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Turning the tide: Understanding estuarine detection range variability via structural equation models

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Abstract

Insight into the detection range of acoustic telemetry systems is crucial for both sampling design and data interpretation. The detection range is highly dependent on the environmental conditions and can consequently be substantially different among aquatic systems. Also within systems, temporal variability can be significant. The number of studies to assess the detection range in different systems has been growing, though there remains a knowledge gap in estuarine habitats. In this study, a two-month experimental set-up was used to assess the detection range variability and affecting environmental factors of an estuary. Given the expected complex interplay of different factors and the difficulties it entails for interpretation, a structural equation modelling (pSEM) approach is proposed. The detection range of this estuarine study was relatively low and variable (average 50% detectability of 106 meters and ranging between 71 and 229 meters) compared to studies of riverine and marine systems. The structural equation models revealed a clear, yet complex, tidal pattern in detection range variability which was mainly affected by water velocity (via ambient noise and tilt of the receivers), water depth and wind speed. The negative effect of ambient noise and positive effect of water depth became more pronounced at larger distances. Ambient noise was not only affected by water velocity, but also by water depth, precipitation, tilt angle and wind speed. Although the tilt was affected by water velocity, water depth and wind speed, most of the variability could be traced back to the receivers themselves. Similarly, the receivers themselves seemed to explain a considerable portion of the detection range variability. Retrospective power analyses indicated that for most factors only a minor gain in explanatory power was achieved after more than two days of data collecting. Redirecting some of the sampling effort towards more spatially extensive measurements seems to be a relevant manner to improve the insights in the performance of telemetry systems in estuarine environments. Since the low and variable detection range in estuaries can seriously hamper ecological inferences, range tests with sound sampling designs and appropriate modelling techniques are paramount.

Keywords: Passive acoustic telemetry; Detection range; Estuary; Structural equation modelling (pSEM); Statistical power analysis

Background

Understanding the limitations of monitoring tools is key to any study design, to a correct interpretation of collected data, and to draw scientifically sound conclusions [?, ?]. Acoustic telemetry, the use of electronic transmitter tags and receivers to study movement behavior is advancing rapidly and is increasingly being used for multiple aquatic species at different spatial and temporal scales [?, ?, ?]. Its technological advancement and increasing use drive the demand for sound methodologies and an improved understanding of its limitations [?, ?]. In acoustic telemetry studies, a key methodological aspect to consider is the detection range (i.e. the relationship between the detection probability and the distance between tag and receiver) and its variability [?]. Payne et al. (2010), for example, found that neglecting detection range variability would have led to opposite conclusions regarding the diel patterns of cuttlefish behavior [?]. Simulation studies have shown how ignoring detection range variability during model development can lead to large biases in parameter estimates, variable degrees of confidence in position estimates and misinterpreted animal behavior [?, ?]. In addition, studies that rely on curtains of receivers to assess whether tagged animals enter and/or leave certain areas, might confuse variables affecting passage success with variables affecting detection range and the effectiveness of the curtain to detect passing animals [?, ?].

Estuaries are of particular importance for fish populations due to their functions as nursery, feeding area and migration route between freshwater and marine habitats [?]. Different fish species at different life stages use estuaries in various ways, giving rise to a broad range of movement behaviors [?]. The diadromous European eel (*Anguilla anguilla*), for example, uses selective tidal stream transport to move from its fresh water feeding habitat to its marine spawning grounds [?]. The estuarine-dependent spotted grunter (*Pomadasys commersonnii*) moves between the upper and lower estuary as a response to fluctuations in temperature and salinity [?], and the piscivorous red drum (*Sciaenops ocellatus*) adapts its home range to food availability [?]. The fine-scale spatiotemporal variation in environmental conditions, inherent to the dynamic nature of estuaries, will not only affect the movement behavior of fish [?], but also the detection range variability at a corresponding scale. To characterize movement behavior and disentangle it from methodological biases, a sound understanding of the detection range variability in estuaries is therefore key. Nevertheless, to our knowledge, there are no dedicated methodological studies evaluating detection range in estuaries. To ensure a sound methodological basis for future studies on estuarine detection range, the estuarine detection range and affecting variables were assessed using different data processing methods and a data analysis technique not previously applied to range studies. Additionally, given the outcomes of this study, the suitability of traditional sampling designs for detection range assessment was evaluated using power analysis.

Studies have identified strong tidal patterns in the performance of marine networks, underlining the importance of considering detection range variability when interpreting results [?, ?]. However, the number of potential explanatory variables in these studies has remained limited and assessments were often restricted to exploratory wavelet analyses [?, ?]. Regression-based models with multiple variables and interactions have been developed to understand detection range variability, yet these models did not explicitly account for causality nor distinguish between indirect and direct drivers [?]. Since insight in the actual contributors to detection range variability is crucial to decide on the sampling design, and given the broad range of potentially correlated and important variables (e.g. tilt angle of the receiver, ambient noise and water velocity) in an estuarine environment, an alternative approach might be more suitable. We propose piecewise structural equation models (pSEMs). pSEMs have been used in many disciplines to test causal structures and to identify whether variables have an indirect or direct relationship with the considered response [?]. Although pSEMs have not been used in any methodological telemetry study yet, they have the potential to provide a better understanding of detection range variability and were therefore used in this study.

In addition, although researchers have come to consider range testing as essential for any telemetry study, guidelines and practical suggestions on how to perform range tests in estuaries have been lacking. Although a general understanding of the most important factors affecting detection range in a specific type of aquatic system will already provide an important baseline [?], it is still recommended to assess and understand the network performance in any new study area. Power analyses are standard in many scientific fields to determine the magnitude and distribution of the required sampling effort. However, to our knowledge, there have not been any methodological telemetry studies that have made use of power analyses to determine how long experiments should run and how many receivers should be used to yield statistically reliable results. Here we assessed the added value of power analyses for methodological telemetry studies using the available data and developed models.

Once the data have been collected, they need to be processed before analysis. To determine the detection probability, detection data are often aggregated over a certain time interval to account for not exactly knowing the exact moment at which a signal is transmitted. Since the transmission rate of most acoustic tags varies randomly about the nominal delay value to avoid collisions and loss of signals, it is often difficult to estimate the exact number of submitted transmissions within a certain time frame. Therefore, if the random burst interval between signals is large and the chosen temporal resolution small, the accuracy of the performance estimates will be poor and unrealistic performance values of more than 100 % might occur. Temporal aggregation is also often applied to align the resolution of the detection data with the resolution of the explanatory variables. However, the chosen resolution of the data does not necessarily reflect the resolution that is most appropriate to describe the variability of the detection range, which might introduce poor inferences and lack of insight in fine-scale processes. More recently, time-logging built-in tags record the exact moment at which a signal is transmitted, allowing to trace each individual detection back to its original transmission and removing the necessity to aggregate the data. Since in this study receivers with time-logging built-in tags were used, both non-aggregated [**?**, **?**] and aggregated data [**?**, **?**, **?**] were available for analysis. To assess the effect of data aggregation, and therefore temporal resolution, models of both datasets were developed and compared.

This study took place in the Permanent Belgian Acoustic Receiver Network (PBARN) which consists of receivers in the Scheldt Estuary and Belgian part of the North Sea (BPNS). This network is being used to monitor the behavior of multiple fish species [**?**]. Our results are of direct use for the optimization of the PBARN and the interpretation of the data it generates, but will also facilitate telemetry studies elsewhere, particularly in estuarine environments.

In summary, the aims of this study are to (i) provide an in-depth assessment of indirect and direct drivers of detection range variability in an estuarine environment through a structural equation modelling approach (i.e. pSEMs), (ii) assess the added value of statistical power analyses and provide practical suggestions regarding the required experimental duration and number of receivers for range tests, and (iii) to assess the difference in inferences drawn from models built on aggregated and non-aggregated data.

