Using satellite-tag locations to improve acoustic detection data for endangered killer whales near a U.S. Navy Training Range in Washington State

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14. ABSTRACT
In this analysis, we integrate limited acoustic detections over a 7-year period with two other data sources: opportunistic visual sightings, and output from a state-space movement model fit to the locations from a single satellite-tagged individual. We illustrate a case study with an application to endangered Southern Resident killer whales, where the focus is understanding the coastal habitat use of this population in winter and spring months. Predictions from our state-space movement model suggest in winter of 2014, SRKWs spent the highest density of time located off the Columbia River and near Westport. Other areas with concentrated effort included off the Olympic Peninsula in Washington State, and near the Mad and Eel rivers in Northern California. Our estimated rates of travel for these whales was 6.27km/ hour (95% CIs = 0.88, 19.47), and we found no evidence for changes in travel speed as a function of latitude or longitude.

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Executive Summary

1. The use of acoustic data to estimate habitat use, and quantify anthropogenic impacts to populations have increased rapidly in ecology, particularly in applications to marine mammals. In some cases, large arrays of acoustic recorders may be deployed, but in other cases, acoustic data is much more limited in space or time.

2. In this analysis, we integrate limited acoustic detections over a 7-year period with two other data sources: opportunistic visual sightings, and output from a state-space movement model fit to the locations from a single satellite-tagged individual.

3. When acoustic or any other dataset is limited by sample size, the advantage of integrating multiple data sources is improved precision of predictions. In this case, estimated rates of travel from the movement model have the effect of constraining the possible movements inferred from the acoustic detection alone.

4. We illustrate a case study with an application to endangered Southern Resident killer whales, where the focus is understanding the coastal habitat use of this population in winter and spring months. Providing better estimates of year-to-year variation will help inform future management actions, such as the extent of critical habitat designated under the US Endangered Species Act.

5. The predictions from our state-space movement model suggest that in the winter of 2014, SRKWs spent the highest density of time located off the Columbia River and near Westport. Other areas with concentrated effort included off the Olympic Peninsula in Washington State, and near the Mad and Eel rivers in Northern California. Our estimated rates of travel for these whales was 6.27km/ hour (95% CIs = 0.88, 19.47), and we found no evidence for changes in travel speed as a function of latitude or longitude.

6. The whales occurred periodically in the waters encompassed by the Navy's Northwest Training Range Complex Area W237, transiting through this area 10 times with a median speed of 6.9 km/hour, representing 11% of the time they were monitored. The whales were only documented to occur in areas W237A, B and E, which represented 30% of their total coastal range. However, they only occupied 8% of W237, and only the more shoreward portion of these areas.

7. Even if the placement of acoustic detection devices is designed to maximize detections, analyses of these types of data for animals that move rapidly over large ranges may be limited if sample sizes are small. Integrating other data sources – particularly in a Bayesian framework that allows for the inclusion of prior information – allows for estimates of detection probabilities, and improved estimates of habitat use.

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Introduction

Over the last decade, acoustic monitoring surveys have become increasingly widespread as a powerful ecological tool to quantify habitat use by terrestrial and aquatic wildlife – recent examples include applications to birds (Dawson and Efford 2009), bats (Patriquin et al. 2003), marine mammals (Moore et al. 2006), fish (Rountree et al. 2006), and frogs (MacKenzie et al. 2002). In addition to monitoring species presence or densities, acoustic monitoring also contributes to soundscape ecology, providing estimates of anthropogenic acoustic disturbances to animal populations (Oleson et al. 2009, Pijanowski 2011, Soldevilla et al. 2011, Erbe et al. 2012, Oleson and Hildebrand 2012, Gassmann et al. 2013, Trickey et al. 2015, Heble et al. 2015, Merchant et al. 2015, Rice et al. 2015).

Acoustic monitoring may be done with active or passive technology, where the latter represents silent monitoring devices (such as microphones or hydrophones). Recent technological advances in hardware has enabled large numbers of passive acoustic arrays to be deployed in terrestrial and aquatic environments (Mellinger et al. 2007, Efford et al. 2009, Blumstein et al. 2011, Oleson and Hildebrand 2012, Trickey et al. 2015, Rice et al. 2015)). These vast arrays have the ability to better understand fine scale movements and density, and recorders that overlap in space may be used to make more precise estimates of an animal's location.

Depending on the species being detected, these acoustic sensors also allow researchers to better understand distribution at the individual level. While these large acoustic arrays represent ideal scenarios, more often the number and placement of acoustic devices may be limited by research budgets or constrained by interference with commercial or military operations. In these data-limited cases, acoustic monitoring data is still a reliable tool, and the utility of these data may be improved by integrating these data with additional data sources.

As a case study of integrating multiple types of data into the analysis of passive acoustic detections, we focus on a small population of fish-eating killer whales distributed off the coast of the western USA, known as the Southern Resident Killer Whale (SRKW) population. Because of its declining trend, this population was listed under the US Endangered Species Act in 2005, and has declined further since then (78 whales at the end of 2014). To identify winter habitat and distribution of these whales in order better assess potential risk factors, passive acoustic recorders have been deployed off the coast since 2006, and data has been collected in most years since. A first challenge in assessing distribution from acoustic data alone is that the number of recorders deployed annually has typically been small (< 6). Second, the number of vocalizations recorded per year is small – in the 120 days between January 1 and May 1 for instance, SRKW have been detected on 16.5 days (Table 1). Part of the reason for the limited number of detections is that the recorders have an unknown, but limited (~8km) detection range. In addition, although resident type killer whales generally vocalize frequently, they do not vocalize all the time. Though the population size of SRKW is known exactly, an additional challenge is that unlike vocalizations from other cetaceans, vocalizations from individual killer whales are not recognizable. This latter point prohibits the use of capture-recapture or methods to estimate density (Buckland 2004, Efford et al. 2009). However, in many cases identification to each of the three pods (J, K, L) can be made acoustically for this population due to the stereotypic calls unique to each pod although in some cases each pod may split into subgroups, complicating assessment of pod movements. Detections may be limited due to ambient noise, both environmental and anthropogenic. Finally, another potential factor limiting detections is recorder placement which needs to mitigate for multiple uses of some areas relative to known whale use. This limitation, can be indirect, e.g., high anthropogenic noise associated with shipping lanes, or direct, e.g., recorder mooring loss due to interactions with commercial fishing.

Though the number of SRKW acoustic detections are limited, these data may be analyzed alongside other data sources to inform the distribution and habitat use of this population. Two other datasets that exist for SRKW are visual sightings of individuals, and a limited number of satellite tagged animals. Each individual SRKW is recognizable by photo-ID, and this knowledge of individual sighting histories has been used in previous studies to estimate demographic rates (Olesiuk et al. 1990, Ward et al. 2009, Ward et al. 2011). During the deployment of acoustic recorders since 2006, several satellite-tags have been deployed on SRKW. Some of these tags detached after 2-3 days, but the most successful of these over the winter of 2012-2013 transmitted for slightly over 3 months.

The objectives of our analysis are to illustrate the utility of passive acoustic detections, even when sample sizes are small and individuals are not distinguishable. Given the availability of other data sources, such as locations from satellite tags, we construct a state-space model of detections, equivalent to Bayesian occupancy models (Royle et al. 2005, Kery and Schaub 2012). Finally, we illustrate how the combination of movement information and acoustic detections (visual and acoustic) can be used to construct maps of habitat use when fine scale satellite locations aren't available. For species at risk, such as the SRKW used in our case study, this integrated approach has the opportunity to (1) inform precise management actions (such as designation of critical habitat) and (2) aid in the deployment of acoustic devices in future surveys.

Methods

Data

We deployed a satellite-linked tag (Wildlife Computers Spot 5) on a SRKW (adult male K25) in Puget Sound on December 29 2012. For the next 93 days, this tag transmitted to the Argos system, providing us multiple locations per day (n = 867 total locations after application of Douglas filter. (available at: http://alaska.usgs.gov/science/biology/spatial/douglas.html

Because we collected these location data in real-time, we were also able to spend 8 days (March 1 – 9) following the tagged whale (as well as the other 60 associated whales) and collecting acoustic data.

