NOVA SCOTIA AQUACULTURE REVIEW BOARD

IN THE MATTER OF: *Fisheries and Coastal Resources Act*, SNS 1996, c 25

- and -

IN THE MATTER OF: An Application by KELLY COVE SALMON LTD. for a boundary amendment and two new finfish aquaculture licenses and leases for the cultivation of Atlantic salmon (*Salmon salar*) – AQ#1205x, AQ#1432, AQ#1433, in Liverpool Bay, Queens County (the **"Application"**)

Rebuttal Affidavit of Adam Turner affirmed on February 16, 2024

I affirm and give evidence as follows:

1. I am Adam Turner, PEng of Saint John New Brunswick. I am a professional engineer licensed to practice in New Brunswick, Nova Scotia and Newfoundland and Labrador and employed by Cooke Aquaculture Inc.

2. I have personal knowledge of the evidence affirmed in this affidavit except where otherwise stated to be based on information and belief.

3. I state, in this affidavit, the source of any information that is not based on my own personal knowledge, and I state my belief of the source.

4. My CV was previously filed in this proceeding and is located at Exhibit A of the Affidavit of Adam Turner affirmed on January 16, 2024. I affirm that my CV is true and accurate.

5. I have received the report of Inka Milewski attached as Exhibit A to her affidavit affirmed on January 15, 2024 and filed in this proceeding by the Group of 22 Fishermen (the **"Milewski Report"**).

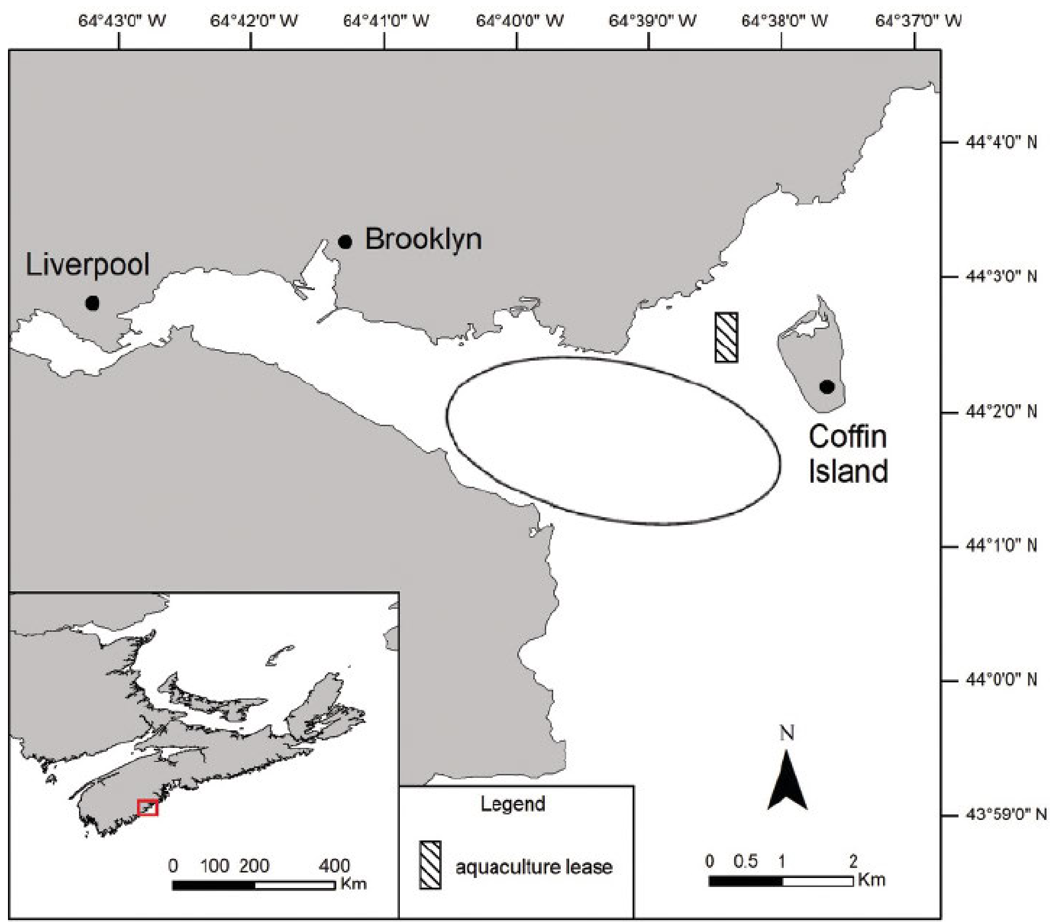
6. In the Milewsky Report, Ms. Milewski cites a peer-reviewed study titled "*Mapping American lobster (Homarus americanus) habitat for use in marine spatial planning*" which was authored by Anne McKee, Jon Grant and Jeffrey Barrell and published in the Canadian Journal of Aquatic Sciences in 2021 (the **"McKee et al. (2021) Study"**).