Methods

Study area

The Schelde Estuary is a well-mixed estuary of 160 km long without transversal man-made migration barriers and is characterized by strong currents, high turbidity and a large tidal amplitude up to 6 m that connects to the North Sea [**?**]. The estuary can be divided in two regions (upstream to downstream): the Zeeschelde, which spans 105 km from Ghent to Antwerp (Belgium), and the Westerschelde, which covers the 55 km from Antwerp to the mouth of the estuary at Vlissingen (The Netherlands). The width of the Zeeschelde varies between 50 to 1350 m while that of the Westerschelde varies between 2000 and 8000 m. The description of the study area was adapted from Bruneel et al. (2020) [**?**].

In the Zeeschelde, a relatively straight river stretch of 1000 meters was selected to place 8 InnovaSea receivers (VR2Tx and VR2AR) with built-in transmitters along the river (Table 1). The experiment took place from the morning of the 1st of March 2020 until the afternoon of the 29th of April 2020. Data from the 1st of March 12:00 until the 29th of April 12:00 were used. The built-in transmitters logged when each transmission was emitted, which allowed to trace back every detection to its original transmission. These receivers also measured temperature, ambient noise and tilt angle every hour. Technical details are provided in Table 1.

Environmental data were collected from nearby measuring stations. Water level measurements (meters TAW (Tweede Algemene Waterpassing): Horizontal water level reference level used in Belgium) with a temporal resolution of one minute from a measuring station at Schoonaarde (zes49a-1066, x:124649.40, y:188333.70, HIC (Hydraulic Information Centre)) were used. Bathymetry measurements (meters TAW) of the study area with a spatial resolution of one meter were obtained from the Triton data base of Flemish Hydrography. The difference between the water level measurements and bathymetry measurements was used as a proxy of the water depth (meters). The receivers were not in direct contact with the river bottom, but rather hovered at some distance above it. In addition, the 17-kg concrete block connected to the lower part of the receivers has the tendency to sink deeper in soft substrate than on hard substrate. Based on expert knowledge, the distance between the bottom and the receivers was assumed to be 0.5 meter for receivers on hard substrate (Rt1, Rt2, and Rt8) and 0.3 meter for receivers on soft substrate (Rt3, Rt4, Rt5, Rt6 and Rt7). A distinction between soft and hard substrate was made based on the Flemish ecotope map. We used salinity and temperature measurements with a temporal resolution of five minutes from a measuring station at Schellebelle (zes54m-SF-CM, x:119267.00, y:189338.00, HIC), precipitation with a temporal resolution of one hour from a measuring station at Zele (plu17a-1066, x:127468.00, y:192887.00, HIC), and wind velocity and direction measurements with a temporal resolution of 15 minutes from a measuring station at Liedekerke (ME07-006, x:130730.00, y:175177.00, VMM (Flemish Environment Agency)). Since no nearby measurements of water velocity or discharge were available during the study period, we used 1D model simulations of water velocity with a temporal resolution of 10 minutes provided by the Hydraulic Information Centre (HIC) instead [**?**].

Data preprocessing

Data preprocessing and analysis were done using the R software (version 3.6.2, R Developer Core Team, R Foundation for Statistical Computing, Vienna, Austria). The data, code and documentation can be found here (link will be provided later: github repository via Zenodo).

Receivers are known to experience a time drift in their internal clocks. To account for this time drift, the exact moments the receivers were activated and data were downloaded, were compared to the internal clock readings of the receivers themselves. Over the entire study period of approximately 60 days the time drift ranged between 15 and 162 seconds. We assumed a linear trend in this time drift to correct the internal clock readings of the receivers.

Two datasets were constructed from the raw data: in a first dataset the detections were combined in hourly bins per receiver-tag combination [**?**, **?**], which we will refer to as the aggregated data. Since the transmission of each signal was time-stamped by the built-in tag of each receiver, we knew exactly when transmissions were sent and how many transmissions were sent per tag per specific hourly bin (Additional file 1). The hourly performance per receiver-tag combination was defined as the hourly number of detected signals divided by the hourly number of emitted signals. Hourly bins at the beginning and end of the dataset did not comprise a full hour. These hourly bins were therefore removed from the dataset. Environmental data with a temporal resolution of less than one hour were aggregated into hourly measurements using the median.

For the second dataset, the non-aggregated data, each individual detection was traced back to its original transmission. Although the linear interpolation is a very simple model to describe the time drift of the internal clocks of the receivers, the time drift itself was fairly limited over the entire study period and of the same magnitude as the shortest random transmission interval. Hence, the time stamp of each transmission could be considered reliable enough to link transmissions to detections and vice versa. For each detection the transmission nearest in time (after linear interpolation) was assigned to it. Being able to link the detections to the original transmissions allowed the identification of any 'double' detections (e.g. transmissions being reflected and detected several times) [**?**]. All detections could be traced back to one specific transmission and vice versa. Some signals may not have travelled in a direct line (e.g. by scattering and reflections along the river bank), yet there were no potential issues of over or under-counting detections in this dataset.

Data analysis

Single-wavelet and cross-wavelet analysis

To identify significant (p-value < 0.05) temporal and environmental patterns in the performance, single-wavelet (to test the periodicity of single variables) and cross-wavelet (to compare the frequency and synchronicity of two variables) analyses were conducted after smoothing the time series of the aggregated data using the R package WaveletComp [**?**].

Piecewise structural equation model

To identify and quantify the most important direct and indirect effects on performance, a piecewise structural equation model (pSEM) was constructed using the R package piecewiseSEM for the aggregated data. First, a full logistic regression model was constructed with the binomial performance (whether or not a transmission was detected) as a response.

Explanatory variables included the distance between transmitter and receiver, water velocity (m/s), current direction (i.e. the angle of the current direction and transmission direction: 0 or 180° (included as a categorical variable)), ambient noise (mV), water depth (m), tilt angle of the receiving receiver (°), tilt angle of the transmitting receiver (°), salinity (PSU), wind speed (m/s), wind angle (i.e. the sinus and cosinus of the angle between the wind direction and direction of the transmission) and precipitation (mm). Since the direction and effect size of these variables may be distance-dependent, the interactions of all above mentioned variables with distance were also included in the model. [**?**], for example, found that the negative effect of ambient noise and wind speed was higher at greater distance. Finally, we also included the following interactions: (1) wind speed and wind direction, (2) water velocity and current direction, and (3) tilt angle and the angle of the current direction and transmission direction. The latter served as a proxy for the direction in which the receiver was being tilted [**?**]. All explanatory variables were normalized (subtraction of mean and division by standard deviation) before model development.

To obtain the most parsimonious model, a forward selection procedure with BIC as selection criterion was used. BIC was chosen over AIC throughout the manuscript, as the former accounts for the sample size in the penalty. Considering the unequal sample sizes of the aggregated and non-aggregated datasets, the BIC was more appropriate to compare the models.

In case some significant temporal autocorrelation was detected in the residuals of the model, we would assess whether a more flexible fit would have improved the model. To this end, a GAM approach as described by [**?**] was tested, with all explanatory variables and a first-order autoregressive error (AR1) included (a more detailed description of the developed GAMs can be found in the provided R scripts). In case the model fit improvement was limited, the aforementioned logistic model was retained in the pSEM.

Two additional models were provided as input to the pSEM to account for any indirect effects on the detection range via noise and tilt angle. First, a linear mixed model was constructed with noise as response variable, and water velocity, water depth, precipitation, wind speed and direction (sine and cosine; see earlier), salinity, and tilt angle as fixed factors and receiver id as random factor. Second, a linear mixed model was constructed with tilt angle as response variable, water velocity, water depth, wind speed and direction (sine and cosine; see earlier) as fixed factors and receiver id as random factor.

Since correlation does not necessarily imply causation, processes that were potentially correlated but were unlikely to hold a causal relationship (i.e. correlated errors) were declared as such before running the model. This was done for ambient noise measured at the receiving receiver and tilt angle of the emitting receiver as they were unlikely to affect each other but might seem so because of their shared assumed dependence on water velocity. This was also done for tilt angle and salinity, and tilt angle of the emitting and receiving receiver.

