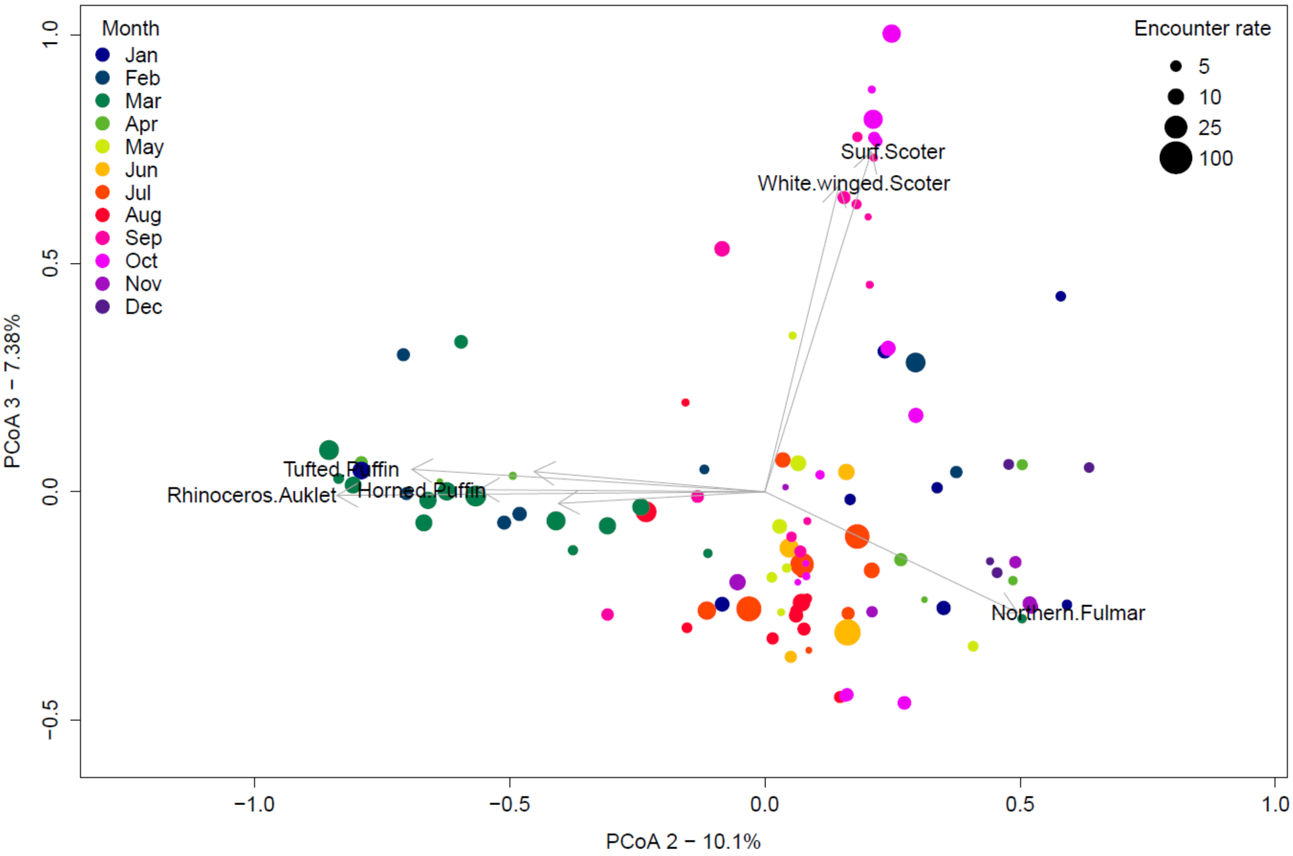

Fig. 9. Second and third PCoA axes of species composition for UME surveys with at least 5 carcasses recorded. Significant species loadings at the alpha level of 0.001 are portrayed.

