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Taking the time for range testing: an approach to account for temporal resolution in acoustic telemetry detection range assessments

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Abstract

Background: In acoustic telemetry studies, detection range is usually evaluated as the relationship between the probability of detecting an individual transmission and the distance between the transmitter and receiver. When investigating animal presence, however, few detections will suffice to establish an animal's presence within a certain time frame. In this study, we assess detection range and its impacting factors with a novel approach aimed towards studies making use of binary presence/absence metrics. The probability of determining presence of an acoustic transmitter within a certain time frame is calculated as the probability of detecting a set minimum number of transmissions within that time frame. We illustrate this method for hourly and daily time bins with an extensive empirical dataset of sentinel transmissions and detections in a receiver array in a Belgian offshore wind farm.

Results: The accuracy and specificity of over 84% for both temporal resolutions showed the developed approach performs adequately. Using this approach, we found important differences in the predictive performance of distinct hypothetical range testing scenarios. Finally, our results demonstrated that the probability of determining presence over distance to a receiver did not solely depend on environmental and technical conditions, but would also relate to the temporal resolution of the analysis, the programmed transmitting interval and the movement behaviour of the tagged animal. The probability of determining presence differed distinctly from a single transmission's detectability, with an increase of up to 266 m for the estimated distance at 50% detection probability (D_{50}).

Conclusion: When few detections of multiple transmissions suffice to ascertain presence within a time bin, predicted range differs distinctly from the probability of detecting a single transmission within that time bin. We recommend the use of more rigorous range testing methodologies for acoustic telemetry applications where the assessment of detection range is an integral part of the study design, the data analysis and the interpretation of results.

Keywords: Animal tracking, Biotelemetry, Detection probability, Presence/absence, Study design, System performance, Temporal resolution

Background

Understanding performance variability of scientific equipment is crucial to correctly interpret patterns in its measurements. In acoustic telemetry, this entails the assessment of the detectability of animal-borne

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transmitter signals by an acoustic receiver set-up [1]. This relationship is subject to the transmitter–receiver distance, environmental conditions and technical features, in addition to the behaviour of the tagged animal itself. Environmental impacts include static features, such as habitat type and bottom depth [2, 3], as well as system dynamics that vary over time, such as wind, water currents, precipitation, biogenic and anthropogenic noise, temperature and stratification [4–6]. The detection range can also be dependent on the specifications of the equipment used, including transmitter type, transmitting power output and transmitter placement [7–9], as well as receiver depth, orientation and deployment method [5, 10, 11]. Biofouling on the receiver can significantly decrease receiver performance over time [12]. The tagged animal's behaviour can influence the detectability, e.g. through the occupancy of a specific depth or a propensity to hide or burrow [13, 14]. Spatiotemporal variability in detection range is commonly investigated with a range test [1, 4, 5], where these patterns are evaluated against a relevant subset of factors of potential interference to transmissions.

Whether to optimize the design of a receiver array or to account for variability in detection probability during a study, a range test must be tailored to a study's specific application [1, 15, 16]. Before and/or during a telemetry study, the detection range is generally evaluated by means of sentinel transmitters at a known, generally fixed, position. Detection range is then typically assessed as the probability of detecting a single transmission at the known distance between receiver and transmitter. This individual detection probability is estimated either for every single transmission [3, 10, 17], or as the probability of detecting a single transmission within a period of time (e.g. for a daily resolution, this represents the probability of detecting a transmission given that day's conditions) [5, 6, 18]. However, many telemetry analyses do not build on single detections as a response variable, but rely on a binary presence/absence metric within a specified time bin (e.g. residency) [19–21]. For these studies, one detection (or at most a few) within a period of time, generally one hour or day, will suffice to classify the animal as present in that time bin. The probability of determining presence, i.e. detecting at least one or a few transmitted signals within a period of time, thus differs distinctly from the probability of detecting a single transmission [22].

For studies investigating presence of a tagged animal within a specified time bin, the assessment of range has to take into account the temporal resolution of interest. Environmental variables may impact detection range differently on distinct temporal scales [23]. The effect of tidal currents for example, can differ between hourly and

daily resolutions. Moreover, the probability of determining presence of a tagged animal will increase if multiple transmissions can be detected. The number of potentially detectable transmissions is related to the chosen time bin and the transmitting interval settings, as well as the behaviour of the animal itself. A larger time bin and shorter transmitting interval result in a higher number of transmissions that can be detected by a receiver and thus in a higher probability that a fish is effectively observed as present within the specified time bin. Fish movement behaviour will also influence the probability of determining presence. An animal passing by a receiver location is expected to spend less time within range of a receiver than an animal that resides at that location. Telemetry researchers already adapt transmitter settings in line with the expectations of residency and movement behaviour to increase the detection probability (e.g. a shorter transmitting interval during the expected migration along a receiver curtain) [15] or reduce the risk of collisions [24]. However, assumptions on movement behaviour are rarely taken into account explicitly in detection range assessments.

In this study, we propose an approach to assess factors that impact the detection range, suitable for studies making use of binary presence/absence metrics. Our conceptual approach builds on the detection probability of a single transmission within a certain time frame to calculate the probability of detecting a given minimum number of transmissions within that time frame. The method can be applied to any receiver array equipped with sentinel transmitters. When investigating the probability of determining the presence of a tagged animal, the number of potentially detectable transmissions is estimated as a function of the chosen time bin, the transmitting interval settings and the behaviour of the animal itself. By applying the method to an extensive data set, the objectives of the current study are to (1) evaluate the predictive performance of the new approach; (2) compare different hypothetical range testing scenarios using this method, and (3) investigate the implications for detection range in study designs with different transmitter settings and animal species.

Methods

All analyses were performed in R software [27]. R scripts are made available on GitHub (<https://github.com/Jolie nGoossens/RangeTestingTime>).

Analytical protocol

Firstly, data are prepared to model the detection probability of individual transmissions π at a given temporal scale (e.g. hourly or daily). For every receiver–sentinel transmitter combination, the number of transmissions

and detections are calculated for the relevant time bin and fitted in a binomial generalized linear model (using a frequentist or Bayesian approach) to predict π in relation to ambient and technical variables. The probability P of discerning k or more detections out of n transmissions throughout that time bin is then calculated as the cumulative distribution function:

$$\begin{aligned}
 P &= P(X \geq k) = 1 - P(X \leq [k - 1]) \\
 &= 1 - \sum_{i=0}^{k-1} \binom{n}{i} p^i (1 - p)^{n-i},
 \end{aligned}
 \tag{1}$$

with p representing the individual detection probability, obtained as the predicted π from the logistic model. In Eq. 1, X denotes the number of detections and n the number of transmissions within the considered time frame. The detection threshold k is the minimum number of detections (X) for a transmitter to be ascertained as present. Therefore, P amounts to the probability of detecting a transmitter at least k times out of the n transmitted signals within a period of time, given the probability π of detecting a single transmission under the prevailing circumstances within that time frame (Fig. 1).

Zero threshold

To address the risk of overestimating P , we propose to set a zero threshold for the modelled probability π . The ‘zero-corrected’ individual probability π^0 is defined as 0 below a set threshold value for π and rescaled to values between

0 and 1 for the remaining range of the predicted π . Even an extremely low individual probability π can generate a high cumulative probability P if n is high (Fig. 1). The zero threshold deals with the concern of cumulating low predicted probabilities. A logistic model can never render a predicted probability of zero, as the logarithm of zero is not defined. The predicted probability π is also associated with uncertainty, which will propagate with the summing and multiplication operations in Eq. 1 [28]. Setting the zero threshold should be a study-specific consideration, where one evaluates the confidence in the logistic model on the one hand and weighs the risk of overestimating versus underestimating π on the other.