Comparison of data types: aggregated versus non-aggregated data

To construct the pSEM and conduct the power analyses (see next section), we decided to use the aggregated data instead of the, temporally much finer, non-aggregated data because of several reasons. First, the lowest resolution of the explanatory variables was one hour and hence the fine-scale variability of the performance could not directly be fitted to the fine-scale variability of all explanatory variables, causing a mismatch between the temporal resolutions of the sub-models. Second, since measurements of performance and explanatory variables were taken at different locations and moments in time, there was no perfect spatial and temporal fit between both. Although we aimed to understand and account for the spatial and temporal gaps between measurements, their remaining effect might still affect model outcomes, which is more likely to be prominent for fine-scale data. Third, the computation time was significantly higher for the non-aggregated data than the aggregated data, as the former dataset was 25 times larger than the latter.

For the non-aggregated data a simple logistic model was constructed. For this model only, the aggregated data of ambient noise and tilt angle were brought to a finer temporal resolution through receiver-unique loess models with time as covariate and a minimal span (0.2%). First, a full logistic model with as response the Bernoulli performance and the same scaled explanatory variables as for the aggregated-data-model was constructed. While the different random burst intervals (RBIs) of the different receivers were no issue for the aggregated-data-model, they should be accounted for in this non-aggregated-data model as they determine the number of transmissions. Therefore, weights were given to the different transmissions in such a way that each receiver contributed equally to the constructed models, i.e. higher weights for transmissions of receivers with higher RBIs. Finally, to obtain the most parsimonious model a forward selection procedure with BIC as selection criterion was used.

Since the pSEM is built "piecewise" by combining different sub-models, the singular logistic performance model of the pSEM (based on the aggregated data) can be compared with the logistic performance model that was developed using the non-aggregated data. Both models have the same model structure and differences in the inferences drawn from both models should therefore be contributed to the data themselves.

Statistical power analysis

We conducted a power analysis to assess the minimal duration and number of receivers needed to identify the driving forces of the performance with sufficient statistical power (≥ 0.80) [**?**]. The most parsimonious performance model for the aggregated data, developed in the first step of the pSEM, was run for different scenarios of experiment durations and numbers of receivers. For each unique combination of durations and number of receivers, 10^4 random subsets of data were created and used to fit the model. The periods were selected randomly. The receivers were picked in the order of their geographical placement (i.e. Rt1, followed by Rt2, Rt3, etc.). The statistical power of each variable in the model was determined for every unique combination.

To assess and compare the effect of duration and number of receivers, a logistic model with as response statistical power and as explanatory variables the standardized number of receivers and the standardized duration of the experiment was constructed.

Results

Exploratory analysis

No false detections, as defined by Simpfendorfer et al. (2015) [**?**], were recorded during the study. Neither the response nor the explanatory variables had any outliers (1.5-IQR-rule). However, as some water depth measurements and corresponding tilt angle measurements suggested that some receivers (mainly Rt1 and Rt2) might have been exposed to air, observations with estimated water depths below zero or tilt angles above 90° were removed (4.0 % of the data). Since temperature and salinity were strongly correlated (r of 0.84), only salinity was used further on. The tilt angles of the submitting and receiving receiver did not show a strong correlation (r of 0.12), unlike the ambient noise (r of 0.86) and temperature (r of 0.98) measurements of both receivers. Ambient noise and temperature measurements of the transmitting receiver were excluded from the analysis. Finally, water velocity and ambient noise showed a less strong correlation (r of 0.73), yet found still sufficient to potentially affect the interpretability of the models if both were retained.

Although a core strength of pSEMs is their ability to include correlated variables while maintaining a good level of interpretability, caution remains key. More specifically, since there were some potentially quite important inaccuracies and biases for both the ambient noise measurements (i.e. one hourly measurement to represent an entire hour (solar-day inspired temporal resolution) of detections, describing a tidal process which has a lunar-day-periodicity) and flow velocity estimates (i.e. actual local conditions and depth dependency of the receivers were not taken into account), the remaining observed effect of the second-added correlated factor could be seriously inflated, hindering interpretation. Given their different origin (measurements versus simulations) and temporal resolution (1 h versus 10 min), it was therefore decided to retain the variable with the strongest fit to the response. Model structures were designed with both variables separately and the variable that resulted in the most parsimonious model (AIC) was retained. There were no other strongly correlated explanatory variables (r > 0.70). The water depth of the submitting and receiving receiver showed a moderate correlation (r of 0.58). The correlation between the water depth at a specific moment in time and the water velocity were low (r=0.17), but increased and peaked when a delay of two hours was considered. The delay between the vertical tides (water depth) and horizontal tides (water velocity) was therefore considered to be two hours. The decreasing trend of detection probability with distance between transmitter and receiver was apparent for all receivers, with the exception of Rt6, for which exceptionally high detection probabilities were recorded.

The unexpectedly high detection probability for Rt6 (both as transmitting and receiving receiver) could not be explained by any of the developed models (see pSEM). The number of available variables describing spatial patterns was limited in this study. Only the tilt angle and depth were available variables with some level of spatial information. The average tilt angle and depth of Rt6 were only the second lowest and highest respectively, and both variables were accounted for in the models. This suggests another series of unmeasured affecting factors. Typically, one would use a mixed-model approach to account for the unique, yet unobserved, properties of the individual receivers. However, since receivers were placed on different distances from each other, it is likely that any random effect would compete with the fixed factor distance for the same information, leading to ambiguous results. That is why no mixed-model approach was used to analyse the detection probability. Given the inability to properly describe the unexpected high detection probability for Rt6, it was decided to omit Rt6 from the analyses.

Wavelet analysis

According to Fig. 1, the single wavelet analyses of the performance suggest a strong tidal pattern with peaks at approximately 4 h (flood), 6 h (ebb) and 12 h (flood + ebb). Weaker, yet still significant periodical peaks can be observed at approximately 24 h and 360 h (spring - neap tide cycle). Tidal patterns are also apparent for ambient noise, tilt angle, water depth and water velocity. A weaker, yet still significant, circadian pattern for wind speed also seems present.

Piecewise structural equation model for aggregated data

The most parsimonious logistic performance model for the aggregated data retained the variables distance, ambient noise, tilt angle of the submitting and the receiving receiver, water depth, the interaction of distance with ambient noise and the interaction of distance with water depth.

After assessment of the residuals of the pSEM using the autocorrelation function (ACF) and single-wavelet analysis, some considerable temporal patterns remained. These temporal patterns corresponded with the tidal processes mentioned earlier, suggesting that the explanatory variables and/or the way they were fitted to the response were insufficient to describe the detectabilty. For the developed GAM, the most important explanatory environmental variables (i.e. noise and water depth) did not benefit from a more flexible fit or integration of AR1 correlation. In addition, the temporal autocorrelation in the residuals persisted and the overall model fit was only marginally better, discouraging further use of the GAM approach. We therefore concluded that the remaining autocorrelation in the residuals was most likely the result of the inadequacy of some measurements to represent the local conditions accurately on a fine scale (i.e. per receiver). The unmeasured fine-scale unique properties of the direct environment of single receivers might have an important effect, which might also result in unique relationships between the performance and the explanatory variables of each receiver-transmitter combination. Were it not for the confounding effect of distance (see Methods), a mixed-model approach could have partially resolved this issue. However, since the retained variables had considerable effect sizes, it is unlikely that a better account of the remaining temporal patterns would have led to a very different model, justifying the further use of the logistic model for the construction of the pSEM.