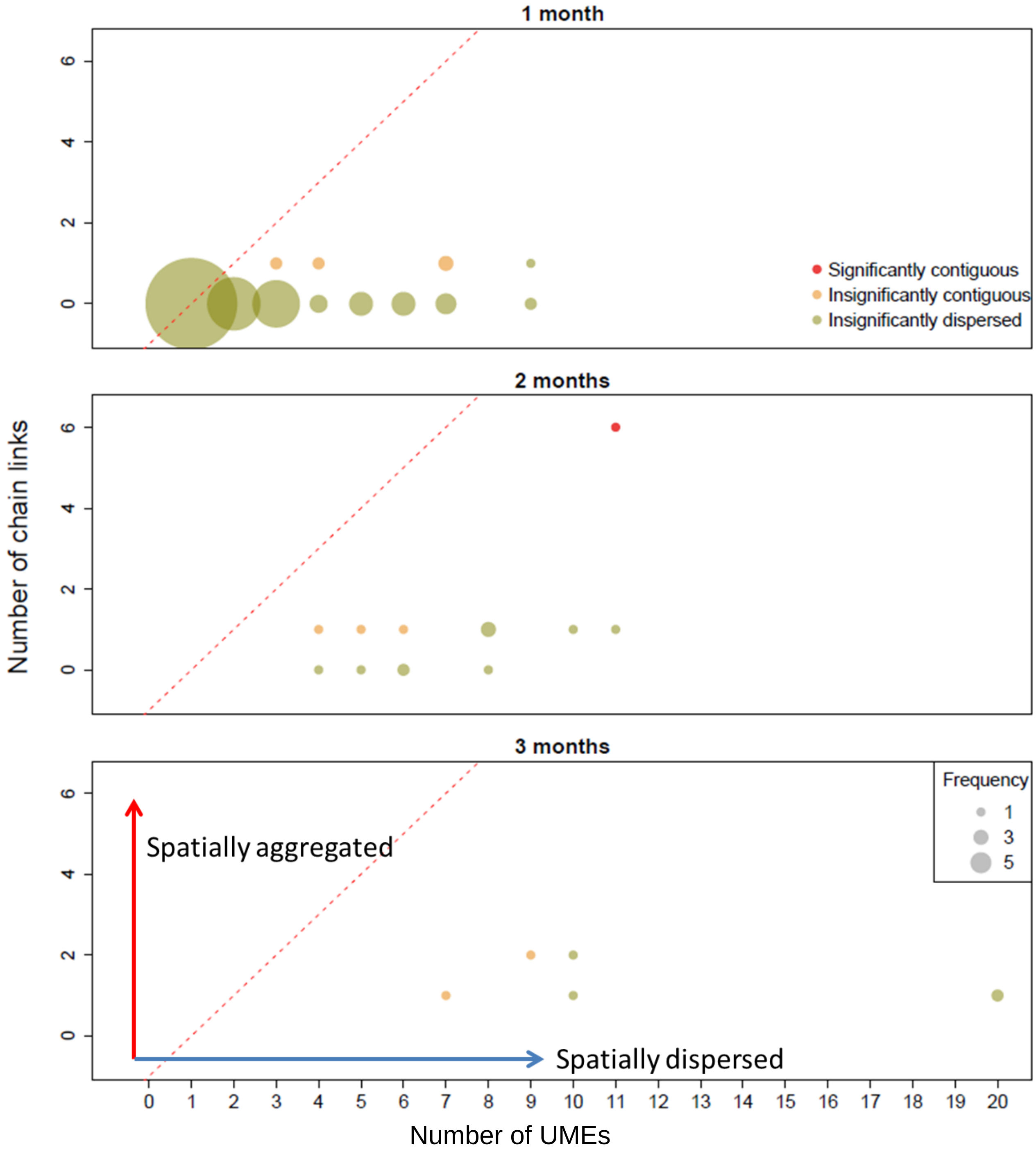

Fig. 10. The spatial chain of contiguous beaches and total number of UMEs within the temporal window was plotted for each UME cluster. The size of the bubble indicates how many UME clusters were observed with that chain length and total number of UMEs. The dotted line indicates the maximum possible chains for the number of UMEs observed (hard boundary); anything above this line is impossible.