Our second dataset consists of acoustic recorders deployed off the coast of California, Oregon, and Washington. The Northwest Fisheries Science Center has been deploying autonomous passive acoustic recorders in most years since fall 2006. These recorders are programmed to record at a sample rate of 25 kHz for 30 seconds every 10 minutes (additional details in (Hanson et al. 2013)). Acoustic recorders were deployed in the fall of 2012, and five of these continued to record acoustic detections until April 2013, overlapping in time and space with the satellite detections of K25. In previous years (winters of 2007-09, 2011), data was recovered from 1 – 6 acoustic recorders (resulting in 2 to 40 days detections per year). Recovered hard drives from the acoustic recorders are manually scored, with vocalizations categorized by species. While each of the three Southern Resident pods has unique vocalizations, 2 of the 3 pods are often not differentiable (K and L pod). Because these latter groups spend more time on the outer coast and were the focus of the satellite tagging, we focused on the combined vocalizations of these groups (assuming they traveled together).

To complement the acoustic recorder data in years without satellite tagged individuals, we compiled a database of visual sightings of these Southern Resident killer whales. The number of visual sightings was smaller than acoustic detections, ranging from 6 to 11 days with detections during the January – April months (See supplemental material).

Because our modeling framework is focused on integrating the satellite-tagged locations with acoustic and visual detections, we limited our analysis to the overlap in space and time across these different datasets. Specifically, we used sightings and detections in the January – April months, and only included groups of whales that associate with the tagged whale (K and L pods, which often associate together).

Analyzing tracking data

We fit a Bayesian state-space movement model to the location data from K25 following the approach of (Jonsen et al. 2005). State-space movement models have been applied to a wide range of tracking data from terrestrial and aquatic species (Jonsen et al. 2003). One of the advantages of these methods is that they improve the precision of estimated locations (and resulting estimates of rates of travel) because they partition the total variance in the observed track into process variance (changes in speeds and turning angles) and observation variance (representing the measurement uncertainty associated with the Argos location quality of each individual location).

Like previous state-space analyses of animal movement (Jonsen et al. 2005), we conducted Bayesian estimation using the JAGS language and the R2jags package in R (Plummer 2003, R Core Development Team 2015, Su and Yajima 2015). We generated 10000 Markov Chain Monte Carlo (MCMC) samples across 4 parallel chains.

We also developed a map to assess high-usage areas in ArcGIS v. 9.2 (ESRI) using the reduced data set (i.e. using only one of each pair or trio of individuals acting in concert). All data were summarized using a vector grid composed of 5 × 5 km cells that encompassed the range of all the tracking locations. We chose grid cells of 5 × 5 km because they are large enough to account for error in Argos locations. A spatial join was used to associate locations within grid cells. Additionally, track lines were developed by connecting the locations in temporal sequence and intersecting the resulting features by the overlay grid. The density for each cell was calculated for total visit duration in each cell, with a late start (only location data were included after a duration of time sufficient for the tagged whale to reach the maximum distance from tagging location) following Baird et al. (2012).

We chose to classify cells with values that were ≥2 SD above the mean duration value as 'high-density areas'. Using the calculated durations between locations along K25's track we estimated the median days expected between detections at the 17 recorders deployed in fall 2014. The median duration within the estimated 8km recorder detection range was also calculated for each recorder site from the K25 track data.

Estimating detection probability

To estimate the detection probability of killer whales from acoustic recorders, we used the overlapping satellite tagging data and five acoustic recorders. We constructed a detection model based on the occupancy modeling framework with latent states (Royle et al. 2005, Kery and Schaub 2012). In this model,

$$y_{t,s} \sim Bernoulli(z_{t,s}p)$$
$$z_{t,s} \sim Bernoulli(\varphi_{t,s})$$

where $y_{t,s}$ represents the detection (0, 1) at time t and location s, conditional on the occurrence $z_{t,s}$ and detection probability p. The parameter $\varphi_{t,s}$ represents the probability of occupancy. The matrices y and z were dimensioned by the number of 10 minute intervals in our satellite tagging model (n = 13722 10-minute intervals) and number of recorders (n = 5). For known detections, we initialized the value of $z_{t,s}$ = 1, but treated all other values of z as latent states. Various approaches exist to model $\varphi_{t,s}$ (Royle and Dorazio 2008), and in this analysis we derived estimates of $\varphi_{t,s}$ from the state space model output (Fig. 1). Specifically, we assumed the detection radius of each recorder to be fixed at 8km, and used the estimated posterior distribution of locations at time t across all 10000 MCMC iterations to calculate the probability of being in the 8km radius of each recorder. Mathematically, this means that $\varphi_{t,s} = \frac{\sum_{i=1}^{n_{MCMC}} I_i}{n_{MCMC}}$, where the indicator function $I_i = \begin{Bmatrix} 1 \text{ if the location} < 8\text{km} \\ 0 \text{ otherwise} \end{Bmatrix}$.

In the occupancy model described above, the only estimated parameter of interest is the detection probability p, which is assumed to be constant over time and space. Variation in the ambient noise near each recorder may lead to differential detection probabilities for example. We initially constructed a model with an uninformative (uniform) prior on p. As a sensitivity analysis, we wanted to examine how more informative priors might be used to improve the precision of the estimated detection probability, as well as how estimates from passive acoustic recorders compared to estimates from other acoustic monitoring studies. We used data from two external active monitoring surveys to develop informative priors. In the first dataset, we used acoustic detections from an 8-day research cruise in March 2013 (NWFSC unpubl. data). These detections were collected from a towed acoustic array while SRKWs were being followed at a distance under 2km and resulted in 63 30-second time intervals being collected, each spaced at least 10-minutes apart (28 of these had killer whale vocalizations). For our second prior, we used similar acoustic data collected from summer research surveys (Holt et al. 2009), where 145 intervals (spaced 20-minutes apart) were collected and vocalizations were present in 128 of them. Each of these priors has associated strengths and weaknesses – for example, the Holt et al. (2012) study includes a larger sample size, but is from a different spatial area and season (inland waters in summer). Both priors was implemented using beta distributions, so that $\pi_1 \sim Beta(29, 36)$ and $\pi_2 \sim Beta(129, 18)$.

Projecting spatial distributions

For winters when resident killer whales have not been tagged, we sought to combine the results from all of the above data sources to make better predictions of coastal habitat use. Because some of the opportunistic visual sightings are from citizen scientists, the date and time and location associated with these sightings may have a high degree of uncertainty, so these data occur at a much coarser scale (daily) compared to the fine scale satellite tracking data.

To estimate a coarse daily estimate of movement from the state-space model, we first used our posterior estimates at 10-minute intervals to generate 2-dimensional kernel densities of movement, with covariance matrix Σ. Second, we summarized each of the visual and acoustic detections in these earlier years on a daily time-step, and fit a random walk model to these locations data, with the covariance matrix Σ. Mathematically, this can be described as,

$$X_{t+1,1:2} = X_{t,1:2} + \delta_t, \text{ where } \delta_t \sim MVN(0, \Sigma)$$

Because this model may also include residual error (observation error), we linked the observed locations $Y_{t+1,1:2}$ to the estimated locations with an observation model,

$$Y_{t+1,1:2} = X_{t,1:2} + \omega_t, \text{ with } \omega_t \sim MVN(0, \mathrm{R})$$

where R was designated as a diagonal matrix (with the diagonal set to 2, corresponding to the detection radius of the recorders).

We used output from this model to make predictions about the spatial distribution of animals in years without satellite tagged animals, as well as to evaluate how the frequency of acoustic detections affects the uncertainty in these estimates.

Results

Overall Coastal Distribution

The predictions from our state-space movement model suggest that in the winter of 2014, SRKWs spent the highest density of time located off the Columbia River and near Westport (Figure 2).

Other areas with concentrated effort included off the Olympic Peninsula in Washington State, and near the Mad and Eel rivers in Northern California (Figure 2). Our estimated rates of travel for these whales was 6.27km / hour (95% CIs = 0.88, 19.47), and we found no evidence for changes in travel speed as a function of latitude or longitude (additional details in the Supplementary Information).

Distribution Associated with Navy Training Areas

The whales occurred periodically in the waters encompassed by the Navy's Northwest Training Range Complex Area W237 (Figure 3), transiting through this area 10 times with a median speed of 6.9 km/hour, representing 11% of the time they were monitored.