7. The McKee et al. (2021) Study is attached as **Exhibit A** to this affidavit.

8 I am informed through my review of the McKee et al. (2021) Study and do verily believe that the authors of the McKee et al. (2021) Study used aerial drone footage to collect lobster trap presence data through the georeferenced photography of lobster trap buoys which was conducted during two days within the fishing season in May 2017.

9 The authors' method is described in the sub section titled "Trap Data" at page 709 of the McKee et al (2021) Study. I am informed by this sub section and do verily believe that the authors assembled a lobster trap presence dataset through a metadata analysis of a collection 2089 photos followed by their visual inspection of a reduced set of 186 photos for Lobster trap buoys.

10 The approximate location of the lobster trap presence dataset created by the McKee et al. (2021) Study is depicted by the oval shape in the following image displayed at Figure 1:



11. I was not involved with the McKee et al. (2021) Study and cannot speak as a fact witness or as an expert to the study's collection or use of lobster presence data in Liverpool Bay. I understand and do verily believe from my review of the McKee et al. (2021) Study that the lobster trap presence data was used as a proxy for lobster presence and used in conjunction with species distribution models (**"SDMs"**) for the purposes of assessing methods for marine spatial planning. I am an engineer, not a marine scientist, and any opinions expressed in the study on its use of the lobster presence data along with species distributional modelling to assess methods of marine spatial planning are outside of my expertise.

12. However, I have observed that at Figure 2 on page 6 of the Milewski Report, Ms. Milewski overlays the proposed lease sites AQ#1205x, AQ#1432, AQ#1433 on Figure 10 of the McKee et al. (2021) Study.

13. Figure 10 is one of two figures in the McKee et al. (2021) Study which depicts information from an SDM (the colouring) along with the lobster trap presence data (the white rectangles) on a map of Liverpool Bay. The other figure is Figure 11, which is also reproduced at page 5 of the Milewski Report, but without the overlay of the proposed lease site locations.

14. Since I am not an expert in Ms. Milewski's field, I cannot comment on the two different SDMs from the McKee et al. (2021) Study or Ms. Milewski's choice to overlay the proposed lease sites on the "relative rate of lobster occurrence" SDM rather than the "probability of lobster occurrence" SDM.

15. However, in light of Ms. Milewski's evidence, and the fact that lobster trap presence data is displayed on other figures in the McKee et al. (2021) study in addition to Figure 10, I understand that the Board and the parties may benefit from a high-resolution overlay of the proposed lease site locations on the lobster trap presence data which was collected during the McKee et al. (2021) Study.

16. As a mechanical engineer, I am qualified and capable of overlaying georeferenced datapoints on a map. I have significant experience creating georeferenced maps of aquaculture sites and other offshore structures. I am generally creating these types of drawings weekly as part of my job. Therefore, overlaying some points from an existing map image to another is a fairly trivial task that I have high confidence in.

17. Accordingly, I have prepared a map which overlays the three proposed lease sites AQ#1205x, AQ#1432, AQ#1433 on the lobster trap presence data. This map is attached to this affidavit as **Exhibit B**.