This parsimonious logistic model in combination with the linear mixed models of the ambient noise and tilt angle were fed into a pSEM. The tests of directed separation (used to evaluate the conditional independence claims) indicated that wind speed and tilt angle could have been important for the performance and measured noise, respectively. Therefore, both factors were also included in the respective parts of the model. The tests of directed separation also suggested to include flow velocity in the performance model. However, it was decided not to include water velocity because of the issues related to the correlated measurements of noise and water velocity in combination with the negligible increase in R^2 of 0.6 % after including water velocity. Additionally, including water velocity had almost no effect on the coefficients of the other factors, with the exception of noise for which the coefficient decreased substantially due to the correlated nature of noise and water velocity. The final pSEM is represented in Fig. 6 and the output is given in Table 2. Under average environmental conditions, the estimated detection probability reached 75, 50, 25 and 10 % at 20, 103, 188 and 275 meters, respectively (Fig. 3). As a result of the strong tidal dependency of the two most important explanatory variables, i.e. the flow-induced noise and water depth, the estimated detection probability also depended strongly on the tidal phase. The median D50 (distance at which the detection probability is 50 %) per tidal phase ranged from 71 to 229 meters (Fig. 4 and 5). During ebb the D50 decreased due to the combined negative effects of the increasing noise and decreasing water depth (Table 5). During flood the D50 initially increased but after two hours decreased due to the competing negative and positive effects of the increasing noise and increasing water depth, respectively (Table 5).

Ambient noise was the most important environmental factor affecting the detection probability according to the pSEM model of the aggregated data. Water velocity, precipitation and wind speed positively affected ambient noise, while water depth negatively affected ambient noise. Water depth had a positive effect on the performance. Tilt had a significant negative effect on the performance. The interaction of flow direction and tilt angle was retained in the non-aggregated-data model, but not in the aggregated-data-model. Tilt angle was most affected by the water velocity and water depth, yet only 3 % of the variability was explained by these factors. 71 % of the variability was explained by the receivers themselves.

Logistic model for non-aggregated data

The most parsimonious logistic model with performance as Bernoulli response for the non-aggregated data, contained most variables that were fed into the model. The most important variables for the model based on aggregated data (i.e. distance, tilt angle, water depth and wind speed) were also among the most important for the model based on non-aggregated data. Nevertheless, there were some clear differences between both approaches. The non-aggregated-data model showed a better fit when water velocity rather than ambient noise was included. The model also retained much more factors compared to the aggregated-data-model. The only factor that was not retained was the interaction between angle wind sine and distance.

Statistical power analysis

For most variables, increasing the number of receivers and duration of the range test had a positive logarithmic effect on the statistical power of the performance model for the aggregated data. When three or more receivers were used, the power for the factor distance became sufficient (0.80) after less than half a day (Table 6). The desired power of the factor noise was reached after 1.75 days, 1 day and 0.5 days when 3, 4 to 6 and 7 receivers were used respectively. The desired power of the tilt angle of the receiving receiver was reached after 1.75 days and 0.5 days when 3 to 4 and 5 or more receivers were used respectively. Although noise showed a minor, yet significant, temporal periodicity of 360 h, related to the spring-neap tide cycle, accounting for this phenomenon was not necessary to have sufficient statistical power. The desired power of the tilt angle of the submitting receiver was reached after 5, 3 and 1.5 days when 4, 3 and 5 or more receivers were used, respectively. The desired power of the water depth was reached after 14, 5, 2.5 and 1.5 days when 3, 4, 5 to 6 and 7 receivers were used, respectively. For wind speed, the duration had a weaker, more linear than logarithmic, effect on the power. When using 3 and 4 receivers, the desired power was not even reached after more than 16 days. When more than 4 receivers were used, the desired power of the wind speed was reached after approximately 8.5 days. Both distance and noise were not affected equally strong by the number of receivers as did water depth and tilt angle. A simple logistic model with as response the statistical power and as explanatory variables the standardized number of receivers and the standardized duration of the experiment revealed that both distance and noise were not affected as much by the number of receivers as were wind speed, water depth and tilt angle. For distance and noise the effect size of the factor duration was 19 and 11 times larger than that of the factor number of receivers. For the tilt angle of the receiving receiver, tilt angle of the submitting receiver, water depth and wind speed, the effect size of the factor duration was 9, 4, 3 and 2 times larger than that of the factor number of receivers.

Discussion

Estuarine detection range

In our study, which took place in the freshwater part of the Scheldt Estuary, the average D50 (distance at which the detection probability is 50 %) was 106 meters and ranged on average between 71 to 229 meters. Studies on the detection range of telemetry systems have been numerous and the range of outcomes extensive [?, ?, ?, ?, ?, ?, ?, ?, ?]. For example, Klinard et al (2019) described a D50 in large deep lakes of more than 1000 meters [?], while Selby et al (2016) found a D50 of no more than 40 meters in high rugosity coral reefs [?]. In the Belgian Part of the North Sea (BPNS), the area into which the Scheldt Estuary transitions, the average D50 was 230 meters [?]. The considerable larger depth (23 versus 2.31 meters) and weaker ambient noise (316 versus 378 mV) of the BPNS compared to our study area are most likely what caused the much higher D50 of the former. Given the pronounced variability in detection range within the Permanent Belgian Acoustic Receiver Network (PBARN), which stretches from the Scheldt Estuary to the BPNS [?], caution is advised when setting up experimental designs and interpreting results. The detection range in the Scheldt Estuary also seemed to be relatively low compared to other aquatic systems, probably because of the strong tidal currents of the estuary and relatively shallow placement of the receivers. The few studies which reported a lower detection range than for this study were characterized by high background noise conditions from hydropower plants [?], shallow waters [?] and high surface complexity [?].

Indirect and direct drivers of estuarine detection range variability

Tidal periodicity

In this study, detection probability was characterized by a pronounced, yet relatively predictable, temporal variation that coincided with the tidal dynamics of the estuary. Although different couples of receivers showed higher and lower peaks of detection probability, the consistent and significant periodicity of the peaks was undeniable. The different peak heights of couples of receivers could generally be traced back to the different distances between them, with larger distances resulting in lower detection probabilities. However, some variation remained as couples with similar distances between receivers could still differ greatly, indicating some additional spatial factors and/or receiver characteristics affecting the detection probability. In the following sections, the observed drivers of estuarine detection range variability are discussed. Differences in conclusions regarding identified drivers drawn from the models built on aggregated and non-aggregated data are discussed

Distance and spatial factors

Distance between transmitter and receiver was not only the most important factor to affect the detection probability, it also had an important interaction effect with other factors such as noise and water depth. If an interaction effect with distance was recorded, it always reinforced the positive or negative individual effect of the considered factor. At a closer range the detectability is sufficient to overcome the most extreme conditions, while at longer distances the more severe absorption and attenuation of the weakened signal causes it to be more susceptible to other affecting factors.

Because of the important effect of distance and pronounced temporal tidal dynamics, one might expect that there would be little variation attributable to spatial factors. However, some of the differences in performance between receivers were neither the result of distance nor tidal dynamics which would suggest some lingering, unaccounted affecting conditions. Sadly, these can not be identified and quantified with this dataset alone. Although this dataset has a good temporal resolution (minutes) and temporal extent (months) of most included factors, the spatial resolution of the environmental measurements (kilometers) and spatial extent of the study area (meters) were relatively poor. In addition, potentially important spatial factors such as habitat [?] (e.g. soil texture and structure, pools and riffles) and actual depth of the receivers, had not been measured. This limited our ability to attribute spatial variation to potential spatial factors and/or receiver characteristics and also made us decide to omit Rt6 from the main analysis.

Ambient noise, wind speed and precipitation

Ambient noise had an important negative effect on the detection probability and seemed to be mainly affected by the flow according to the aggregated-data-model, corroborating the results of other studies on the flow-induced nature of the ambient noise [?]. Though the fit of the noise model was already relatively good (R^2 of 0.71), some of the remaining unaccounted variation might have been the result of boats passing through the study area. Unfortunately, the available sluice operation data turned out to be insufficient to predict the moment of boat passage through the study area. Real-time boat location data or cameras to detect passing traffic can be useful in future studies to assess the effect of boat traffic on detection range. In the aggregated model, ambient noise was the preferred variable to retain while for the non-aggregated model this was water velocity. This is most likely because of the type of data aggregation and the characteristics of the hourly noise measurements versus the 10-min resolution flow estimates. If the flow estimates are aggregated into hourly averages it is reasonable that the hourly noise measurements provide a better proxy of the flow-noise-related effects on the detection probability. In contrast, if a simple loess model is used to artificially inflate the temporal resolution of the ambient noise measurements, than it makes sense that the high resolution flow estimates, derived from a complex process-based model, provide a better proxy of the flow-noise-related effects.