The whales were only documented to occur in areas W237A, B and E, which represented 30% of their total coastal range.

However, they only occupied 8% of W237, and only the more shoreward portion of these areas.

Detection Probability and Future Prediction

Our estimates of killer whale detection from the autonomous passive acoustic recorders suggest that the detection probability is near 80% when an uninformative prior is used for p. Each of the two informative prior distributions were centered around the posterior from the uninformative case. The vocalization rate from the winter research cruise was less than that observed in the summer (Table 2, Figure 4). This difference may be due to different survey methodology, or differential vocalization rates in summer months when SRKW are primarily feeding on Chinook salmon (Hanson et al. 2010). As expected, including prior information from either survey also improved the precision of these estimates relative to the uninformative case (Table 2).

Our predictive maps across years suggest agreement with the distribution of Southern Residents in 2012 (Figures. 2 and 5), with a concentration of utilization near the mouth of the Columbia River and Westport. The coarseness of predictions in early years (e.g., 2007) is largely a function of the number of days with detections. For example, in 2007 SRKW were detected on only 2 days in February, but in 2009 and 2011, the detections increased to 12 and 11 days, respectively. Even with this increase in detections, the distribution of detections was still patchy (with a mean of 2.24 and 2.81 days between detections in 2009 and 2011, respectively).

To illustrate how quickly uncertainty increases as the time between acoustic detections increases, we focused on a 11-day window of April 2011. On April 9, Southern Resident killer whales were detected by the Cape Flattery acoustic recorder, and on April 19, the same whales were detected by the Westport acoustic recorder. Our daily spatial predictions of distribution during this period indicate that as expected, the locations of these animals is precisely estimated on the days of detection, but between detections uncertainty balloons as a function of time (with highest uncertainty in day 5, Figure 6).

We deployed 17 acoustic recorders in fall 2014 targeting high density use areas based on the duration of time spent by SRKW K25 (Figure 3). We estimated that the median days between potential detections along K25's track at these 17 recorders were 0.26 days. It was estimated that K25 would have spent a median of 2.2 hours each time he came within 8 km of each recorder.

Discussion

As the use of passive acoustic recorders has increased rapidly in ecology, one of the fundamental uncertainties is the acoustic detection probability (Alldredge et al. 2007). Detection is a function of several factors: the peak transmission frequency of the species of interest (Mellinger et al. 2007) , ambient noise (Clark et al. 2009), and the detection range of the instrument to the animal – but one of the most important determinants is likely the behavioral characteristics that influences the acoustic production of the focal species (Oswald et al. 2003). In other words, the use of passive acoustic recorders to quantify presence / absence or density is most effective for species that vocalize frequently, and may be uninformative for species that rarely vocalize. Based on the 4-month overlap between our satellite tag and acoustic recorder data, we estimate that fish-eating killer whales vocalize approximately 80% of the time in the vicinity of the recorders (Fig. 4). This rate of vocalization is expected to vary by species, and even ecotype – for example, marine mammal-eating killer whales likely have a different vocalization rate than fish-eating killer whales, because of different behaviors (BarrettLennard et al. 1996). For social animals, like killer whales, vocalizations are also affected by factors such as group size (Filatova et al. 2012).

We considered the inclusion of several other datasets on vocalization rates from ship-based acoustic data collection, and these data were used to construct priors in our Bayesian modeling. Ultimately we used the posterior result from an uninformative prior to generate spatial predictions because the posterior result from the uninformative case was centered between the two ship-based studies, and the data collection from ship-based platforms was potentially problematic. In each ship-based survey, acoustic data were collected for several days (generally only during daylight hours), and each 10-minute interval within this period was assumed to be independent. Extrapolating these short surveys to the much longer time scale used in our analysis (4 months) is potentially problematic, particularly if vocalization rate varies in space, or as a function of environmental conditions (such as prey). In addition, there also may be inter-annual variability in vocalization rates.

The inclusion of acoustic recorder data with other data types (satellite tracks, visual sightings) offers the opportunity to improve precision of estimates (Barlow and Taylor 2005, Akamatsu et al. 2008), and identify opportunities for improvements in future study design. Each of these data types has strengths and overall weaknesses, as well as economic costs. Although, opportunistic visual sightings can be obtained at no cost, they potentially have inaccurate spatial locations and times. Dedicated visual surveys are costly and limited in their effectiveness by short day length and inclement weather in winter. Satellite tags provide high resolution spatial information that is unbiased, but deployed tags may not remain attached on animals for more than a few weeks, and tagging small or endangered populations, such as the one included in our analysis, may be logistically challenging. Finally, although acoustic recorders have a small detection range, they possess the ability to continuously sample for large time scales (up to a year). Integrating these three types of data, our analysis highlighted that for time periods when continuous satellite tag data doesn't exist, acoustic recorders should be deployed in a manner to minimize the number of days between detections. This objective can likely be achieved by reallocating the spatial distribution of recorders to match regions of high habitat use, or by increasing the total number of recorders. We estimated that an increase in the number recorders (7 to 17), if strategically placed to coincide with areas where high use was previously observed, has the potential to allow multiple detections per day, compared to only a detection every few days when a smaller number of recorders used. This substantial level of improvement in detections would be important in allowing mitigation of operations that might impact the whales. However, it is important to note that achieving multiple detections per day is dependent of the whales vocalizing at all times which has been shown not to be the case.

An additional consideration is that these monitoring efforts are potentially constrained by factors inherent to the study area that may affect the ability to maintain a mooring at a site for an extended duration. For example, in some portions of this study area, commercial fishing activity, which has the potential to damage or free the recorder moorings is high. Despite efforts to locate recorder moorings in areas of SRKWs high habitat use while mitigating for high fishing activity (Figure 7), two recorders were prematurely released by fishing activity during the 2014-2015 deployment season. Although both were located adjacent to areas of relatively low fishing effort, these two sites represented the highest fishing effort of the 12 moorings located off the Washington coast.

The methods developed here for integrating animal tracks, acoustic recorders, and visual sightings are widely applicable to other species where acoustic data are collected in parallel with other data types. Examples include applications to other marine mammals, including other killer whale populations (resident and transient whales in the NE Pacific), pilot whales, sperm whales, or beaked whales. Our approach could also be extended to better address questions about habitat use in terrestrial species, including elephants (Thompson et al. 2010), birds (Alldredge et al. 2007), and bats(Adams et al. 2012).

Table 1. Number of acoustic detections and unique days with acoustic detections ('detection days') and visual sightings between January 1 and May 1, 2006-2013.

Data source	2006	2007	2008	2009	2011	2013
Detections	4	3	9	21	40	33
Detection days	4	3	9	21	36	26
Visual sightings (days)	8	6	10	11	7	

Table 2. Posterior distributions of the probability of Southern Resident killer whales being detected by acoustic recorders during January – April 2013. Posterior distributions also shown graphically in Figure 3.

	Lower 95%	Upper 95%	Median	Mean	SD
Uninformative	0.696	0.871	0.784	0.784	0.045
PODS cruise	0.607 (0.328)	0.732 (0.567)	0.667 (0.446)	0.667 (0.446)	0.032
Holt et al. 2012	0.796 (0.817)	0.896 (0.925)	0.850 (0.879)	0.849 (0.876)	0.026

Figure 1. Estimated density around a single recorder (in this instance, the recorder near Westport). The heat map is scaled relative to a uniform distribution of habitat use (e.g. dark red values indicate 15x higher than expected by chance). The quartered circle represents the location of the acoustic recorder – in this instance there's a 26% probability that the whale is within 8km of the recorder in a given 10-minute segment.