18. This map was not based on the raw latitude and longitude trap location data. It is an overlay of the image in the McKee et al. 2021 Study onto a new map drawing with the lease and site locations. I affirm that this map is accurate to the best of my technical abilities.

19. I make this affidavit in support of KCS's application and for no other purpose.

AFFIRMED before me in Saint John, New Brunswick, on February 16, 2024.

[redacted]

New Brunswick Commissioner of Oaths

COLIN CORBY MACKINNON NOTARY ★ PUBLIC NEW BRUNSWICK

[redacted]

Adam Turner

KCS Application re AQ#1205X, AQ#1432, AQ#1433 in Liverpool Bay, Queens County

This is **Exhibit A** referred to in the Affidavit of Adam Turner, affirmed before me on February 16, 2024.

[redacted]

New Brunswick Commissioner of Oaths

NRC Research Press

ARTICLE

Mapping American lobster (*Homarus americanus*) habitat for use in marine spatial planning

Anne McKee, Jon Grant, and Jeffrey Barrell

Abstract: Marine spatial planning (MSP) is a management tool that could help mitigate the conflict that exists between the American lobster (*Homarus americanus*) fishery and the net pen salmon aquaculture industry in the Canadian Maritime prov inces. We developed adult American lobster species distribution models (SDMs) for use in MSP in Liverpool, Nova Scotia, through remote sensing data collection methods. A single beam echo sounder was used to collect bathymetry and seafloor substrate data, and an aerial drone collected lobster presence data through the georeferenced photography of lobster trap buoys. The SDMs display trends in lobster presence likelihood that correspond with established patterns of habitat selec tion in adult lobsters. The areas where lobsters are predicted to have the highest likelihood of presence are sections of hard and rocky substrate, though that association is confounded by depth. The uncertainty of the SDMs was quantitatively assessed and the importance of explicitly analysing the effects of scale and resolution of spatial data are highlighted.

Résumé : La planification spatiale marine (PSM) est un outil de gestion qui pourrait aider à atténuer le conflit actuel entre le secteur de la pêche au homard (*Homarus americanus*) et celui de la salmoniculture en parcs à filet dans les provinces mari times canadiennes. Nous avons développé des modèles de répartition de l'espèce (MRE) pour les homards adultes à utiliser pour la PSM à Liverpool (Nouvelle Écosse), en faisant appel à des méthodes de collecte de données télémétriques. Un écho sondeur à faisceau unique a été utilisé pour recueillir des données bathymétriques et sur le substrat marin et un drone aér ien a recueilli des données sur la présence de homards par photographie géoréférencée de bouées de pièges à homards. Les MRE révèlent des tendances de probabilité de présence de homards qui correspondent à des motifs établis de sélection d'ha bitats chez les homards adultes. Les zones où les plus grandes probabilités de présence de homards sont prédites sont des secteurs de substrat dur et rocheux, bien que la profondeur complique cette association. L'incertitude associée aux MRE est évaluée de manière quantitative et l'importance d'analyser explicitement les effets de l'échelle et de la résolution des don nées spatiales est soulignée. [Traduit par la Rédaction]

Introduction

Coastal marine waters in Atlantic Canada are used for a variety of activities, including fishing, aquaculture, resource extraction, transport, shipping, and recreation. The proximity and occasional overlap of some activities in these coastal waters can lead to conflict among users (Wiber et al. 2012; Marshall 2001; Ivany et al. 2014). Marine spatial planning (MSP) is a planning framework that is designed to manage such user–user conflicts through structuring the spatial and temporal distribution of ocean-based activities in an efficient manner that is sensitive to the needs of ecosystem, economic, and social objectives (Foley et al. 2010). However, one of the major weaknesses with MSP is a chronic lack of geospatial layers that detail the required data in suitable spatial and temporal scales (St. Martin and Hall-Arber 2008; Holmes et al. 2008; Crowder and Norse 2008; Harris and Stokesbury 2006). Specifically, spatial habitat representations for species of note are important components that are frequently missing from the MSP process.