Given that these models were constructed with data of different temporal resolutions and with different factors, it was likely that they would yield different insights. Indeed, even though the direction of the effects of each considered factor was the same for both models, the relative effect size often differed. This was for example the case for precipitation, which had a relatively strong effect on the detection probability in the non-aggregated model compared to the aggregated model, causing it even to be omitted in the latter. Wind speed, on the other hand, seemed to negatively affect the detection probability directly for both models, which was most likely the result of the mixing of air bubbles that attenuates the acoustic signals [?]. However, according to the pSEM there also seemed to be an indirect effect as wind speed increased the ambient noise, which was most likely the result of the sound produced by the entrained air of the mixed bubbles [?]. Given the relatively strong effect of precipitation on noise, the apparent necessity to include precipitation to explain detection probability would indeed be much greater in a model that only accounted for the flow-induced noise (i.e. the non-aggregated model with water velocity instead of noise as explanatory factor). Finally, there was more ambient noise when the water was more shallow, which is most likely the result of the greater effect of the bottom (see further) [?].

Tilt

The negative effect of tilt is most likely the result of the increased angle between the sound wave and receivers and the shadowing effect of the receiver itself [?]. Multiple studies have found a significant relationship between flow and tilt angle [?] and although flow was the most important variable to affect the tilt angle in this study, the differences between the receivers themselves were much more pronounced than any effect caused by flow. This might be due to their placement in the water, the surrounding obstacles affecting the local flow regime or some other unaccounted factors. According to the non-aggregated model, it seemed that for receivers that tilted more towards each other the negative effect of tilt angle was less pronounced. Although to some extent confounded with the flow dependency of the tilt angle, signals moving against the current seemed to have had a lower detection probability. However, this direct effect of water current was only minor compared to the indirect effect of water current via the tilt direction. Ammann et al (2020) also found that receivers tilting downstream because of the current were more likely to detect transmitters downstream [**?**], corroborating our results on the importance of tilt direction in addition to tilt angle. The established direct effect of current should also be considered with care. Not only was the effect minor, the unexpectedly low correlation between tilt angle and water velocity, and the large discrepancy of the tilt angle between receivers, suggests that local flow conditions were considerably different for each of the receivers. Local flow measurements might be an added value in future studies, either to account for directly or to assess the viability of tilt angle as a proxy for water velocity in this specific system [**?**]. In addition, researchers have recently also been using more sturdy frames to reduce the tilting and improve detection probabilities [**?**].

Water depth

The number of methodological telemetry studies to consider water depth have been limited and the few studies that did include it, mainly focused on larger depths (> 10 meters) [**?**] and/or were limited to the assessment of the variable depth of the transmitters alone [**?**, **?**]. In these studies, the depth of the receivers was either fixed by design or considered as such. In addition, water depth is often considered a mainly spatial factor, which is a reasonable assumption for most lakes, rivers and deeper seas [**?**], but in shallow seas and estuaries, the tidal dynamics lead to important temporal, sometimes even dominant, depth variability. Sound speed is known to increase with depth due to the increasing ambient pressure. However, since the increase in sound speed is only 0.016 m/s per meter depth it is unlikely that the almost negligible increase in sound speed at depths of maximally 7 meter is responsible for the considerable observed effect [**?**]. It is much more likely that it is the increased interaction with the bottom and water surface and larger reflection angle under shallow conditions that affects the detection probability. Not only will the increased number of interactions with the bottom and water surface cause sound energy to be absorbed (mainly through contact with the bottom) scattered and lost more often, the larger reflection angle will also increase the amount of energy to be absorbed with each bottom interaction.

It is expected that in shallow waters there will be relatively more wind-and-rain induced air bubbles which will increase the attenuation of signals through absorption and scattering, negatively affecting the detection probability [**?**, **?**]. However, in this study, the interaction effects of water depth with wind speed and precipitation were negligible for all developed models, providing no evidence for such an indirect effect of water depth.

Temperature and salinity

The presence of a thermocline (i.e. an abrupt temperature gradient) is another potentially confounding factor of water depth that has been found to affect the detection probability, yet estuaries are typically well-mixed which prevents the formation of a thermocline. Even if a thermocline, a horizontal boundary in the water, would have existed, transmitters and receivers were most often at comparable depths causing the signal to move mainly in a horizontal direction along, and not across, any potential thermocline. The presence of a temperature gradient between receiver and transmitter and the resulting refraction of the signal (due to differences in speed of sound within the thermocline) are typically more important for the detection probability than the reduced sound speed at lower temperatures. salinity exhibited a positive, yet relatively poor, effect on detection probability which would be expected because of the higher sound speed in saline water [**?**]. However, salinity showed a relatively strong positive correlation with temperature, which is known to also positively affect sound speed [**?**]. Since the speed of sound is known to increase with 4.5 meter per $1°C$ and with 1.5 meter per 1 psu increase, it is much more likely to be temperature (range of $10.3°C$) than salinity (range of 0.22 psu) to affect the detection probability [**?**].

Causes of tidal periodicity

In summary, the tidal periodicity of the detection probability was mainly the result of the tidal periodicity of the two most important environmental explanatory variables: flow-induced noise (associated with the horizontal tide) and water depth (associated with the vertical tide). Although the direction of the horizontal tide had almost no effect on the detection probability (as it was only the magnitude of the water velocity and not its direction to impact the magnitude of the noise), the direction of the vertical tide (i.e. ebb versus flood) did have a strong effect on the detection probability because of the changing water depth. During ebb the water flow (and noise) increased and water depth decreased. Given the opposite effects of these factors on the detection probability, the detection probability decreased consistently during ebb. During flood on the other hand both the water flow (and noise) and water depth increased. At the first half of flood the increasing water depth dominates over the increasing noise, resulting in an increasing detection probability. At the second half the increasing noise dominates over the increasing water depth, resulting in a decreasing detection probability. Because of the delay between the vertical and horizontal tide in combination with the contrasting effects of noise and water depth, the two peaks of detection probability took place approximately one hour into ebb and approximately two hours into flood.

Sampling design

For most assessed variables the duration of the experiment turned out to be unnecessarily long and the number of receivers unnecessarily high. Variables that exhibited some level of spatial variation, such as water depth and tilt angle, benefited more from an increased spatial sampling effort, i.e. more receivers, than variables exhibiting a negligible level of spatial variation, such as ambient noise. However, for wind speed this was not the case. All receivers were assumed to be subjected to the same wind speed at a certain moment in time, yet there was a very strong effect of changing the number of receivers on the statistical power. This might be the result of the small range of wind speed susceptibility of the first four southernmost receivers. The reason for this difference in wind speed susceptibility remains unclear. The fifth and sixth receivers were positioned relatively deep compared to the first four receivers, but as indicated earlier, depth does not seem to affect the wind speed susceptibility.

The established statistical power analyses of this study had some clear limitations: only one set of eight receivers, limited to just one fixed location were used and these receivers most likely had different levels of susceptibility to different measured and unmeasured factors. In addition, the different distances between receivers complicated interpretability. More specifically, since the effect of most factors intensified at larger distances, the gain in power was most apparent when the range in distances was as large as possible. Hence, although the statistical power almost always increased with increasing number of receivers, its increase was also partially due to the increasing range of available distances between receivers as it increased the range of the susceptibility of the detection probability to the different factors.

The variability in the duration required to obtain a power of more than 80 % was extensive among the scenarios and ranged from half a day to 16 days, depending on the variable of interest and the number of receivers used. As indicated, the obtained results are not universal and should not simply be extrapolated to different systems. They do serve however as a more mathematically under-built guideline for detection range test designs than the currently available rules of thumb. For example, the suggestion of Gjelland et al (1998) to collect data for at least one full tidal cycle would have been adequate for most variables if 7 or more receivers were used and if hourly data was available. Less receivers and temporally coarser data would however have resulted in insufficient statistical power to assess variables [**?**]. Rather than the provision of guidelines for sampling designs, these results highlight the potential that additional power analyses have. A global power study on all the available large datasets to assess detection range variability in different systems would provide a statistically sound baseline to set up sampling designs in a much more optimal way.