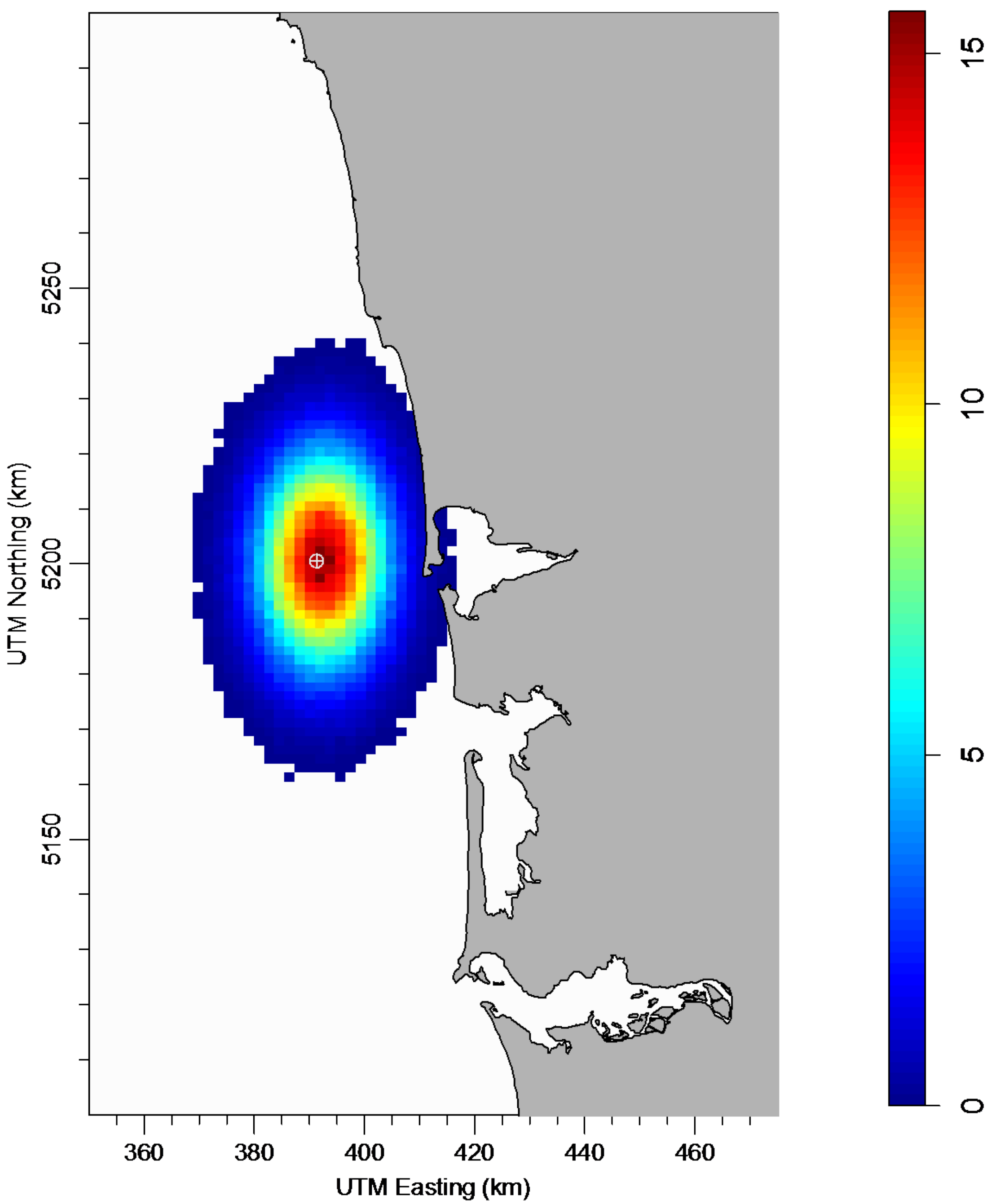


Figure 2. Estimated density for the K25 movement track using a state space movement model, with 10-minute intervals. The heat map is scaled relative to a uniform distribution of habitat use (e.g. dark red values indicate 50x higher than expected by chance). The five quartered circle symbols represent the distribution of acoustic recorders.

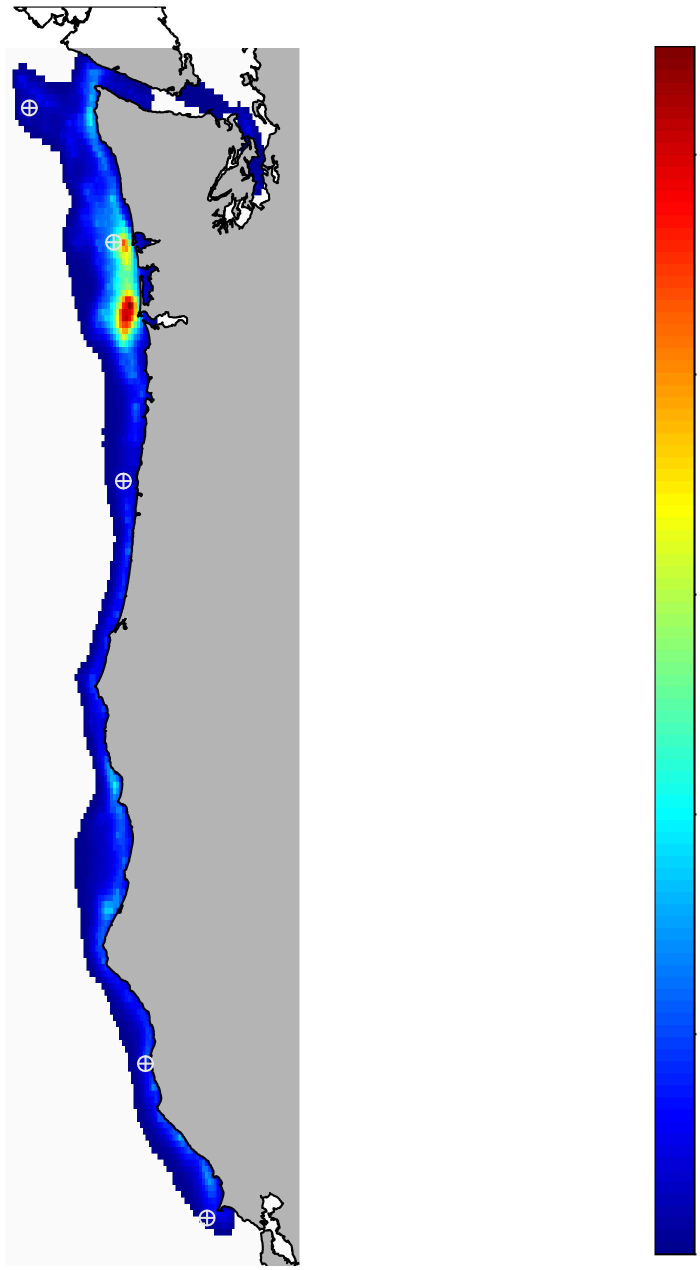


Figure 3. Locations of 2014 -2015 season acoustic recorders and 2013 track of satellite-tagged SRKW K25 relative to Navy training ranges. Density 5x5 km grid cells based on duration of occurrence are shown in red.