Table 1. Comparison of UME identification by the iterative GAM approach, cross validation method, and jackknife sampling

		Cross Validation				**Jackknife sampling**	
	% data selected to train GAM	**90% data**		**95% data**		**Single point removed**	
		Not UME	**UME***	**Not UME**	**UME***	**Not UME**	**UME**
Iterative GAM procedure	**Not UME**	3582	3	3582	3	3592	1
	UME	78	87	77	88	85	80

*Surveys that were identified as UMEs at least once in all iterations

Table 2. Seasonal average and variance of encounter rate (carcasses km^{-1}), and number of UMEs identified by the iterative approach for all regions. Seasons are defined as follows: Spring=Mar, Apr, May; Summer=Jun, Jul, Aug; Fall=Sep, Oct, Nov; Winter=Dec, Jan, Feb. Seasons that had the most UMEs identified for surveys conducted were highlighted for each region

$Region$	$N_{beaches}$	Season	$N_{surveys}$	N_{UMEs}	$\frac{N_{UMEs}}{N_{surveys}}$	Average encounter rate	Variance
Washington North Coast	15	Spring	258	8	0.031	0.57	1.34
		Summer	545	29	0.053	0.83	2.49
		Fall	403	33	0.082	2.90	60.53
		Winter	381	21	0.055	1.36	7.56
		Total	***1587***	***91***			***19.02***
Washington South Coast	11	Spring	187	6	0.032	1.60	5.44
		Summer	376	19	0.051	2.41	14.38
		Fall	293	7	0.024	4.16	28.29
		Winter	290	8	0.028	2.55	12.65
		Total	***1146***	***40***			***16.77***
Oregon North Coast	8	Spring	154	15	0.097	2.39	17.62
		Summer	309	10	0.032	2.56	20.39
		Fall	241	4	0.017	3.86	14.39
		Winter	236	5	0.021	2.93	23.19
		Total	***940***	***34***			***19.36***

Table 3. Residuals of the X^2 test of homogeneity and number of carcasses observed for intactness and location found in UME and baseline surveys as identified by the iterative procedure. Highlighted cells indicate heightened proportions for identified UMEs.

Region	Characteristic	State	Baseline surveys $(n_{carcasses})$	UME surveys $(n_{carcasses})$	P-value
North Washington	Intact	No	2.270 *(2424)*	-3.972 *(647)*	$2.67e^{-19}$*
		Yes	-3.589 *(692)*	6.752 *(371)*	
	Location found	High	2.847 *(1202)*	-4.981 *(267)*	$1.03e^{-12}$*
		Wrack	-2.326 *(1702)*	4.070 *(687)*	
		Surf	0.275 *(212)*	-0.481 *(64)*	
South Washington	Intact	No	0.412 *(2814)*	-1.340 *(242)*	0.010*
		Yes	-0.659 *(1071)*	2.143 *(125)*	
	Location found	High	0.002 *(1843)*	-0.007 *(174)*	0.016*
		Wrack	-0.311 *(1754)*	1.012 *(180)*	
		Surf	0.783 *(288)*	-2.547 *(13)*	
North Oregon	Intact	No	1.749 *(3085)*	-3.491 *(655)*	$1.05e^{-20}$*
		Yes	-3.821 *(531)*	7.625 *(253)*	
	Location found	High	1.648 *(1480)*	-3.289 *(294)*	$1.34e^{-06}$*
		Wrack	-1.558 *(1927)*	3.110 *(571)*	
		Surf	0.534 *(209)*	-1.066 *(43)*	

** Indicates statistical significance at theα level of 0.01.*

Table 4. Results of Chi-square tests of homogeneity for intactness and recorded carcass location for baseline and UME events with (1) ≤5 carcasses/km, (2) >5 carcasses/km, and (3) ≥10 carcasses/km. Highlighted cells indicate heightened proportions for identified UMEs