Defining n

In Eq. 1, n represents the number of transmissions that can be detected by a receiver. For a fixed sentinel transmitter, n is defined as the number of executed transmissions within the considered time bin. For a non-stationary animal-borne transmitter, however, n needs to reflect the number of transmissions broadcasted while the tagged animal is within a certain range around a receiver. Therefore, the value of n will depend on the programmed transmitting interval and the time bin, in addition to the movement behaviour of the tagged animal. Here, we calculate the integer n as

$$n = \left\lfloor \frac{t_{\min}}{T} \right\rfloor,
 \tag{2}$$

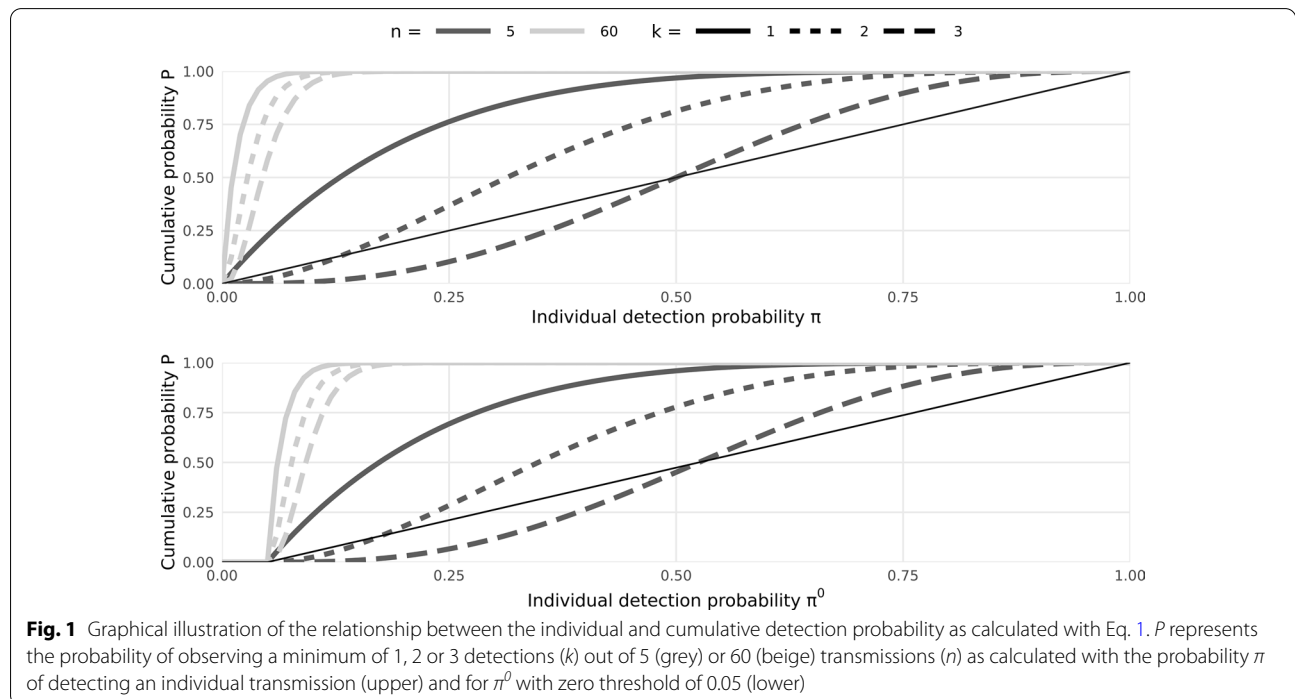


Fig. 1 Graphical illustration of the relationship between the individual and cumulative detection probability as calculated with Eq. 1. P represents the probability of observing a minimum of 1, 2 or 3 detections (k) out of 5 (grey) or 60 (beige) transmissions (n) as calculated with the probability π of detecting an individual transmission (upper) and for π^0 with zero threshold of 0.05 (lower)

where \bar{T} is the mean transmitting interval and t_{min} is the minimum time an animal is hypothesized to spend within range of the receiver. When defining t_{min} , we make assumptions based on the expected movement behaviour (e.g. speed or residency) of the species of interest. For example, high residency or low activity would result in a higher estimate for t_{min} than for migrating behaviour. The less is known about a study species and/or area, the more conservatively low t_{min} should be set.

Empirical data set

Between 13 May and 12 October 2020, an array of 27 VR2AR receivers (InnovaSea Systems Inc., USA) was set up in the Belwind offshore wind farm in the Belgian part of the North Sea. Receivers were deployed with tripod moorings [10], with distance between receivers ranging from 125 to 1628 m (Fig. 2). The array design was purposed to investigate presence and fine-scale movement patterns of plaice (*Pleuronectes platessa*), Atlantic cod (*Gadus morhua*) and European seabass (*Dicentrarchus*

labrax) in the framework of ongoing studies, for which the VR2AR receivers' built-in transmitters (mean transmitting interval of 10 min) served as synchronization tags for a fine-scale positioning application. Transmitting power output was set as high (154 dB) for the entire study period for all built-in transmitters, except for three (Fig. 2) that were programmed as low (142 dB) before 16 June 2020 in the interest of assessing the effect of power output on detection range. Detections on the dates of receiver installation, receiver recovery and power setting changes were excluded from the analysis, making for a total of 150 days of detection data.

Ambient and technical conditions taken into account consisted of wind and current speed and azimuth, noise, receiver tilt angle, temperature and days since deployment (Table 1). Wind measurements were obtained from 'Meetnet Vlaamse Banken' from station Westhinder (51.38°N, 2.44°E). Modelled current data originated from a forecast model [29]. From the hourly wind and current velocities, daily median current and direction were calculated using trigonometry principles. For both wind and

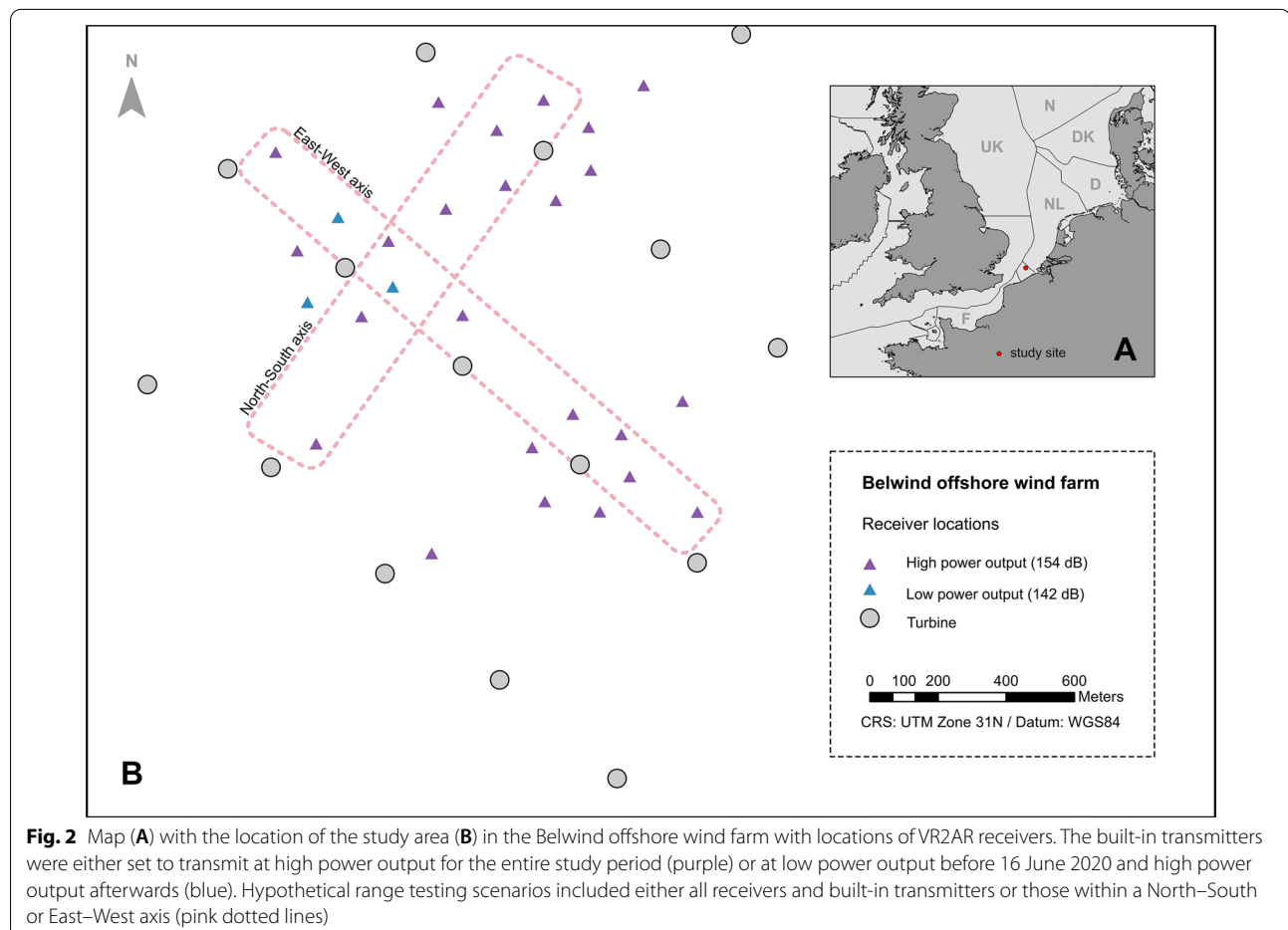


Table 1 Overview of ambient and technical conditions during the study (14 May–11 October 2020)