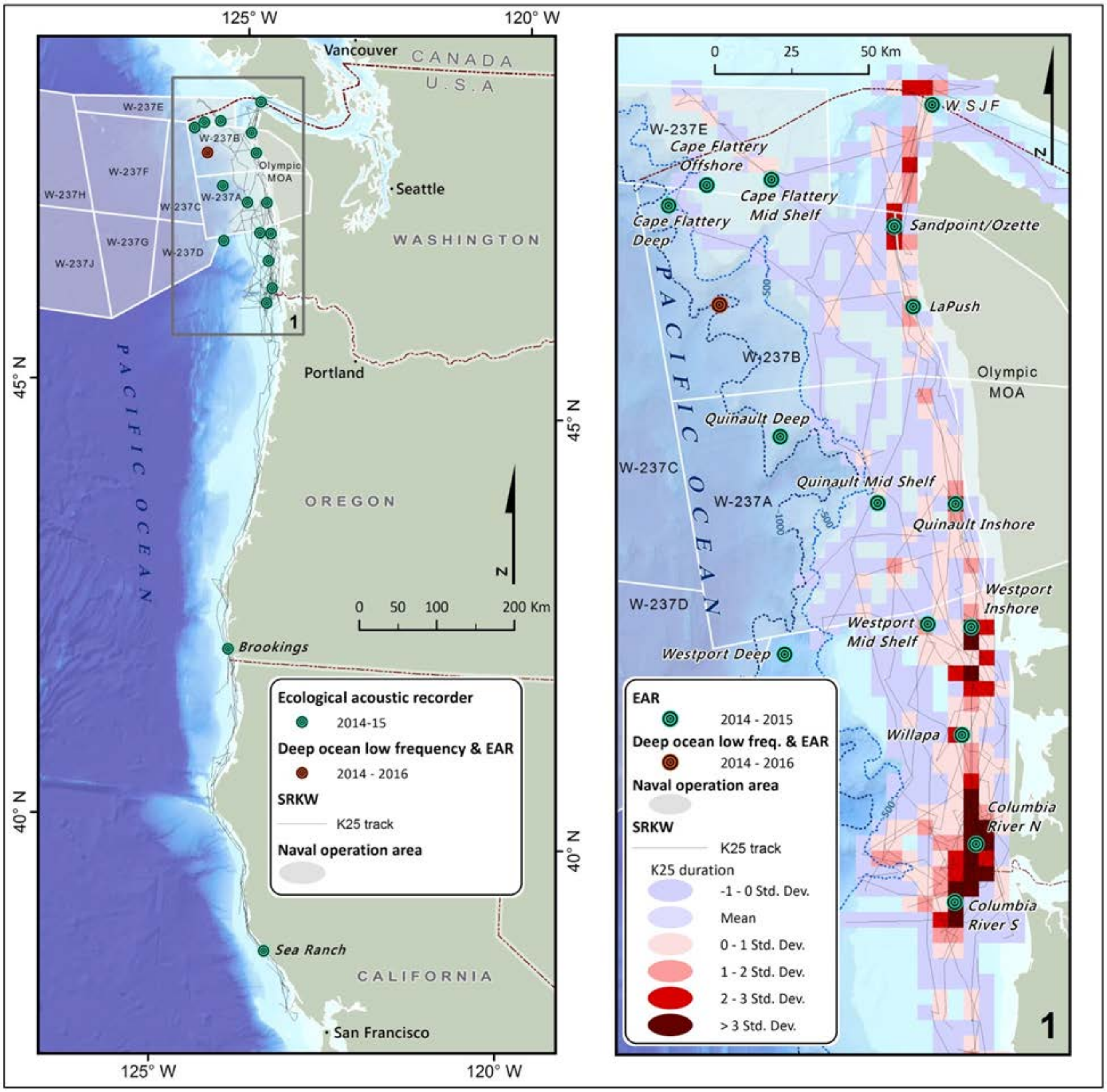


Figure 4. Prior and posterior distributions of detection probabilities from passive acoustic recorders for Southern Resident killer whales, January – April 2013.

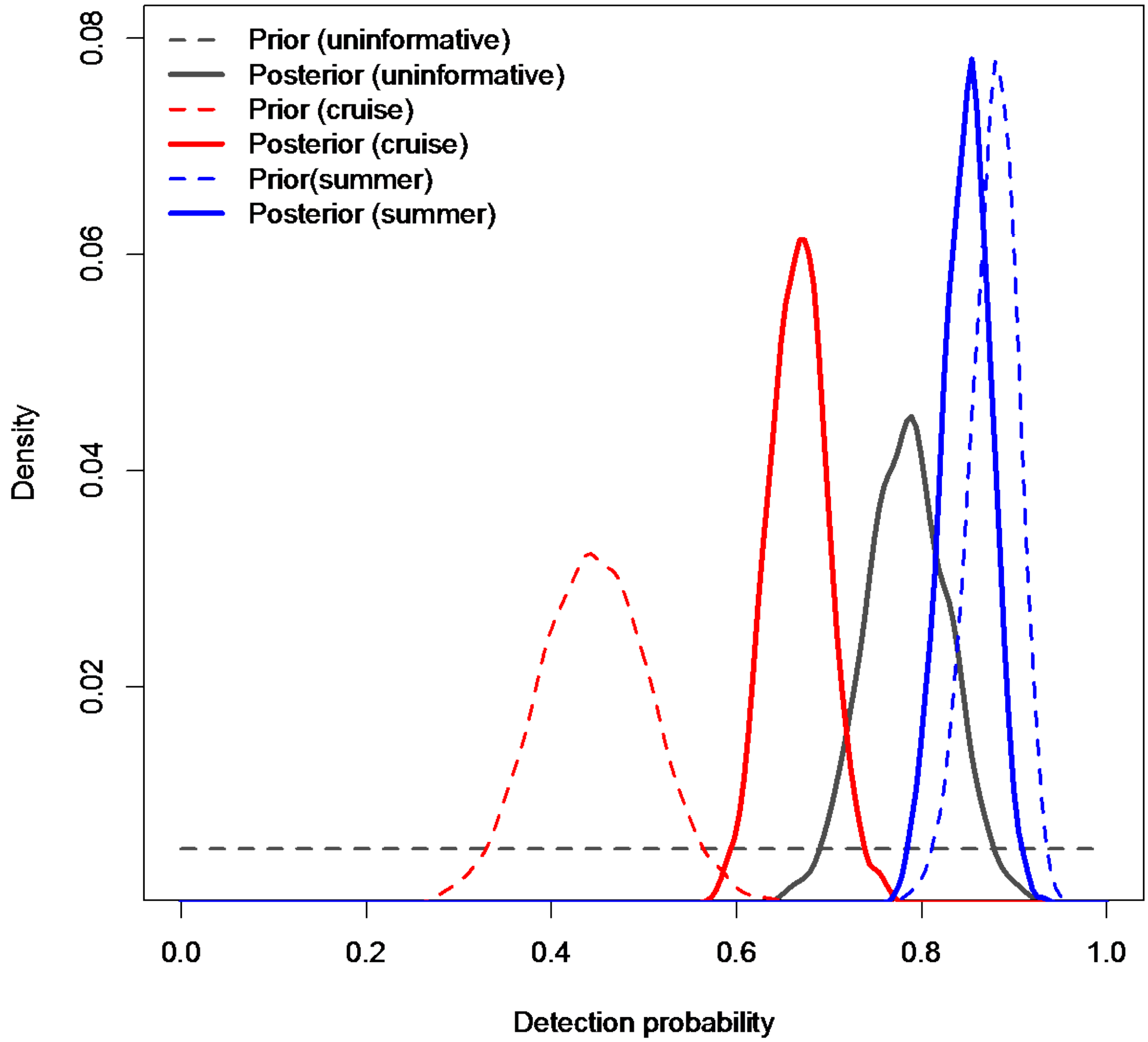


Figure 5. Spatial predictions of Southern Resident killer whale distribution in years without satellite tagged animals, based on acoustic recorder detections and visual sightings. All maps represent predictions for the month of February, and are shown on the same color scale relative to a uniform distribution (e.g. dark red values indicate 120x higher than expected by chance).