Availability of data and materials

The data, code and documentation can be found here (Code and data will be provided via GitHub (Zenodo)).

Competing interests

The authors declare that they have no competing interests.

Author's contributions

S.B., P.V.: Conceptualization, S.B.: Data curation, Visualization, Writing - original draft, Formal analysis, Software, P.V, P.G.: Funding acquisition, S.B., P.V: Supervision, P.V: Project administration, S.B., P.V.: Investigation, S.B., P.V.: Methodology, P.V.: Resources, All authors: Writing - review and editing. All authors have read and agreed to the published version of the manuscript.

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Figures

Tables

Table 1 Technical details and placement details of the receivers (Rec) with built-in tags. The average (standard deviation) values of the hourly ambient noise (), tilt angle () measurements and depth (m) are given. RBI: random burst interval. DTB: distance to border. The VR2Tx combines a VR2W receiver with a built-in V16 transmitter. The VR2AR combines an acoustic release with a VR2Tx.

Rec	Distance	Code	Noise	Tilt angle (°)	RBI (sec)	Depth
Rt1	0	VR2Tx-480873	392 (149)	15 (15)	60-120	1.98 (1.13)
Rt2	50	VR2Tx-480874	376 (147)	21 (19)	60-120	1.83 (1.09)
Rt3	200	VR2Tx-480875	370 (136)	30 (4)	60-120	1.65 (1.02)
Rt4	300	VR2Tx-480876	357 (135)	20 (10)	540-660	2.20 (1.14)
Rt5	400	VR2Tx-480877	341 (127)	23 (6)	60-120	3.93 (1.14)
Rt6	500	VR2Tx-480878	316 (116)	18 (7)	60-120	3.89 (1.14)
Rt7	600	VR2AR-546043	344 (121)	51 (5)	540-660	1.71 (1.05)
Rt8	1000	VR2AR-546044	473 (166)	28 (12)	540-660	2.02 (1.13)

Table 2 pSEM model output for aggregated data without Rt6. For the different sub-models (i.e. performance, noise and tilt angle), for each variable, the coefficient estimates (Est), standard error (SE), critical value (Crit.Value), p-value and standardized estimates (Std.Est) are given.

Response	Predictor	Est	SE	Crit.Value	p-value	Std.Est
Performance	Distance	-3.5378	0.0480	-73.6953	<0.0001	-0.7479
	Noise	-1.1846	0.0413	-28.6946	<0.0001	-0.2504
	Tilt angle (rec)	-0.4859	0.0173	-28.0736	<0.0001	-0.1027
	Tilt angle (sub)	-0.4361	0.0178	-24.4391	<0.0001	-0.0922
	Water depth (sub)	0.7096	0.0282	25.1729	<0.0001	0.1500
	Wind speed	-0.1634	0.0149	-10.9844	<0.0001	-0.0345
	Distance * Water depth	0.6283	0.0328	19.1276	<0.0001	0.1228
	Distance * Noise	-0.4859	0.0437	-11.1115	<0.0001	-0.1090
Noise	Water velocity	0.7667	0.0025	304.8459	<0.0001	0.7667
	Water depth	-0.3011	0.0030	-99.4709	<0.0001	-0.3011
	Precipitation	0.0963	0.0024	39.9616	<0.0001	0.0963
	Wind speed	0.0147	0.0024	6.0353	<0.0001	0.0147
	Angle wind cosine	0.0097	0.0024	3.9988	0.0001	0.0097
	Angle wind sine	-0.0026	0.0024	-1.0502	<0.2936	-0.0026
	Tilt angle	0.0497	0.0042	11.9443	<0.0001	-0.0497
Tilt angle	Water velocity	0.1637	0.0025	66.0641	<0.0001	0.1637
	Water depth	-0.0723	0.0031	-23.5307	<0.0001	-0.0723
	Wind speed	0.0417	0.0025	16.9224	<0.0001	0.0417

Table 3 R^2 of the sub-models of the pSEM for data without Rt6. The marginal R^2 comprises the variance explained only by fixed effects while the conditional R^2 comprises the variance explained by the entire sub-model, i.e., both fixed and random effects. The R^2 of the performance was determined using the McFadden method.

Response	Marginal R^2	Conditional R^2
Performance	0.57	/
Noise	0.61	0.71
Tilt angle	0.03	0.71

Table 4 Model output of the most parsimonious logistic model for the non-aggregated-data without Rt6 with as response the Bernoulli performance. For each variable, the coefficient estimate (Est), standard error (SE), z-value, and p-value are given.

Predictor	Est	SE	z-value	p-value
(Intercept)	-3.263	0.004	-762.596	<0.001
Distance	-3.509	0.005	-660.289	<0.001
Water velocity	-0.943	0.003	-366.882	<0.001
Tilt angle (sub)	-0.377	0.003	-143.880	<0.001
Water depth (rec)	0.463	0.002	192.471	<0.001
Tilt angle (rec)	-0.566	0.003	-180.606	<0.001
Water depth (sub)	0.560	0.003	218.772	<0.001
Wind speed	-0.271	0.003	-101.365	<0.001
Precipitation	-0.263	0.004	-63.537	<0.001
salinity	0.115	0.003	43.318	<0.001
Current signal angle (180°)	-0.058	0.005	-11.312	<0.001
Angle wind cosine	-0.003	0.002	-1.393	0.164
Angle wind sine	-0.005	0.001	-3.400	0.001
Distance * Water depth (rec)	0.286	0.004	81.413	<0.001
Distance * Water depth (sub)	0.519	0.004	138.567	<0.001
Distance * Water velocity	-0.276	0.003	-94.911	<0.001
Distance * Tilt angle (sub)	-0.180	0.003	-55.389	<0.001
Distance * Wind speed	-0.148	0.003	-43.414	<0.001
Distance * Precipitation	-0.202	0.005	-42.800	<0.001
Distance * Tilt angle (rec)	-0.130	0.004	-33.972	<0.001
Tilt angle (rec) * Current signal angle (180°)	0.222	0.003	70.690	<0.001
Tilt angle (sub) * Current signal angle (180°)	-0.154	0.003	-59.489	<0.001
Distance * salinity	0.095	0.003	27.620	<0.001
Distance * Current signal angle (180°)	-0.080	0.007	-12.305	<0.001
Water velocity * Current signal angle (180°)	0.015	0.003	5.489	<0.001
Distance * Angle wind cosine	0.014	0.003	4.443	<0.001
Wind speed * Angle wind sine	0.007	0.001	5.363	<0.001
Wind speed * Angle wind cosine	-0.006	0.001	-4.717	<0.001

Table 5 Per tidal phase the D50 (distance at which the detection probability was 50%), median noise, median water depth, median tilt angle and median water velocity are given. The tidal cycle was subdivided in hourly tidal phases. No distinction was made between neap tide, spring tide or intermediate tide. The detection probability was estimated using the developed logistic submodel of the pSEM under median conditions of noise, water depth and tilt angle for all the considered tidal phases. For each tidal phase the distance at which the detection probability was 50% was given.

Phase (hours)	D50 (m)	Noise ()	Water depth (m)	Tilt angle ()	Water velocity (m/s)
HW (1)	171	326.80	3.60	19.00	-0.65
Ebb (1)	229	224.35	3.28	18.00	0.11
Ebb (2)	200	223.40	2.72	21.00	0.62
Ebb (3)	123	370.00	2.30	23.00	0.72
Ebb (4)	100	443.20	1.81	23.00	0.72
Ebb (5)	89	468.95	1.35	24.00	0.71
Ebb (6)	83	482.25	0.92	25.00	0.70
Ebb (7)	71	472.15	0.52	29.00	0.68
LW (1)	88	418.40	0.46	28.00	0.64
Flood (1)	189	193.45	0.88	21.25	0.04
Flood (2)	203	192.90	1.51	20.00	-0.38
Flood (3)	157	283.45	2.46	23.00	-0.66
Flood (4)	88	474.00	3.32	23.00	-0.88
HW (1)	171	326.80	3.60	19.00	-0.65

Table 6 Required number of days to reach a statistical power of 80 % for different variables and different numbers of receivers.