Variable	Range	Median	Method
Distance (m)	125–1628	743	
Transmitting power output	142 dB (Low)/154 dB (High)		
Wind speed (m/s)	0.4–24.9	7.1	Measured (Westhinder)
Wind azimuth (°)	0–180	90	Measured (Westhinder)
Current speed (m/s)	0.09–0.69	0.36	Modelled
Current azimuth (°)	0–180	90	Modelled
Temperature (°C)	10.7–20.6	17	Measured (VR2AR)
Tilt (°)	0–17	4	Measured (VR2AR)
Noise (mV)	150–917	287	Measured (VR2AR)
Days since deployment	1–158		

current, the azimuth was calculated as the angle between the transmitter–receiver bearing and the direction. Noise (mV), tilt angle (°) and temperature (°C) were drawn from the VR2AR built-in sensors. The hourly measurements were linearly interpolated to the stroke of every hour, from which daily medians were calculated. Before inclusion in the model, all continuous variables were standardized.

Application of the approach

The described protocol was applied to the empirical data set to assess the detection range for determining presence in hourly and daily time bins.

Logistic model

We evaluated for every sentinel transmission whether it was detected by the receivers in the study set-up. To account for internal clock drift of the acoustic receivers, the recorded time of detection had to be within 100 s before or after the registration of the successful transmission on the built-in transmitter's receiver (D. Webber, pers. comm.), after applying a linear time correction on the offloaded receiver data (VUE software, InnovaSea Systems Inc., USA). For every transmitter–receiver combination, the hourly and daily numbers of transmissions and detections were calculated. Transmitter–receiver combinations spaced more than 1100 m were excluded from the analysis. Generalized linear models with a binomial distribution were applied to predict π_{hour} and π_{day} . Response variables were the hourly and daily number of transmissions successfully detected versus those undetected. The inclusion of different explanatory variables was evaluated for (1) relevance by data exploration [30];

(2) statistical significance by backwards model selection using the Akaike information criterion (AIC) and likelihood ratio test (LRT) [31], and (3) practical significance on the basis of effect size [32, 33], whereby factors were excluded from the model if the effect estimate was below |0.2|.

Cumulative detection probability

Cumulative detection probabilities P_{hour} and P_{day} were then calculated (Eq. 1) and validated for the entire study period. The detection threshold k was set at 2, as applied by many studies [19–21]. The number of tries n was set as the registered number of sentinel transmissions within the hour or day. Individual detection probabilities π_{hour} and π_{day} were obtained using the logistic model formulae. P_{hour} and P_{day} were then calculated with individual detection probabilities π_{hour}^0 and π_{day}^0 at a zero threshold of 0.05. If $P \geq 0.5$, sentinel transmitters were classified as present versus not present for $P < 0.5$ [34]. These binary predictions were compared with the determined presence throughout every day and hour (0/1, with 1 meaning at least 2 (k) transmissions were detected). To assess the predictive performance, a confusion matrix was inspected from which the performance metrics sensitivity, specificity and accuracy were calculated, in addition to the computation of area under the curve (AUC) [35]. High values for accuracy and AUC suggested a good overall performance, whereas sensitivity and specificity depicted the model's ability to correctly predict positive and negative values, respectively. For range testing, we favoured high scores for specificity over sensitivity, as a high number of false positives would indicate an overestimation of range.

Scenarios for detection range assessment

Using our empirical data set, we evaluated different scenarios for detection range assessment with a cross-validation approach. Therefore, we split the full data set of sentinel transmissions and detections into different training and test subsets (Table 2), as if we were assessing detection range (training set) for an actual telemetry study (test set). For each of the test subsets, we considered 16 June 2020 as the start of the hypothesized study. Training sets either contained 'range test' data from before this date, 'reference tag' data from during this study, or both. 'Range test' training data considered the data of 8, 16, 24 or 32 days before the start of the hypothetical study. Spatially, these training sets consisted either of all 27 receiver–sentinel transmitter combinations, a North–South axis (8 receivers) or East–West axis (9 receivers), approximately parallel and perpendicular to the dominant current direction,

Table 2 Overview of training and test data subsets to test different range assessment scenarios, with the number of days, built-in transmitters (T) and receivers (R) included in the subsets

	Training set		Test set	# Models (per time bin)
	Before study 32 days	During study 118 days	During study 118 days	
Range test	8/16/24/32 days		27 T–27 R	4
	27 T–27 R		27 T–27 R	4
	9 T–9 R (East–West)		27 T–27 R	4
	8 T–8 R (North–South)			
Reference tag		1 T–27 R	26 T–27 R	27
		2 T–27 R	25 T–27 R	351
		3 T–27 R	24 T–27 R	2925
Range test + reference tag	32 days	1 T–27 R	26 T–27 R	27
	27 T–27 R	2 T–27 R	25 T–27 R	351
	27 T–27 R	3 T–27 R	24 T–27 R	2925
	27 T–27 R			

respectively (Fig. 2). The ‘reference tag’ training data on the other hand consisted of detections on all 27 receivers of 1, 2 or 3 sentinel transmitters during the hypothesized study. When the model was trained on both ‘range test’ and ‘reference tag’ data, training data consisted of 32 days of all 27 receiver–transmitter combinations before the start date, in addition to the detections of 1, 2 or 3 sentinel transmitters during the study. Test data subsets consisted of detection data from after the start of the study (118 days), excluding transmitter detections included in the training subset, if any. The cross-validation was performed for both hourly and daily probabilities.

For the cross-validation, logistic models were trained on each of the specified training sets. The included variables were drawn from the model selection based on the full hourly and daily data sets. As sentinel transmitters were all set to transmit at high power output after 16 June 2020, power output was not included in the logistic models for the ‘reference tag’ training data. Using the logistic model formulae from the training model, π_{hour} and π_{day} were predicted for the test data. Cumulative probabilities P_{hour} and P_{day} were calculated with Eq. 1, with k set as 2 and n as the number of registered sentinel transmissions in each specific hour or day. Transmitters were thus predicted as detected in that hour or day if $P \geq 0.5$ and as not detected (0) if $P < 0.5$. The predictive capacity of these models was assessed by calculating root mean square error (RMSE) of the true detection percentage and the predicted π and by calculating specificity, AUC and the Brier Skill Score (BSS) for the binary predictions based on the cumulative probability P (Table 2). For the calculation of BSS, the Brier score of the full model was used as the reference value Brier score [36].

Assessing range for different study species

Detection range in our study area was estimated in the context of ongoing telemetry studies investigating hourly or daily presence of different species. The expected minimum time t_{min} was hypothesized to be 15 min per hour and 30 per day for very mobile species (e.g. European seabass), 30 and 60 min for less active species (e.g. Atlantic cod) and 1 and 3 h for species that would mostly stay put (e.g. plaice). Using these t_{min} estimates in Eq. 2, n was calculated for the different species at mean transmitting intervals \bar{T} of 90, 180 and 360 s. P_{hour} and P_{day} were calculated (Eq. 1) for distances from 100 to 1100 m with $k=2$ and the predicted π^0_{hour} and π^0_{day} at median hourly and daily conditions, respectively. The distance at which detection probability was predicted to be 50% ($=D_{50}$) was calculated using one-dimensional root-finding.