			Low encounter rate (≤5 carcasses/km)			High encounter rate (>5 carcasses/km)			Mass mortality (≥ 10 carcasses/km)		
Region	Characteristic	State	Baseline months ($n_{carcasses}$)	Wreck months ($n_{carcasses}$)	P value	Baseline months ($n_{carcasses}$)	Wreck months ($n_{carcasses}$)	P value	Baseline months ($n_{carcasses}$)	Wreck months ($n_{carcasses}$)	P value
North WA	Intact	No	0.297 *(1611)*	0.687 *(471)*	0.119	2.486 *(813)*	-2.816 *(513)*	1.07e^{-11}*	3.810 *(347)*	-1.047 *(286)*	1.40e^{-16}*
		Yes	-0.583 *(648)*	-1.303 *(112)*		-3.789 *(253)*	4.29 *(318)*		-4.885 *(108)*	1.791 *(277)*	
	Location found	High	0.294 *(1170)*	-0.657 *(222)*	0.007*	1.635 *(296)*	-1.852 *(183)*	7.70e^{-05}*	1.852 *(101)*	-1.665 *(87)*	6.66e^{-06}*
		Wrack	-0.633 *(1535)*	1.415 *(337)*		-0.425 *(743)*	0.482 *(600)*		-0.135 *(347)*	0.121 *(435)*	
		Surf	1.074 *(210)*	-2.402 *(24)*		-2.333 *(27)*	2.642 *(48)*		-3.121 *(7)*	2.805 *(41)*	
South WA	Intact	No	0.083 *(2722)*	-0.314 *(184)*	0.579	-0.090 *(1361)*	0.234 *(206)*	0.72	-0.400 *(552)*	0.875 *(127)*	0.166
		Yes	-0.137 *(987)*	0.520 *(73)*		0.122 *(746)*	-0.317 *(107)*		0.459 *(437)*	-1.002 *(80)*	
	Location found	High	-0.348 *(1765)*	-2.561 *(158)*	0.059	-0.453 *(891)*	1.175 *(148)*	0.005*	-0.126 *(387)*	0.275 *(84)*	0.001*
		Wrack	0.174 *(1668)*	-0.661 *(108)*		0.015 *(1054)*	-0.040 *(156)*		-0.433 *(516)*	0.946 *(120)*	
		Surf	0.464 *(276)*	-1.762 *(11)*		1.075 *(162)*	-2.789 *(9)*		1.446 *(86)*	-3.160 *(3)*	
North OR	Intact	No	0.658 *(3003)*	-1.790 *(365)*	2.54e^{-06}*	1.940 *(1594)*	-2.809 *(649)*	1.79e^{-14}*	1.112 *(563)*	-1.047 *(580)*	0.003*
		Yes	-1.509 *(528)*	4.106 *(112)*		-3.933 *(294)*	5.693 *(252)*		-1.901 *(158)*	1.791 *(233)*	
	Location found	High	0.941 *(1469)*	-2.561 *(158)*	6.24e^{-06}*	1.277 *(706)*	-1.848 *(288)*	0.014	1.091 *(260)*	-1.027 *(257)*	0.144
		Wrack	-1.096 *(1856)*	2.982 *(305)*		-1.046 *(1088)*	1.514 *(571)*		-0.629 *(436)*	0.592 *(520)*	
		Surf	0.875 *(206)*	-2.381 *(14)*		0.202 *(94)*	-0.292 *(42)*		-0.686 *(25)*	0.646 *(36)*	

Table 5. Results of testing spatial linkages of clusters, and cluster counts of temporal windows against random permutations of identified anomalous events. Observed number of links and clusters that did not frequently occur by random chance (i.e. <0.01-0.1 times of 1000 permutations) are reported

	Spatial aggregation	Dispersion across temporal windows	
	Number of clusters	Number of temporal windows	
Proportion of occurrence by random chance	Links$_{obs}$ > Links$_{exp}$	Clusters$_{obs}$ < Clusters$_{exp}$	Clusters$_{obs}$ > Clusters$_{exp}$
<0.01	1	2	0
0.01-0.05	2	1	0
0.06-0.1	4	1	0
	More aggregated than by random chance		*More dispersed than random*