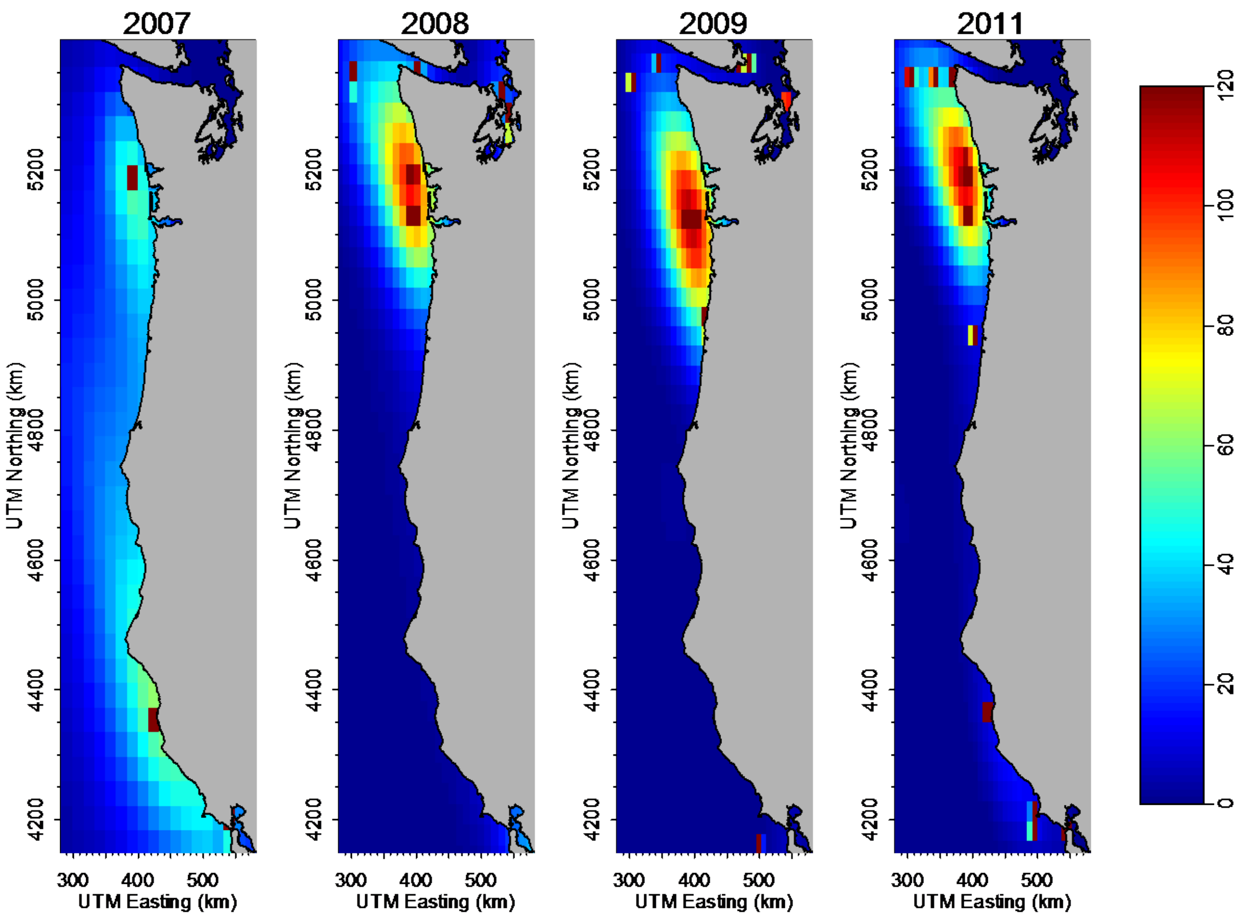


Figure 6. Spatial predictions of Southern Resident killer whale distribution on the outer coast during a 11 day period (March 9 – March 19, 2011). The whales were detected on days 1 and 11. Between that period, uncertainty increases as a function of time (peaking at day 5). All maps are shown on the same color scale relative to a uniform distribution (e.g. dark red values indicate 120x higher than expected by chance).

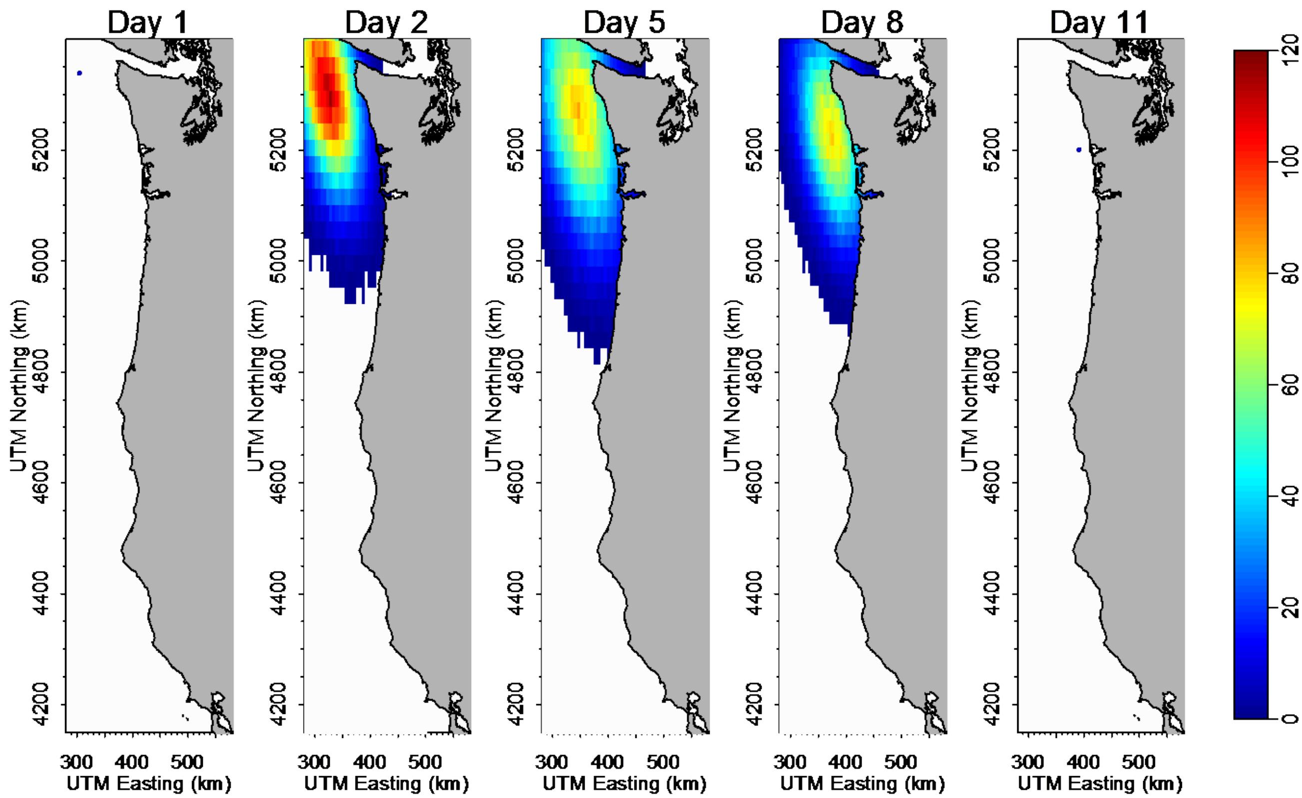


Figure 7. Locations of acoustic recorder mooring placement in 2014-2015 in relation to other SRKW location data sources and fishing intensity along the Washington coast.