Results

Logistic model

After variable selection, the final logistic regression models for both hourly and daily response variables included the explanatory variables distance, noise, power output, the interactions of distance–noise and distance–power output (Table 3). Visual inspection of the relationship with distance led us to include distance transformed to the second power [37], which contributed to an improved model fit. In summary, high levels of ambient noise and low transmitting output power significantly reduced the probability of a transmission being detected, whereby these negative effects were exacerbated at greater distance (Fig. 3). At shorter distance (< 300 m) of a receiver, the detection probability of a low power output transmitter exceeded that of one with high power output, which was likely due to close proximity detection interference [2, 26]. Details of the model selection were fully described in Additional file 1.

Table 3 Summary of the GLM with binomial distribution for individual detection probability π_{hour} (left) and π_{day} (right). Hourly noise measurements were linearly interpolated to the stroke of every hour (left), from which daily medians were calculated (right)

Coefficients	Estimate	Std. Error	p-value	Coefficients	Estimate	Std. error	p-value
Intercept	- 2.299	0.0018	< 0.001	Intercept	- 2.320	0.0018	< 0.001
Distance	- 3.425	0.0037	< 0.001	Distance	- 3.327	0.0037	< 0.001
Distance ²	- 0.963	0.0025	< 0.001	Distance ²	- 0.866	0.0025	< 0.001
Noise	- 1.056	0.0021	< 0.001	Noise (median)	- 1.012	0.0020	< 0.001
Power (low)	- 3.203	0.0197	< 0.001	Power (Low)	- 3.187	0.0198	< 0.001
Distance: noise	- 0.448	0.0020	< 0.001	Distance: Noise (median)	- 0.388	0.0019	< 0.001
Distance: power (low)	- 2.732	0.0184	< 0.001	Distance: Power (Low)	- 2.561	0.0185	< 0.001

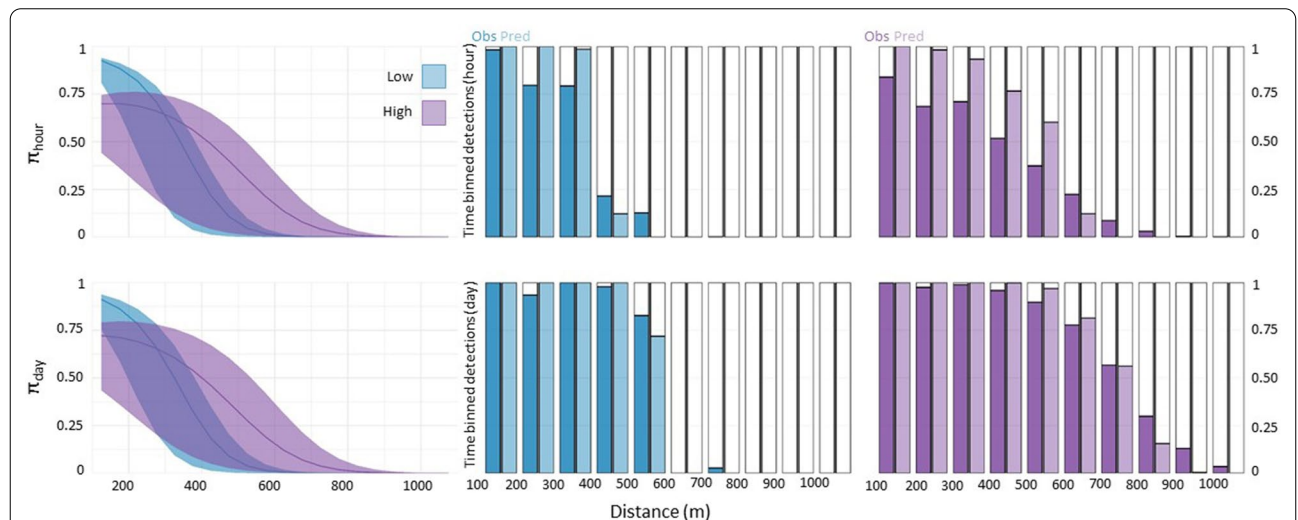


Fig. 3 Estimated probabilities of detection over distance for high (purple) and low (blue) transmitting power output at an hourly (upper) and daily (lower) resolution. Left: range and median (line) logistic model predictions. Middle and right: bar plots of observed (left bar, darker colouration) and predicted (right bar, lighter colouration) binary detection metric (at least $k=2$ detections out of n transmissions) per distance bin of 100 m

Table 4 Performance metrics for binary predictions calculated with and without zero thresholds for P_{hour} and P_{day}

Individual detection probability	Sensitivity	Specificity	Accuracy	AUC
π_{hour}	84.9	83.6	84.1	84.3
π^0_{hour}	81.9	85.8	84.4	83.8
π_{day}	96.3	56.2	82.0	76.3
π^0_{day}	86.5	86.5	86.5	86.5

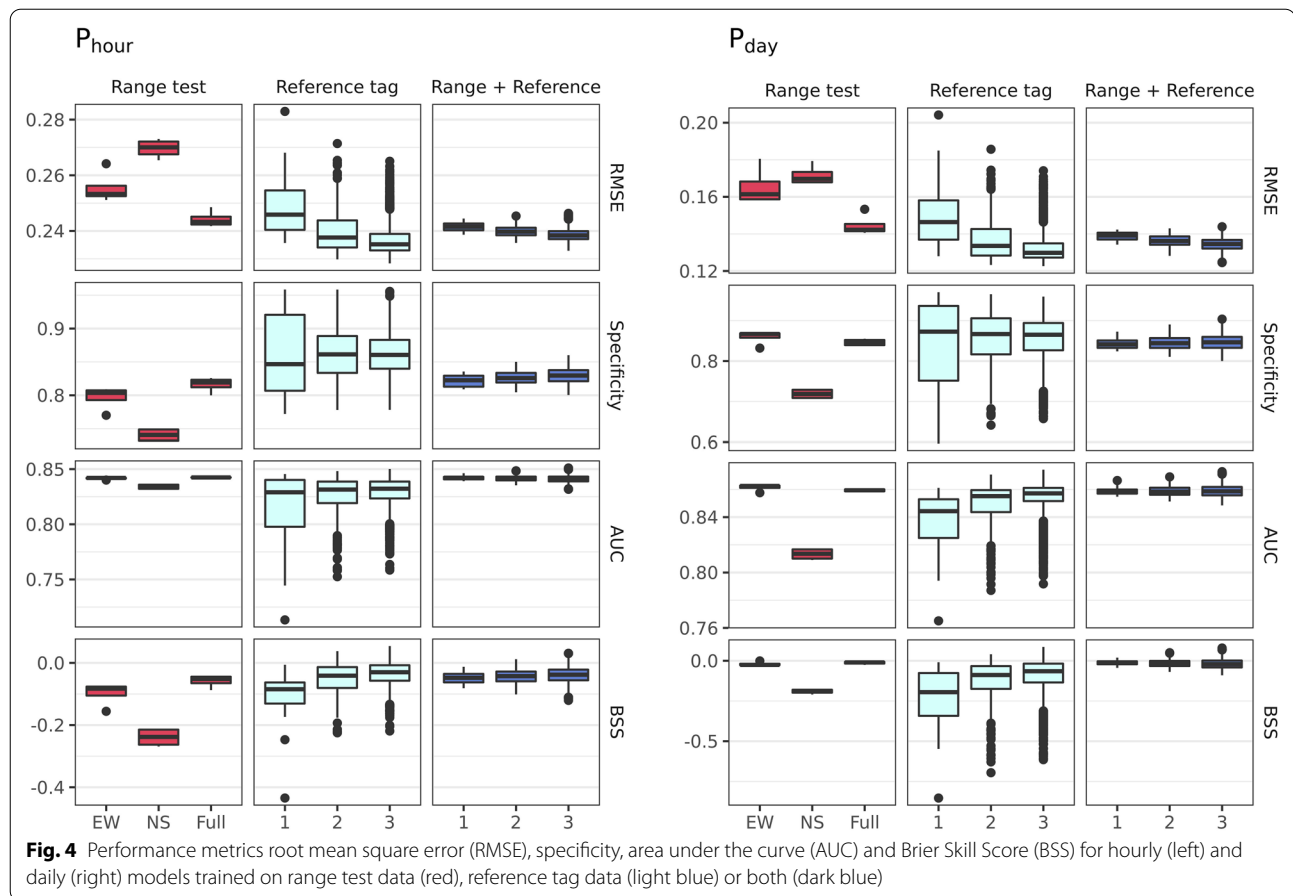
Cumulative detection probability

Performance metrics were compared for calculations of P_{hour} and P_{day} ($k=2$, n : median 143 per day, 6 per hour) using π and π^0 (Table 4). While the predictive performance differed only slightly for P_{hour} , it markedly improved with the zero threshold for P_{day} . Aside from a

higher overall performance (accuracy and AUC), specificity increased by 30.3% for the daily model (2.2% for the hourly model). Whereas P_{hour} was overestimated at short distance (< 600 m), the accuracy of the daily predictions was more consistent over distance (Fig. 3).