Commercial fisheries and net-pen finfish aquaculture frequently share coastal space in Atlantic Canada. In Nova Scotia, the American lobster (*Homarus americanus*) is the most valuable commercial catch, with landings totalling to more than $802 million in 2017 (DFO 2017). However, inshore lobster fishing grounds are often used as farming sites for Atlantic salmon (*Salmo salar*). This overlap can cause conflict in local fishing communities, particularly regarding concerns about water pollution, lobster stock health, and trapping access (Wiber et al. 2012; Marshall 2001; Ivany et al. 2014). MSP strategies can be applied here through the delineation of local benthic lobster habitat, thereby allowing the placement of aquaculture sites in a manner that minimizes their overlap with lobster habitat. Describing the lobster habitat can be accomplished through species distribution models (SDMs). SDMs, which are also referred to as habitat suitability models, are a common type of habitat map that describe the suitability of an environment to support a species by representing where mapped environmental conditions, such as substrate, match the niche conditions of the species (Brown et al. 2011; Franklin 2010).

MSP is often conducted at regional scales to incorporate activities that also encompass those scales (e.g., shipping, offshore fishing, marine protected areas). Fish farms are located at designated sites occupying much smaller areas of several square kilometres. The extent of their spatial interactions with other activities must also be examined at similar scales. In the case of Nova Scotia, the Atlantic coastline is in many places divided into discrete bays that also contain inshore lobster fisheries. MSP involving these activities is similarly defined by these bays. In the following study, we examine the potential for acoustic discrimination of lobster habitat as the basis for an SDM and its applicability to MSP involving fish farms. The application of both SDM and MSP at small spatial scales results in attention to some of the potential pitfalls of this approach.

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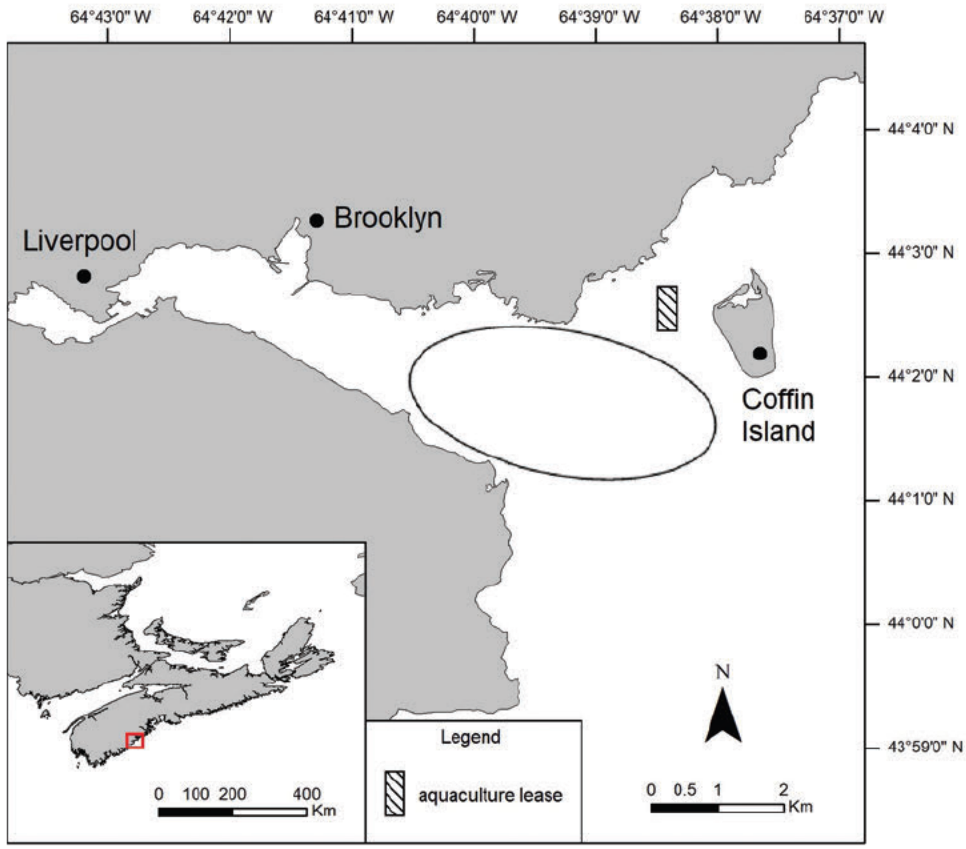
Fig. 1. Map of Liverpool Bay, with inset showing location within Nova Scotia. The hashed rectangle represents the location of the salmon net pens, and the oval represents the approximate study location. Map creation information can be found in Materials and methods.