Variables	Number of receivers				
	3	4	5	6	7
Noise	1.75	0.75	0.75	0.75	0.50
Distance	0.50	0.25	0.25	0.25	0.25
Tilt angle (rec)	1.75	1.75	0.50	0.50	0.50
Tilt angle (sub)	3.00	5.00	0.75	0.75	0.50
Water depth	12.00	4.00	2.50	2.50	1.25
Wind speed	16.00	16.00	8.00	8.00	8.00

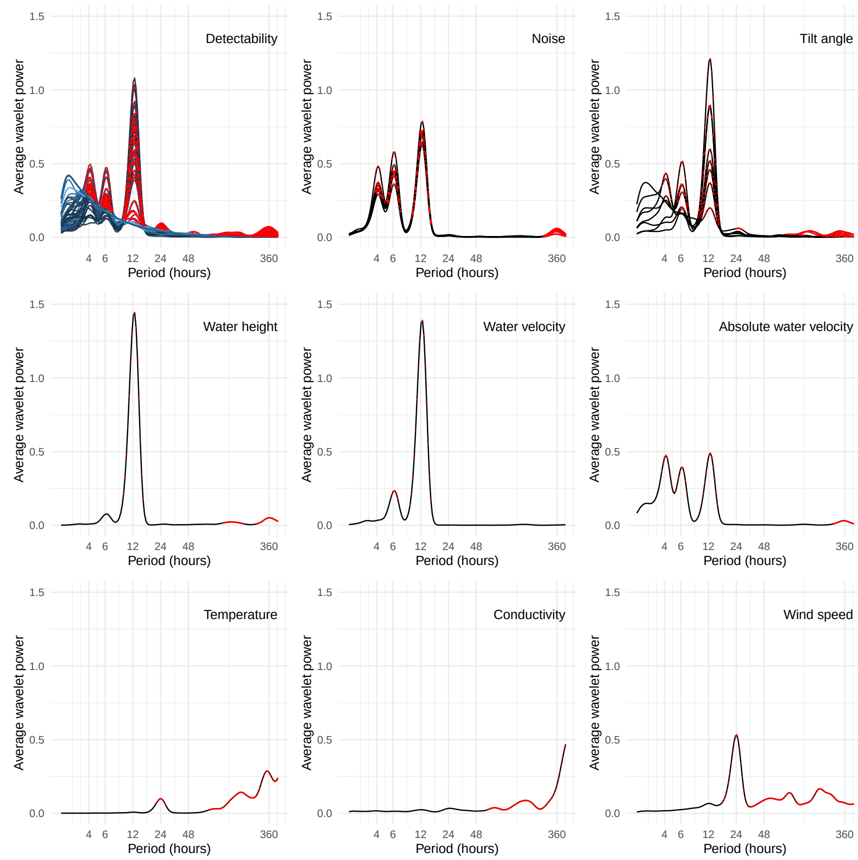

Figure 1 Average wavelet power in function of period (hours) for different variables. For the performance all different distances between receivers are depicted. Darker blue colors represent smaller distances. For the tilt angle and ambient noise measurements, the different measuring receivers are depicted. Significant values ($p<0.05$) are depicted with red dots.

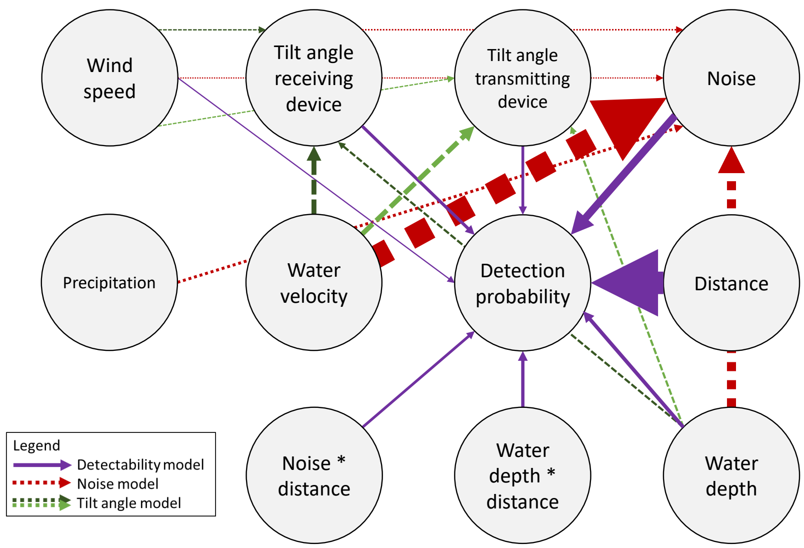

Figure 2 pSEM model with depiction of the different sub-models (i.e. performance, noise and tilt angle). The width of the arrows represents the standardized estimate of the relationship which is a measure of its relative importance.

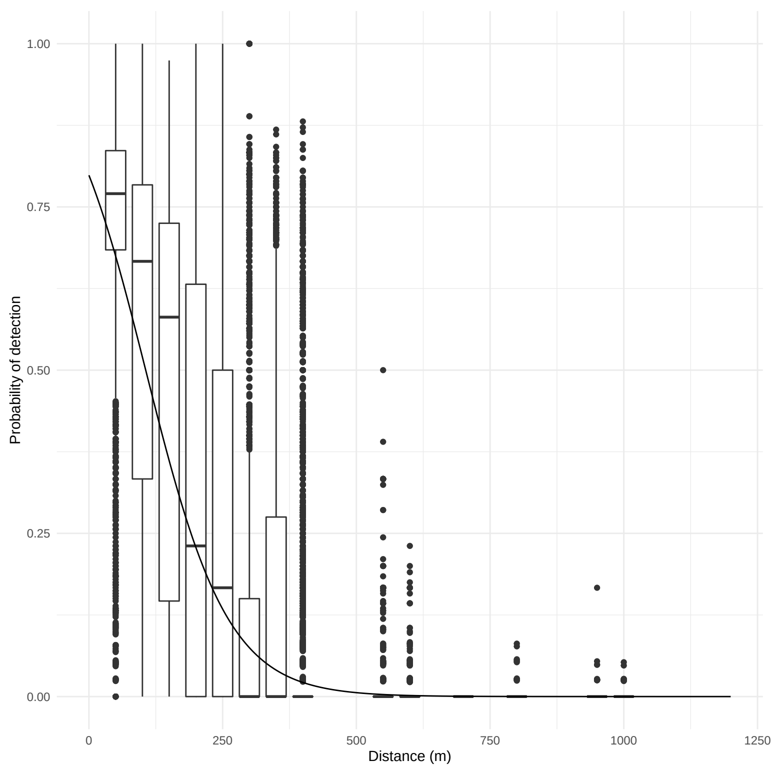

Figure 3 Detection probability in function of the distance between receiver and transmitter. Measurements (boxplots) and estimates (line) of detection probability in function of distance are depicted. The detection probability was estimated using the developed logistic submodel of the pSEM under average conditions of all other explanatory variables of the model.