Scenarios for detection range assessment

The performance of distinct scenarios for the assessment of detection range varied considerably (Fig. 4). When models were trained exclusively with ‘range test’ data before the hypothesized start of the study, the performance of the scenarios using the full receiver set-up and the East–West axis were comparable. Training sets with receivers located parallel to the dominant current direction along the North–South axis, resulted in a lower performance (higher RMSE and lower specificity and AUC). The variation in performance between different



study durations was considered to be minor for the ‘range testing’ set-ups. For the ‘reference tag’ training data, the logistic models were trained on the detections of 1, 2 or 3 sentinel transmitters during the study period. The overall median performance persisted or improved (i.e. lower RMSE, higher specificity, AUC and BSS) as more sentinel transmitters were included. Still, variation was very large, indicating the representativeness of the ‘reference tag’ training set varied strongly with the sentinel transmitter locations. Finally, including both ‘range test’ and ‘reference tag’ data yielded much more consistency in the performance metrics. Yet, specificity for ‘reference tag’ training sets excluding the ‘range test’ data was often higher than for those where it was included, therefore seemingly resulting in improved predictions.

To understand the variation in the performance metrics, AUC and BSS were plotted against specificity and RMSE (Fig. 5). AUC and BSS displayed a parabolic relationship with specificity, meaning higher specificity came at the cost of lower overall prediction performance. An optimal approach for range assessment should be found at the trade-off between specificity and general

performance, i.e. at the top of the parabola. Importantly, the training models combining ‘range test’ and ‘reference tag’ data were all found to be comparable in this relationship. Finally, low RMSE values for individual detection probability π produced more accurate cumulative probability predictions, as could be expected.

Assessing range for different study species

Using hypothesized t_{min} values for species with distinct movement patterns, we calculated n at different mean transmitting intervals (Table 5). For a fast moving species, thought to spend at least 30 min throughout a day around a receiver if present that day, and equipped with a tag transmitting on average once every 180 s, n would result in minimum 10 transmissions that could be detected by that receiver throughout the day. Notice that different values for t_{min} can result in a similar n , depending on the transmitting interval.

Using these values for n , detection probabilities P_{hour} and P_{day} were calculated (Eq. 1; $k=2$) using the logistic model predictions of π over distance for median noise conditions and high transmitting power output. The

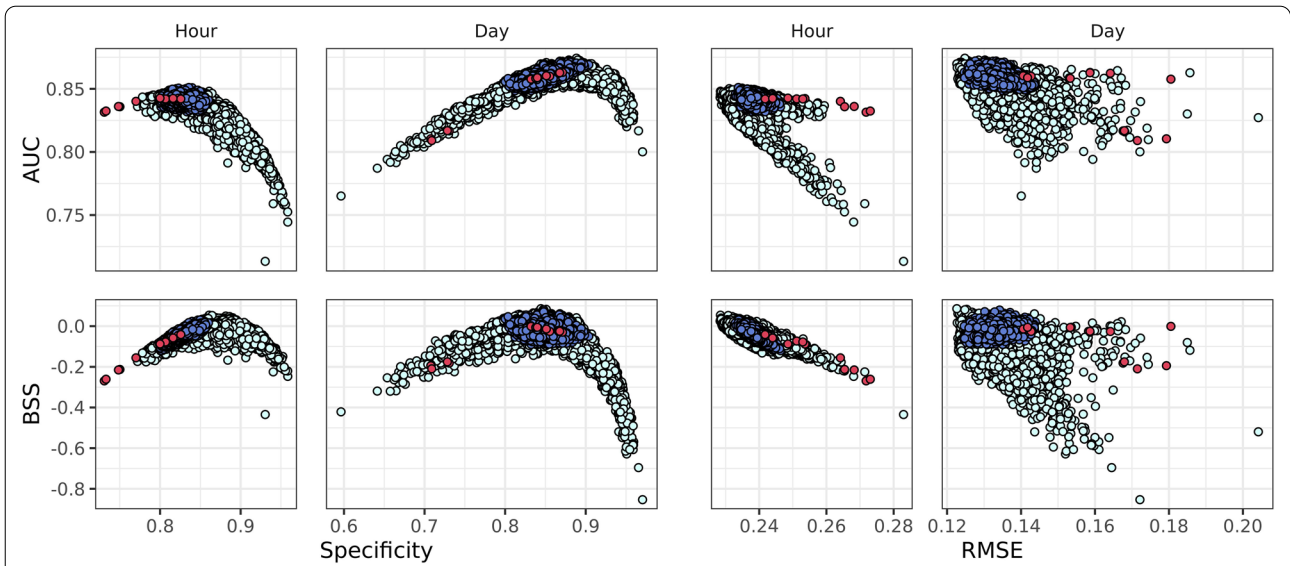


Fig. 5 Relationship between performance metrics root mean square error (RMSE), specificity, area under the curve (AUC) and Brier Skill Score (BSS) for hourly and daily models trained on range test data (red), reference tag data (light blue) or both (dark blue)

Table 5 Calculation of detectable transmissions n for different values of the expected minimum time t_{min} and mean transmitting interval \bar{T}

	$t_{min} = 15 \text{ min}$	$t_{min} = 30 \text{ min}$	$t_{min} = 60 \text{ min}$	$t_{min} = 180 \text{ min}$
$\bar{T} = 90 \text{ s}$	10	20	40	120
$\bar{T} = 180 \text{ s}$	5	10	20	60
$\bar{T} = 360 \text{ s}$	2	5	10	30

visualizations in Figs. 6 and 7 illustrate the impact of temporal resolution, transmitter interval settings and (expected) movement behaviour on detection range. Detection range as predicted by P_{hour} and P_{day} markedly exceeded π_{hour} and π_{day} . The estimated D_{50} increased by 84 to 266 m, depending on n . These results illustrate the distinction between the probability π of detecting an individual transmission in a given time frame versus the