Adult American lobsters consistently demonstrate preferential selection for shelter-forming substrates in the benthic marine environment. The most strongly preferred substrate is complex, preformed shelter such as boulders and cobble (Tremblay et al. 2009; Selgrath et al. 2007; Bologna and Steneck 1993; Spanier 1994), but shelter can also be constructed as burrows in stable mud (Spanier 1994; Lawton and Lavalli 1995; Cooper and Uzmann 1980) or shallow bowl-shaped depressions in sand (Cooper and Uzmann 1980). If boulders are scarce, adult lobsters will typically choose to live on mud instead of sand; if boulders and mud are both scarce, they will live on sand (Cooper and Uzmann 1980; Spanier 1994; Bologna and Steneck 1993). Adult lobsters have been shown to move into artificial reefs that are introduced on mud or sand barrens (Spanier 1994; Bologna and Steneck 1993). However, detection and mapping of these potential habitat characteristics can be difficult due to the water that covers the seafloor. A common approach to resolving this issue is through echo sounding, which is a form of acoustic remote sensing that detects the physical attributes of the seafloor substrate through high-frequency sound pulses (Brown et al. 2011). Both multibeam (MBES) and single-beam (SBES) echo sounder systems have been used in tandem with acoustic ground discrimination systems (AGDS; when used with SBES, SB-AGDS), which group the echo sounder signals according to their characteristics. These systems are commonly used to map shelf and coastal seafloor substrate distributions and have been used for the purpose of providing environmental layers to SDMs for decades (Brown et al. 2011; Freitas et al. 2011).