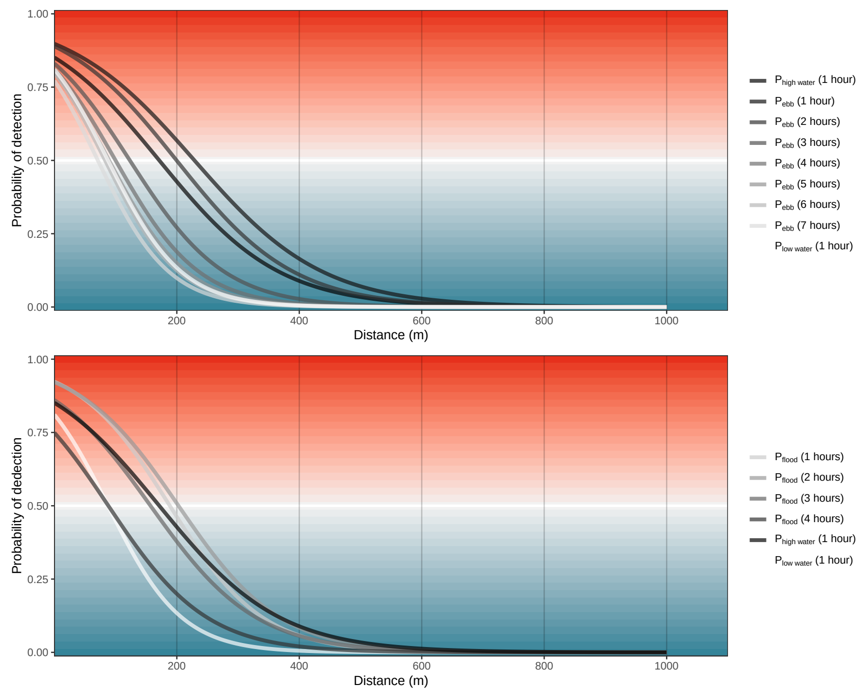

Figure 4 Detection probability in function of the distance between receiver and transmitter for different tidal phases. The tidal cycle was subdivided in hourly tidal phases. Each curve represents the detection probability (P) for each subsequent hourly tidal phase. No distinction was made between neap tide, spring tide or intermediate tide. The detection probability was estimated using the developed logistic submodel of the pSEM under median conditions of noise, water depth and tilt angle for all the considered tidal phases. R code to create this figure was adapted from [?].

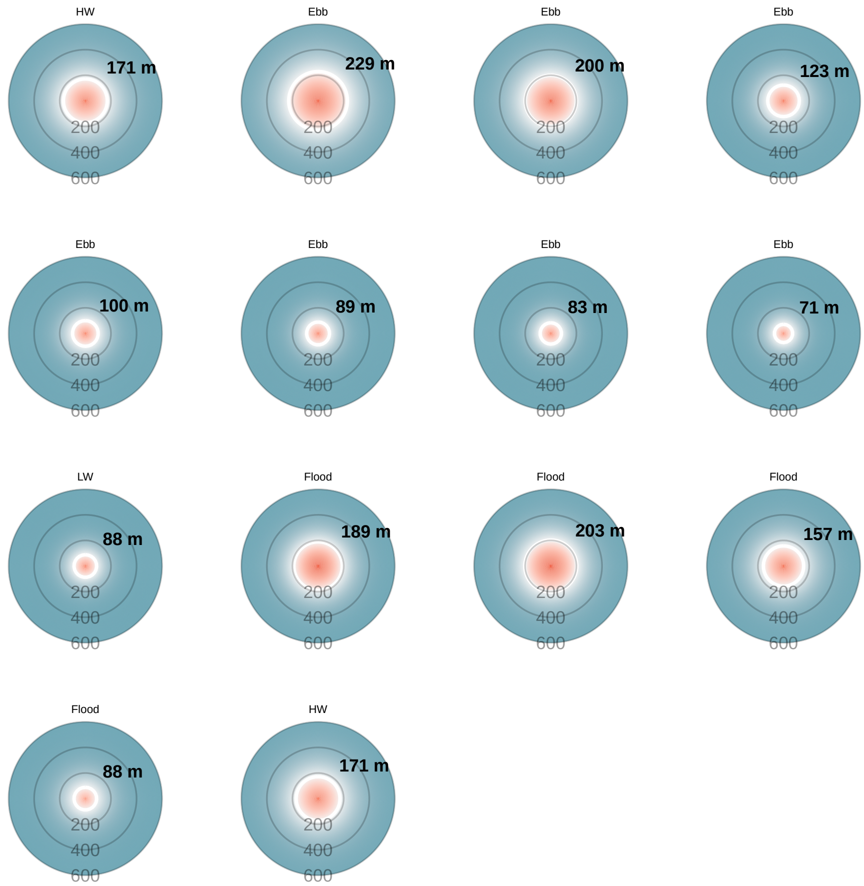

Figure 5 Detection probability in function of the distance between receiver and transmitter for different hourly tidal phases The tidal cycle was subdivided in hourly tidal phases. Each plot represents a subsequent hourly tidal phase. No distinction was made between neap tide, spring tide or intermediate tide. The detection probability was estimated using the developed logistic submodel of the pSEM under median conditions of noise, water depth and tilt angle for all the considered tidal phases. For each tidal phase the distance at which the detection probability was 50% was given. HW and LW stand for high water and low water respectively. R code to create this figure was adapted from [?].

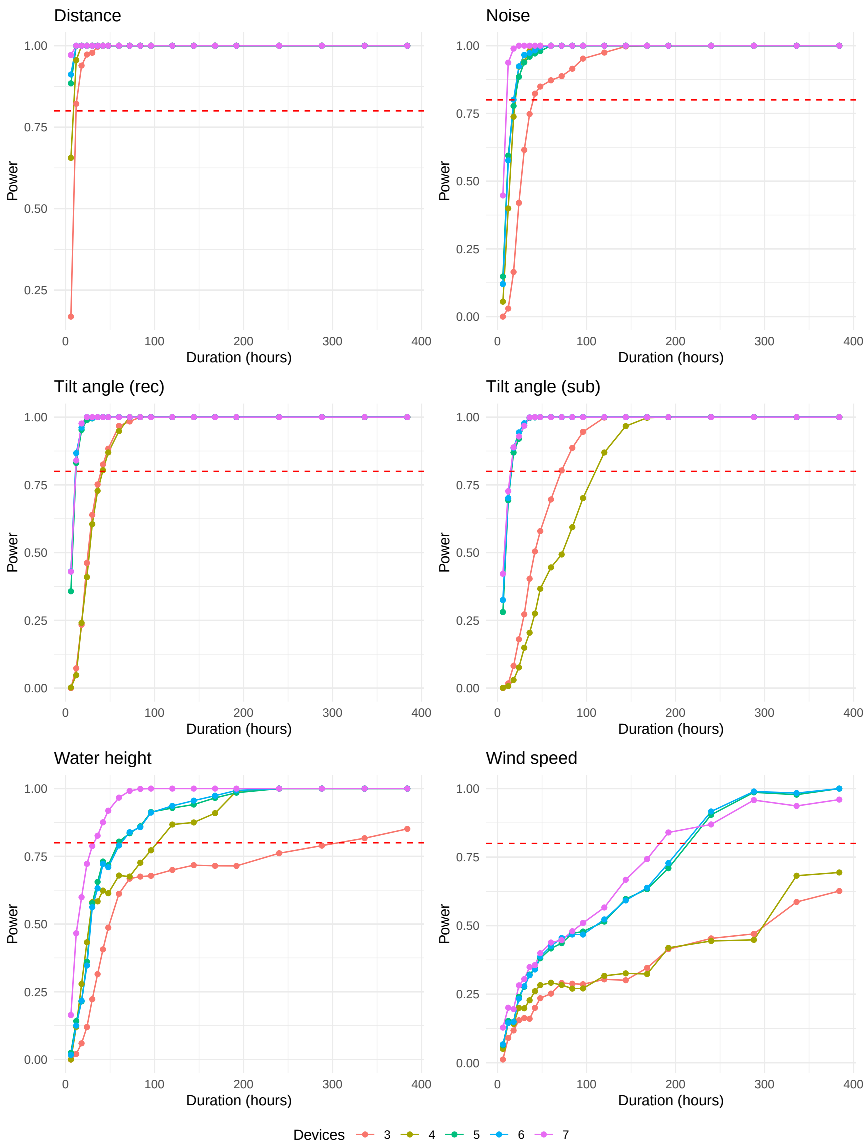

Figure 6 Statistical power analysis for the assessment of the drivers behind the performance based on the aggregated data without Rt6. The statistical power is given in function of the duration of the experiment. The different colored lines represent scenarios with different numbers of receivers with built-in transmitters. The horizontal red dashed line represents the threshold of 0.8 at which the power is considered sufficient.