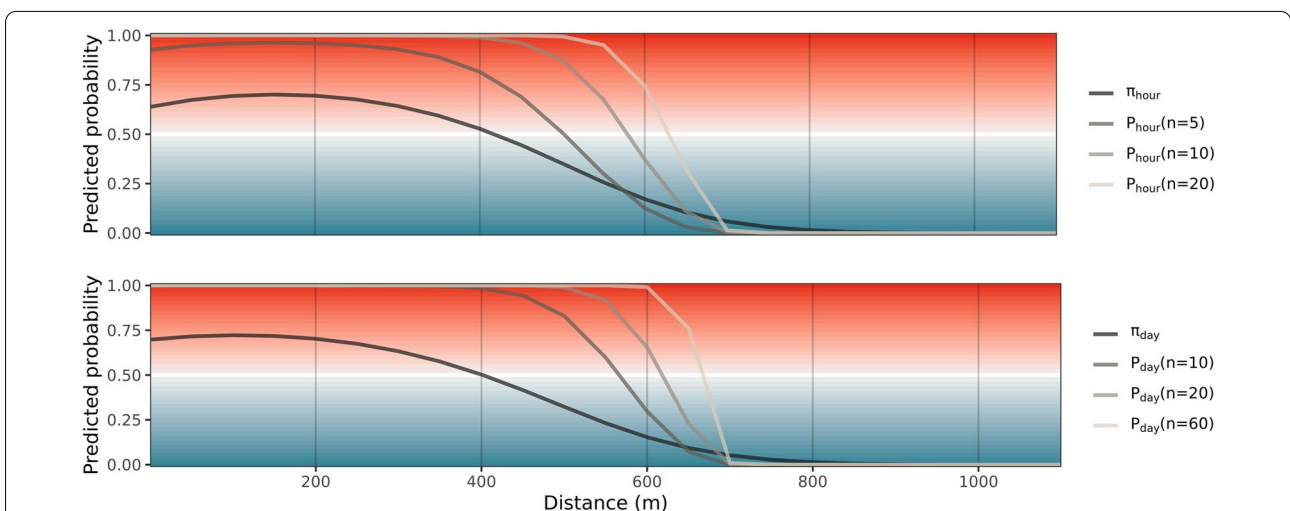
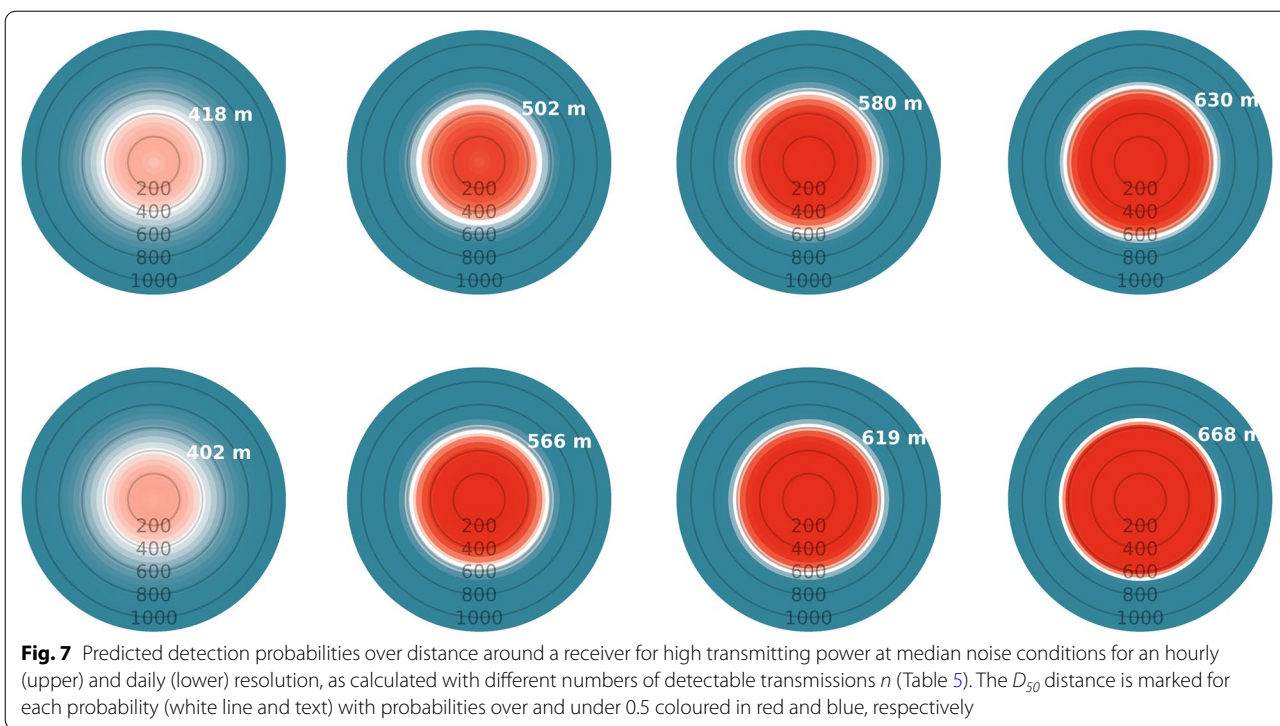


Fig. 6 Predicted detection probabilities over distance for high transmitting power at median noise conditions for an hourly (upper) and daily (lower) resolution, as calculated with different numbers of detectable transmissions n (Table 5). The intersection of the curves with a probability of 0.5 (white line) indicates the D_{50} . The intersection of the curves of π and P was a result of setting the detection threshold k at 2, whereas π and P at $k=1$ would never intersect (Fig. 1)



probability P of determining presence during that time frame.

Discussion and conclusion

Importance of considering time

Our results stress the importance of explicitly accounting for time when assessing detection range. When few detections of multiple transmissions suffice to ascertain presence within a time bin, predicted range differs distinctly from the probability of detecting a single transmission within that time bin. Our results showed that detection range might be severely underestimated when applying the individual detection probability for studies making use of binary presence/absence metrics. Moreover, a single receiver station can result in different detection ranges for animals occupying the space at that location differently. High values of t_{min} , e.g. for animals known to move slowly and/or to exhibit high residency (or for transmitters set at short transmitting intervals), were demonstrated to result in a higher estimated range.

Evaluation of the proposed method

To our knowledge, this study offers the first framework to quantify the detection range for presence/absence metrics within a given time frame. The proposed formula (Eq. 1) provides a mathematically straightforward tool that builds on the commonly estimated probability

of detecting a single transmission π . The accuracy and specificity of over 84% shows the developed approach performs adequately. However, the performance of the hourly model varied with distance, whereas the accuracy of the daily predictions was more consistent. The formula’s parameters zero threshold, detection threshold k and number of tries n should therefore be set and evaluated according to the specific needs of a study.

The zero threshold can explicitly deal with the risk of cumulating low logistic probabilities. The selected value for this threshold depends on the confidence in the binomial model predictions and the trade-off of the risks of over- and underestimating detection range. We believe that the relatively simple concept of a zero threshold—“below what threshold value do I not trust my logistic model outcome to exceed zero”—is to be preferred over a more sophisticated, yet mathematically exceedingly complex alternative of calculating the logistic error propagation [28]. For the purpose of understanding hourly and daily presence within the study area, we explicitly wanted to limit the amount of false positives as to not overestimate detection range. In contrast, telemetry studies that build on a smaller detection range [38] need to favour higher sensitivity. Applying the zero threshold in our study improved the daily predictions more dramatically than it did for the hourly model. This was in part attributed to a larger n , which made for a steeper curve than P_{hour} (Fig. 1).

When setting a zero threshold therefore, the number of transmissions n , as well as the detection threshold k , should always be taken into consideration.

In addition to the estimated π_0 , the proposed approach requires values for n and k that are tailored to the telemetry study. Firstly, though a minimum of (generally 2) detections is often applied to qualify a time bin with fish presence [19–21], this detection threshold k has never been considered in range assessments. Secondly, the formula obliges a researcher to contemplate on the presumed number of detectable transmissions n in an animal study. Reflecting the hypothesized minimum time an animal would be in range of a receiver, t_{min} depends on the animal's behaviour in a certain habitat (e.g. proneness to residency or a tendency to burrowing) and the considered time bin. Depending on the species, t_{min} may even be assumed to vary over time, for example if an animal is only seasonally resident [19] or exhibits diel variation in movement behaviour [41]. If little is known about the animals, researchers can opt to set precautionary low values for t_{min} and therefore n . Likewise, if a study requires to pick up nearly every transmission of a tagged animal in a certain area (e.g. during migration), researchers have to program the transmitting interval settings and/or space between receivers in the array accordingly [15]. The predicted cumulative probability P would then reach values similar to or even lower than the individual detection probability π (Fig. 1). In many cases, however, information is available on the expected movement behaviour (e.g. if the species was tagged before), which can be used for a more adequate assessment of range. Intuitively, one may resist the idea of seemingly imposing a bias on the analysis. In practice, however, the formula for calculating n (Eq. 2) builds on parameters that are otherwise presumed implicit when designing a telemetry study (e.g. for the choice of transmitting interval settings) [15, 39, 40]. By specifying how these parameters relate (Eqs. 1 and 2), they can explicitly be taken into account in the assessment of detection range and in the design of a telemetry study.

Accounting for range

Despite an increasing recognition in the telemetry community for the need of range testing, only few range test studies [38, 42] evaluate their own design or the applicability to the telemetry study and analytical application. As a standard practice, receivers and sentinel transmitters are placed on a line to investigate range [4, 5, 43]. In this study, we show that the orientation of that line can influence the estimation of detection range, likely in relation to the direction of the dominant currents [23]. Likewise, detections of sentinel transmitters used during this study

weren't necessarily representative of the performance of the entire array. In our case, the optimal strategy to obtain reliable detection errors was to assess range before the study using the entire receiver array, in addition to sentinel transmitter data during the study.