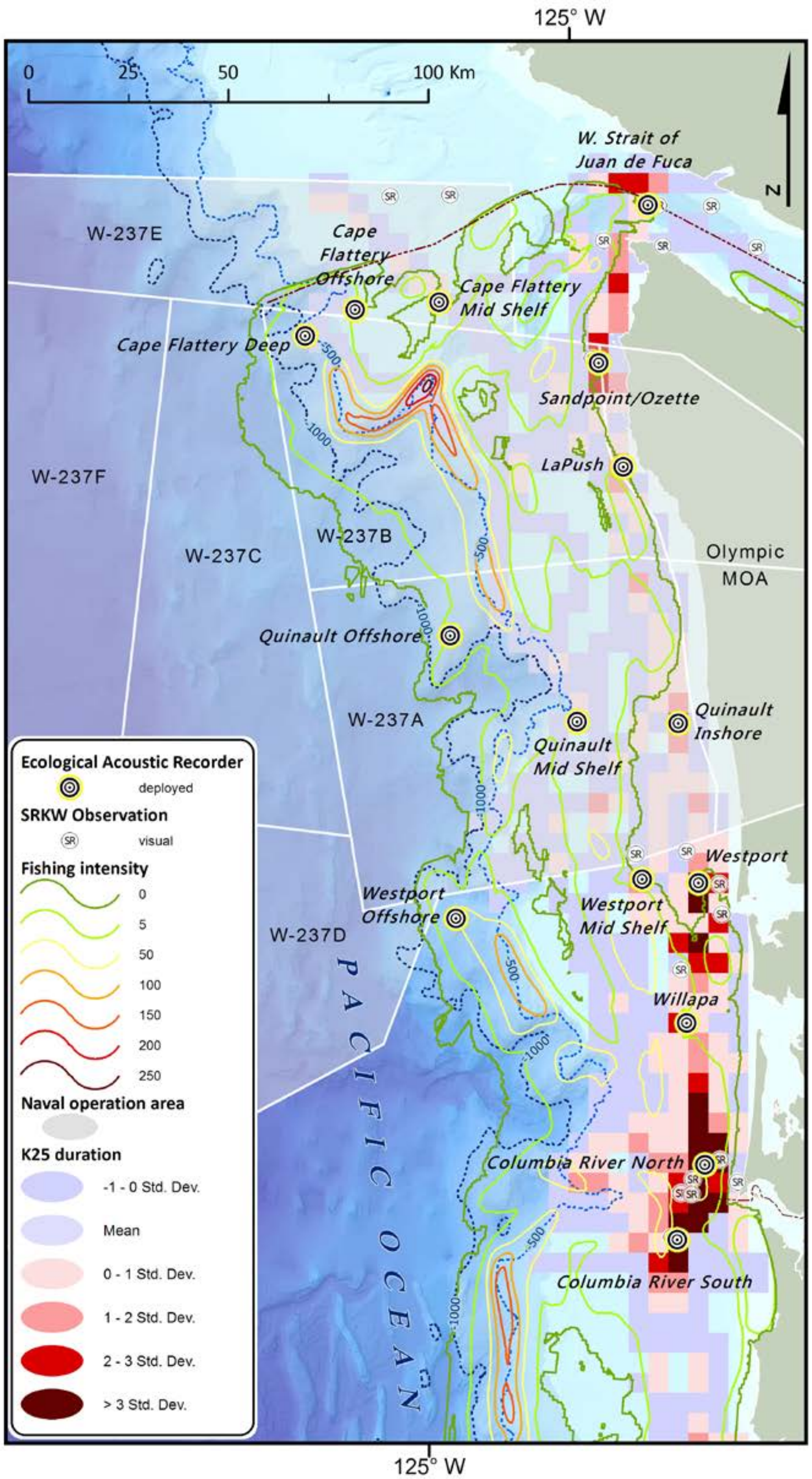


Table S1. Visual sighting of SRKWs in U.S. coastal waters 2006-2011.

Year	Location	Latitude	Longitude	Julian day	Month	Day	Pod
2006	Pt Reyes	37.8956	123.0224	26	January	26	L pod
2006	Dana Passage	47.1628	122.8685	62	March	3	K,L12 pod
2006	Saratoga Passage	48.1853	122.5603	64	March	5	K,L pod
2006	Saratoga Passage	48.1853	122.5603	65	March	6	Prob SRKW
2006	Saratoga Passage	48.1853	122.5603	66	March	7	Prob SRKW
2006	Columbia River	46.1653	124.2848	89	March	30	K, L pod
2006	Columbia River	46.1653	124.2848	90	March	31	Prob SRKW
2006	Westport	48.9682	124.2353	94	April	4	L pod
2007	San Fransisco	37.8167	122.4833	24	January	24	K pod
2007	Fort Bragg	39.3519	123.8831	77	March	18	L pod
2007	Gorda, CA	36.5833	121.85	79	March	20	Prob SRKW
2007	Monterey Bay	36.7083	121.91	83	March	24	K,L pods
2007	Monterey Bay	34.7477	121.8967	84	March	25	K,L pods
2007	Fort Bragg	39.3519	123.8831	88	March	29	Prob SRKW
2008	Puget Sound	47.8102	122.4274	1	January	1	K pod
2008	Puget Sound	47.8102	122.4274	2	January	2	Prob K pod
2008	Puget Sound	47.8102	122.4274	6	January	6	K pod
2008	Admiralty Inlet	47.9498	122.6013	7	January	7	Prob K pod
2008	Admiralty Inlet	47.9498	122.6013	8	January	8	Prob K pod
2008	Puget Sound	47.8102	122.4274	10	January	10	K pod
2008	Tacoma	47.2856	122.4446	11	January	11	Prob K pod
2008	Monterey Bay	36.9583	122.017	32	February	2	L pod
2008	Monterey Bay	36.9583	122.017	38	February	8	K,L pod
2008	Sekiu	48.261	124.3061	91	February	29	L pod
2009	Depoe Bay	44.808	124.061	21	Jan	21	L pod
2009	Depoe Bay	44.808	124.061	24	Jan	24	L pod
2009	Victoria	48.4079	123.39	37	Feb	6	J,K,L
2009	Gabriola	49.15	123.733	38	Feb	7	J,K,L

2009	Haro	48.5065	123.1786	40	Feb	9	K pod ?
2009	Puget Sound	47.8102	122.4274	50	Feb	19	K?,L pods
2009	Puget Sound	47.8102	122.4274	51	Feb	20	L pod
2009	Monterey Bay	36.9583	122.017	64	March	5	L pod
2009	Farrallones	37.6986	123.0022	66	March	7	L pod
2009	Westport	47.01167	124.5127	85	March	26	L pod
2009	Columbia River	46.263	124.2283	86	March	27	L pod
2011	Point Cabrillo, CA	39.3488	123.8234	39	2	8	20+ kw seen
2011	Fort Bragg, CA	39.3519	123.8831	39	2	8	"pod"
2011	10-12 mi W of Golden Gate Bridge	37.8167	122.4833	40	2	9	L
2011	Monterey Bay, CA	36.9583	122.017	41	2	10	L
2011	Just outside Golden Gate Bridge	37.8167	122.4833	43	2	12	12-15 whales
2011	San Fransisco Bay (NW)	37.8167	122.4833	45	2	14	L
2011	Umatilla Reef	48.1845	124.7544	83	3	24	K12s,K14s

Data source: Orca Network sighing archives - http://www.orcanetwork.org/Archives/index.php?categories_file=Sightings%20Archives%20Home

Figure S1. Diagnostic plots of observed and predicted values of latitude and longitude. Each plot included predictions at 10-minute intervals for the K25 track, with the mean of each marginal posterior distribution shown in the upper left corner (a 1:1 reference line is also included).

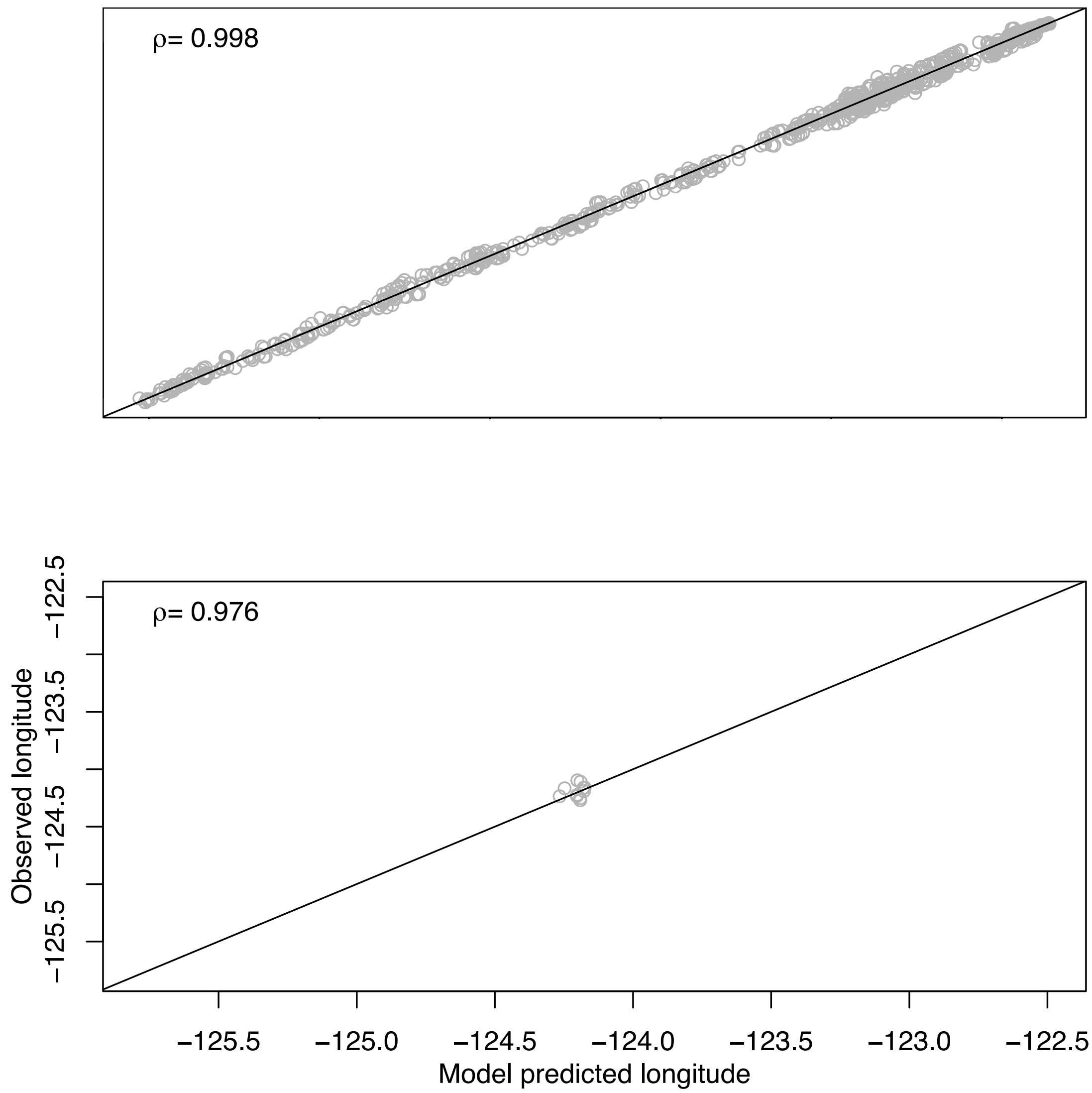


Figure S2. Diagnostic plots of estimated rates of travel (km / hour) as a function of latitude (confidence intervals not shown).