Aside from the range test itself, the method to account for detection error must be tailored to the analytical application and its temporal resolution. From the method elaborated in this study, the cumulative probability P enables the calculation of detection error at the same temporal resolution of the presence metric of interest. When analysing patterns in presence, this measurement error can be directly included either as a Bayesian error structure in a generalized model [44] or in a state-space modelling framework [45–47]. For telemetry analyses that do not build on presence/absence as a response variable, different methods have been developed to account for range or detection efficiency [16]. Detection counts for example can be directly recalibrated using a correction factor [25], whereas error can also be included in the calculation of centres of activity based on detection counts [48, 49]. When investigating the sequence of detections in space, range can be assessed specifically for migratory routes [50] or network analysis [38]. For fine-scale positioning, horizontal position errors would be quantified within an entire receiver array [8], potentially accounting for individual receiver's contributions [51] and system settings [52].

Implications for study design

We strongly argue to consider the assessment of range as a fundamental aspect of the study design, the data analysis and the interpretation of results. Aside from factors beyond a researcher's control, such as environmental conditions and movement behaviour [15], range is an interplay of distance to a receiver [1], the deployment set-up [10] and receiver type [38], tag attachment [9], transmitting power output [2, 7] and depending on the application: transmitting interval and temporal resolution of the analysis. Therefore, researchers can fine-tune more aspects in the design of a telemetry study than simply the lay-out of a receiver array. Understanding the effect of these factors on detection range, is also advantageous for budget management of expensive telemetry equipment. Adequate range assessments may optimize transmitter battery life times, e.g. by carefully deciding on transmitting interval and power output [2], or reduce the number of receivers required in an array [53–55]. Building on the multitude of detection range studies, this study can serve as a plea to rethink detection range as a spatiotemporal interplay of many factors.

Abbreviations

AIC: Akaike information criterion; AUC: Area under the curve; BSS: Brier Skill Score; D_{50} : Distance at which detection probability is predicted to be 50%; k : Detection threshold; LRT: Likelihood ratio test; n : Number of signals transmitted within a certain range of a receiver; P : Probability of determining presence of an acoustic transmitter within a given time frame; π : Probability of detecting a single transmission within a given time frame; π^0 : Probability π with application of a zero threshold; RMSE: Root mean square error; t_{min} : Hypothesized minimum time an animal would be within a certain range of a receiver; \bar{T} : Mean transmitting interval.

Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1186/s40317-022-00290-2>.

Additional file 1: Appendix model selection.

Acknowledgements

Data and infrastructure were provided by VLIZ as part of the Flemish contribution of the LifeWatch ESFRI funded by the Research Foundation—Flanders (FWO). We thank the crew of RV Simon Stevin and RHIB Zeekat, as well as Annelies De Backer, for their help with the field work. We thank the reviewers for their constructive feedback.

Author contributions

JG analysed the data and wrote the manuscript. JR, JB and JG designed the study and collected the data. JR, JB, PV and SB contributed to the data analysis. JB created the map. All authors critically contributed to the drafts and gave final approval for publication. All the authors read and approved the final manuscript.

Funding

This study makes use of data and infrastructure provided by the VLIZ and funded by the Research Foundation—Flanders (FWO) as part of the Belgian contribution to the LifeWatch European Research Infrastructure (I002021N-LIFEWATCH). JG holds a doctoral grant from FWO (1S14821N).

Availability of data and materials

The datasets generated and analysed during the current study are available in the DOI repository <https://doi.org/10.14284/545> [56], with detection data also accessible on the data platform of the European Tracking Network (www.lifewatch.be/etn).

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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Received: 28 January 2022 Accepted: 6 May 2022

Published online: 23 May 2022

References

- Kessel ST, Cooke SJ, Heupel MR, Hussey NE, Simpfendorfer CA, Vagle S, et al. A review of detection range testing in aquatic passive acoustic telemetry studies. *Rev Fish Biol Fish.* 2014;24(1):199–218.
- Scherrer SR, Rideout BP, Giorli G, Nosal EM, Weng KC. Depth- and range-dependent variation in the performance of aquatic telemetry systems: understanding and predicting the susceptibility of acoustic tag-receiver pairs to close proximity detection interference. *PeerJ.* 2018;6:e4249.
- Selby TH, Hart KM, Fujisaki I, Smith BJ, Pollock CJ, Hillis-Starr Z, et al. Can you hear me now? Range-testing a submerged passive acoustic receiver array in a Caribbean coral reef habitat. *Ecol Evol.* 2016;6(14):4823–35.
- Reubens J, Verhelst P, van der Knaap I, Deneudt K, Moens T, Hernandez F. Environmental factors influence the detection probability in acoustic telemetry in a marine environment: results from a new setup. *Hydrobiologia.* 2019;845:81–94.
- Huveneers C, Simpfendorfer CA, Kim S, Semmens JM, Hobday AJ, Pederson H, et al. The influence of environmental parameters on the performance and detection range of acoustic receivers. *Methods Ecol Evol.* 2016;7(7):825–35.
- Winter ER, Hindes AM, Lane S, Britton JR. Detection range and efficiency of acoustic telemetry receivers in a connected wetland system. *Hydrobiologia.* 2021;848(8):1825–36.
- Kessel ST, Hussey NE, Webber DM, Gruber SH, Young JM, Smale MJ, et al. Close proximity detection interference with acoustic telemetry: the importance of considering tag power output in low ambient noise environments. *Anim Biotelemetry.* 2015;3(1):5.
- Stott ND, Faust MD, Vandergoot CS, Miner JG. Acoustic telemetry detection probability and location accuracy in a freshwater wetland embayment. *Anim Biotelemetry.* 2021;9(1):19.
- Dance MA, Moulton DL, Furey NB, Rooker JR. Does transmitter placement or species affect detection efficiency of tagged animals in biotelemetry research? *Fish Res.* 2016;183:80–5.
- Goossens J, T'Jampens M, Deneudt K, Reubens J. Mooring scientific instruments on the seabed—design, deployment protocol and performance of a recoverable frame for acoustic receivers. *Methods Ecol Evol.* 2020;11(8):974–9.
- Welsh J, Fox R, Webber D, Bellwood D. Performance of remote acoustic receivers within a coral reef habitat: implications for array design. *Coral Reefs.* 2012;31:693–702.
- Heupel MR, Reiss KL, Yeiser BG, Simpfendorfer CA. Effects of biofouling on performance of moored data logging acoustic receivers. *Limnol Oceanogr Methods.* 2008;6(7):327–35.
- Grothues T, Able K, Pravatiner JH. Winter flounder (*Pseudopleuronectes americanus* Walbaum) burial in estuaries: acoustic telemetry triumph and tribulation. *J Exp Mar Biol Ecol.* 2012;438:125–36.
- Swadling DS, Knott NA, Rees MJ, Pederson H, Adams KR, Taylor MD, et al. Seagrass canopies and the performance of acoustic telemetry: implications for the interpretation of fish movements. *Anim Biotelemetry.* 2020;8(1):8.
- Heupel MR, Semmens JM, Hobday AJ. Automated acoustic tracking of aquatic animals: scales, design and deployment of listening station arrays. *Mar Freshw Res.* 2006;57(1):1–13.
- Whoriskey K, Martins EG, Auger-Méthé M, Gutowsky LFG, Lennox RJ, Cooke SJ, et al. Current and emerging statistical techniques for aquatic telemetry data: a guide to analysing spatially discrete animal detections. *Methods Ecol Evol.* 2019;10(7):935–48.
- Cimino M, Cassen M, Merrifield S, Terrill E. Detection efficiency of acoustic biotelemetry sensors on Wave Gliders. *Animal Biotelemetry.* 2018;6(1):16.
- O'Brien MHP, Secor DH. Influence of thermal stratification and storms on acoustic telemetry detection efficiency: a year-long test in the US Southern Mid-Atlantic Bight. *Anim Biotelemetry.* 2021;9(1):8.
- Doyle TK, Haberlin D, Clohessy J, Bennison A, Jessopp M. Localised residency and inter-annual fidelity to coastal foraging areas may place sea bass at risk to local depletion. *Sci Rep.* 2017;7(1):45841.
- Novak AJ, Becker SL, Finn JT, Danylchuk AJ, Pollock CG, Hillis-Starr Z, et al. Inferring residency and movement patterns of horse-eye jack *Caranx latus* in relation to a Caribbean marine protected area acoustic telemetry array. *Anim Biotelemetry.* 2020;8(1):12.
- Ramsden S, Cotton C, Curran M. Using acoustic telemetry to assess patterns in the seasonal residency of the Atlantic stingray *Dasyatis sabina*. *Environ Biol Fish.* 2017;100:89–98.