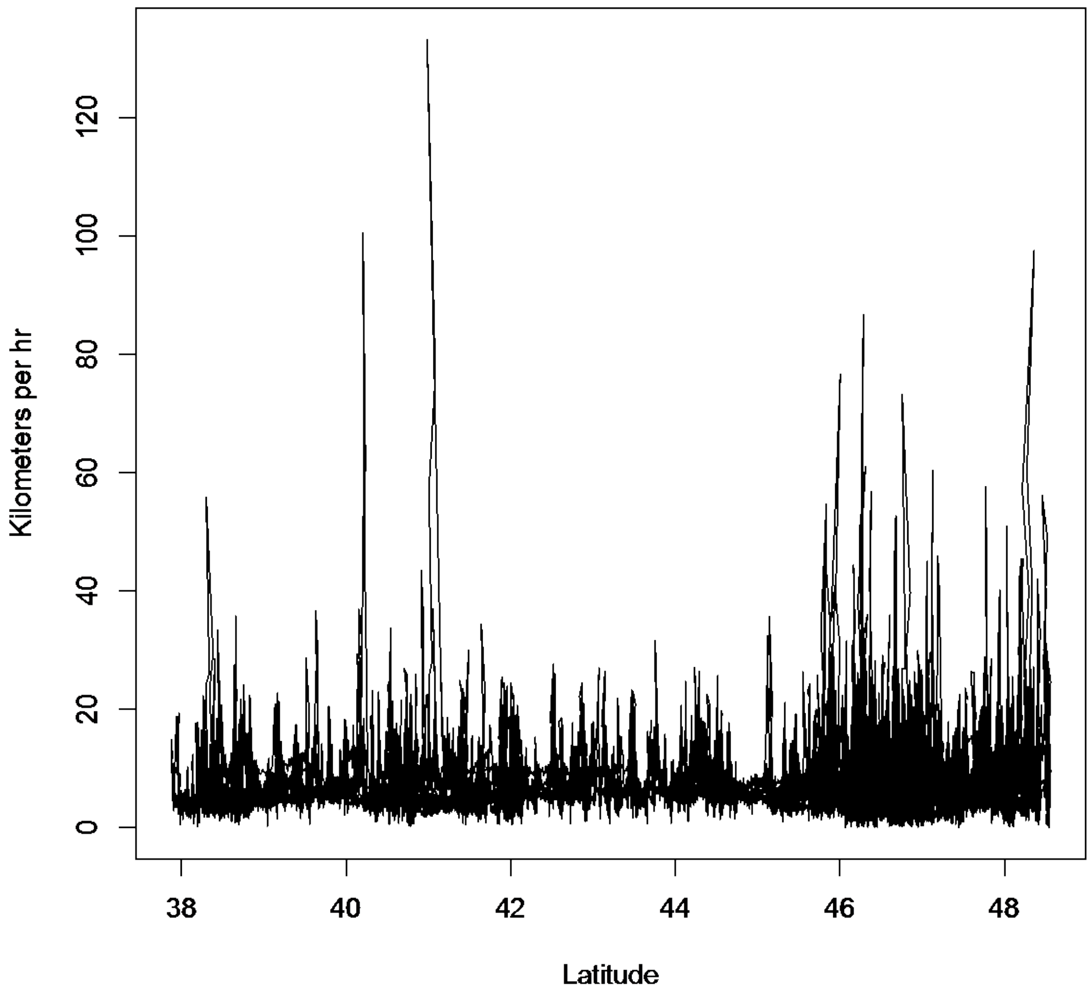
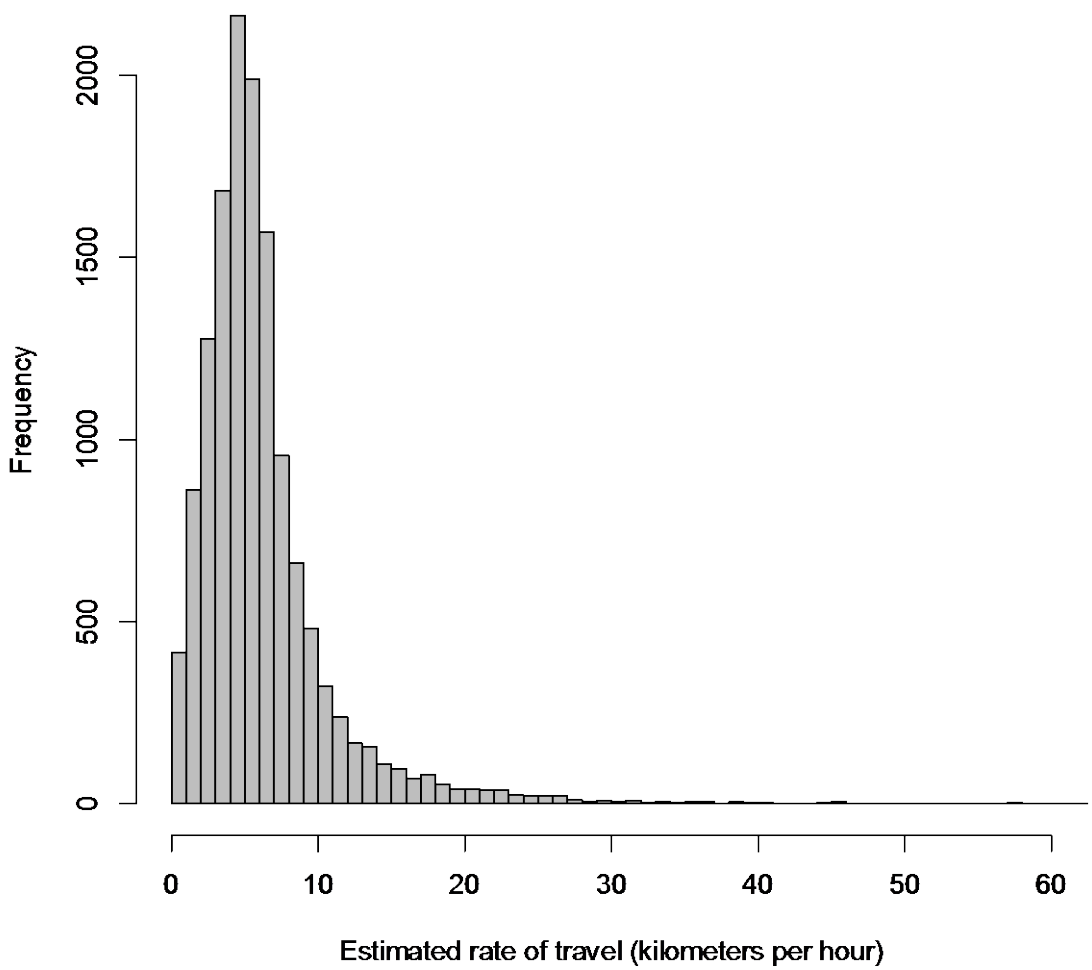


Figure S3. Distribution of estimated rates of travel (km / hour) for 13723 data points. The mean = 6.27, and median = 5.22, and 95% CIs = (0.88, 19.47).



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