22. Melnychuk M. Detection efficiency in telemetry studies: Definitions and evaluation methods. In: Adams N, Beeman J, Eiler J, editors. *Telemetry techniques: a user guide for fisheries research*. Bethesda: American Fisheries Society Books; 2012. p. 339–57.
23. Mathies NH, Ogburn MB, McFall G, Fangman S. Environmental interference factors affecting detection range in acoustic telemetry studies using fixed receiver arrays. *Mar Ecol Prog Ser*. 2014;495:27–38.
24. Brownscombe JW, Lédée EJ, Raby GD, Struthers DP, Gutowsky LFG, Nguyen VM, et al. Conducting and interpreting fish telemetry studies: considerations for researchers and resource managers. *Rev Fish Biol Fish*. 2019;29(2):369–400.
25. Brownscombe JW, Griffin LP, Chapman JM, Morley D, Acosta A, Crossin GT, et al. A practical method to account for variation in detection range in acoustic telemetry arrays to accurately quantify the spatial ecology of aquatic animals. *Methods Ecol Evol*. 2020;11(1):82–94.
26. Klinard NV, Halfyard EA, Matley JK, Fisk AT, Johnson TB. The influence of dynamic environmental interactions on detection efficiency of acoustic transmitters in a large, deep, freshwater lake. *Anim Biotelemetry*. 2019;7(1):17.
27. R Core Team. R: A language and environment for statistical computing. 2021.
28. Ku H. Notes on the use of propagation of error formulas. *J Res Natl Bur Stand*. 1966;70C(4):263–73.
29. Legrand S, Baetens K. Hydrodynamic forecast for the Belgian Coastal Zone. *Physical State of the Sea-Belgian Coastal Zone—COHERENS UKMO*: Royal Belgian Institute of Natural Sciences; 2021.
30. Zuur AF, Ieno EN, Elphick CS. A protocol for data exploration to avoid common statistical problems. *Methods Ecol Evol*. 2010;1(1):3–14.
31. Zuur A, Ieno EN, Walker N, Saveliev AA, Smith GM. *Mixed effects models and extensions in ecology with R*. New York: Springer; 2009.
32. Ellis S, Steyn HS. Practical significance (effect sizes) versus or in combination with statistical significance (p-values). *Manag Dyn*. 2003;12:51–3.
33. Sullivan GM, Feinn R. Using effect size—or why the p value is not enough. *J Grad Med Educ*. 2012;4(3):279–82.
34. Peng C-YJ, Lee KL, Ingersoll GM. An introduction to logistic regression analysis and reporting. *J Educ Res*. 2002;96(1):3–14.
35. Hanley JA, McNeil BJ. The meaning and use of the area under a receiver operating characteristic (ROC) curve. *Radiology*. 1982;143(1):29–36.
36. Brier GW. Verification of forecasts expressed in terms of probability. *Mon Weather Rev*. 1950;78(1):1–3.
37. Rönkkö M, Aalto E, Tenhunen H, Aguirre-Urreta MI. Eight simple guidelines for improved understanding of transformations and nonlinear effects. *Organ Res Methods*. 2021;25(1):48–87.
38. Mourier J, Bass NC, Guttridge TL, Day J, Brown C. Does detection range matter for inferring social networks in a benthic shark using acoustic telemetry? *Roy Soc Open Sci*. 2017;4(9): 170485.
39. Ellis RD, Flaherty-Walia KE, Collins AB, Bickford JW, Boucek R, Walters Burnsed SL, et al. Acoustic telemetry array evolution: from species- and project-specific designs to large-scale, multispecies, cooperative networks. *Fish Res*. 2019;209:186–95.
40. How JR, de Lestang S. Acoustic tracking: issues affecting design, analysis and interpretation of data from movement studies. *Mar Freshw Res*. 2012;63(4):312–24.
41. Reubens JT, De Rijcke M, Degraer S, Vincx M. Diel variation in feeding and movement patterns of juvenile Atlantic cod at offshore wind farms. *J Sea Res*. 2014;85:214–21.
42. Baktoft H, Zajicek P, Klefoth T, Svendsen JC, Jacobsen L, Pedersen MW, et al. Performance assessment of two whole-lake acoustic positional telemetry systems—is reality mining of free-ranging aquatic animals technologically possible? *PLoS ONE*. 2015;10(5): e0126534.
43. Loher T, Webster RA, Carlile D. A test of the detection range of acoustic transmitters and receivers deployed in deep waters of Southeast Alaska, USA. *Anim Biotelemetry*. 2017;5(1):27.
44. Zuur AF, Ieno EN, Saveliev AA. *Beginner's guide to spatial, temporal, and spatial-temporal ecological data analysis with R-INLA*. In: Zuur AF, editor. *Using GLM and GLMM*, vol. 1. Newburgh: Highland Statistics Ltd; 2017. p. 362.
45. Pedersen MW, Weng KC. Estimating individual animal movement from observation networks. *Methods Ecol Evol*. 2013;4(10):920–9.
46. Auger-Méthé M, Newman K, Cole D, Empacher F, Gryba R, King AA, et al. A guide to state–space modeling of ecological time series. *Ecol Monogr*. 2021;91(4): e01470.
47. Alós J, Palmer M, Balle S, Arlinghaus R. Bayesian state-space modeling of conventional acoustic tracking provides accurate descriptors of home range behavior in a small-bodied coastal fish species. *PLoS ONE*. 2016;11(4):e0154089-e.
48. Simpfendorfer CA, Heupel MR, Collins AB. Variation in the performance of acoustic receivers and its implication for positioning algorithms in a riverine setting. *Can J Fish Aquat Sci*. 2008;65(3):482–92.
49. Winton MV, Kneebone J, Zemeckis DR, Fay G. A spatial point process model to estimate individual centres of activity from passive acoustic telemetry data. *Methods Ecol Evol*. 2018;9(11):2262–72.
50. Melnychuk M, Walters C. Estimating detection probabilities of tagged fish migrating past fixed receiver stations using only local information. *Can J Fish Aquat Sci*. 2010;67:641–58.
51. van der Knaap I, Slabbekoorn H, Winter HV, Moens T, Reubens J. Evaluating receiver contributions to acoustic positional telemetry: a case study on Atlantic cod around wind turbines in the North Sea. *Anim Biotelemetry*. 2021;9(1):14.
52. Vergeynst J, Baktoft H, Mouton A, De Mulder T, Nopens I, Pauwels I. The influence of system settings on positioning accuracy in acoustic telemetry, using the YAPS algorithm. *Anim Biotelemetry*. 2020;8(1):25.
53. Pedersen MW, Burgess G, Weng KC. A quantitative approach to static sensor network design. *Methods Ecol Evol*. 2014;5(10):1043–51.
54. Kraus RT, Holbrook CM, Vandergoot CS, Stewart TR, Faust MD, Watkinson DA, et al. Evaluation of acoustic telemetry grids for determining aquatic animal movement and survival. *Methods Ecol Evol*. 2018;9(6):1489–502.
55. Kendall MS, Williams BL, Ellis RD, Flaherty-Walia KE, Collins AB, Roberson KW. Measuring and understanding receiver efficiency in your acoustic telemetry array. *Fish Res*. 2021;234: 105802.
56. Goossens J, Buyse J, Reubens J, Ghent University Marine Biology Research Group, Institute for Agricultural and Fisheries Research, Flanders Marine Institute. *Detection range assessment Belwind offshore wind farm*. Belgium, 2021.

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