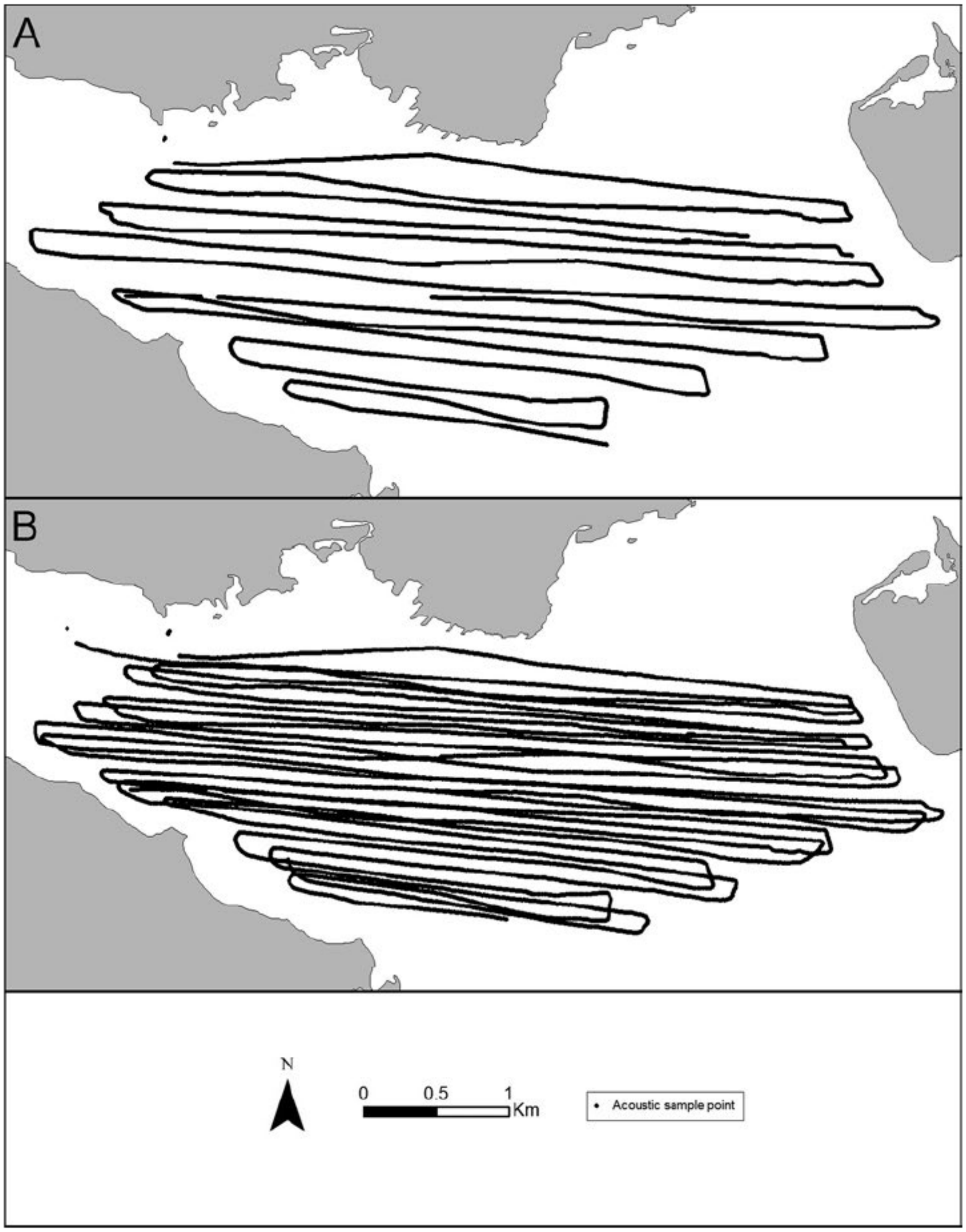
It is this approach that we used in the following study to model habitat for *H. americanus* in a small bay in Atlantic Canada where salmon aquaculture and the lobster fishery currently coexist and where aquaculture expansion is under consideration by provincial regulators. By developing continuous data maps of seafloor substrate and bathymetry, then adding points of lobster presence — represented by proxy with lobster trap buoys — we created habitat suitability models with the intent of lessening spatial overlap between the lobster fishery and aquaculture. These models can be applied to the MSP process, adding the missing habitat layers for this important commercial species and allowing for more effective distribution of coastal space through spatial management.

Materials and methods

Study site

Liverpool Bay is on the southwestern shore of Nova Scotia, Canada, on the Atlantic coast (44°2′N, 64°40′W) (Fig. 1; all maps in this study were created in ArcMap 10.5 with Nova Scotia shorelines from GeoNova (2015) and additional shorelines from Natural Resources Canada (2010)). A narrow bay at 4.5 km long and 2.6 km wide at the maximum, it is the exit point of the Mersey River, which extends trumpet-like into the ocean to form the bay. The tidal range of the bay is ~1–2 m. Coffin Island, a small island of ~0.75 km^2 that is located 1.5 km northeast of the mouth of the bay, provides some shelter to the salmon aquaculture pens tucked between the island and the mainland. The town of Liverpool is at the head of the bay and the village of Brooklyn is on the north shore; the bulk of the activity on the bay is from commercial fishing. The research was focused in the eastern half of the bay, partially due to the location of the fish farm and partially due to the placement of lobster traps.

Fig. 2. The acoustic data survey, with track spacing resolutions of 100 m (A) and 50 m (B). Map creation information can be found in Materials and methods.



Data collection

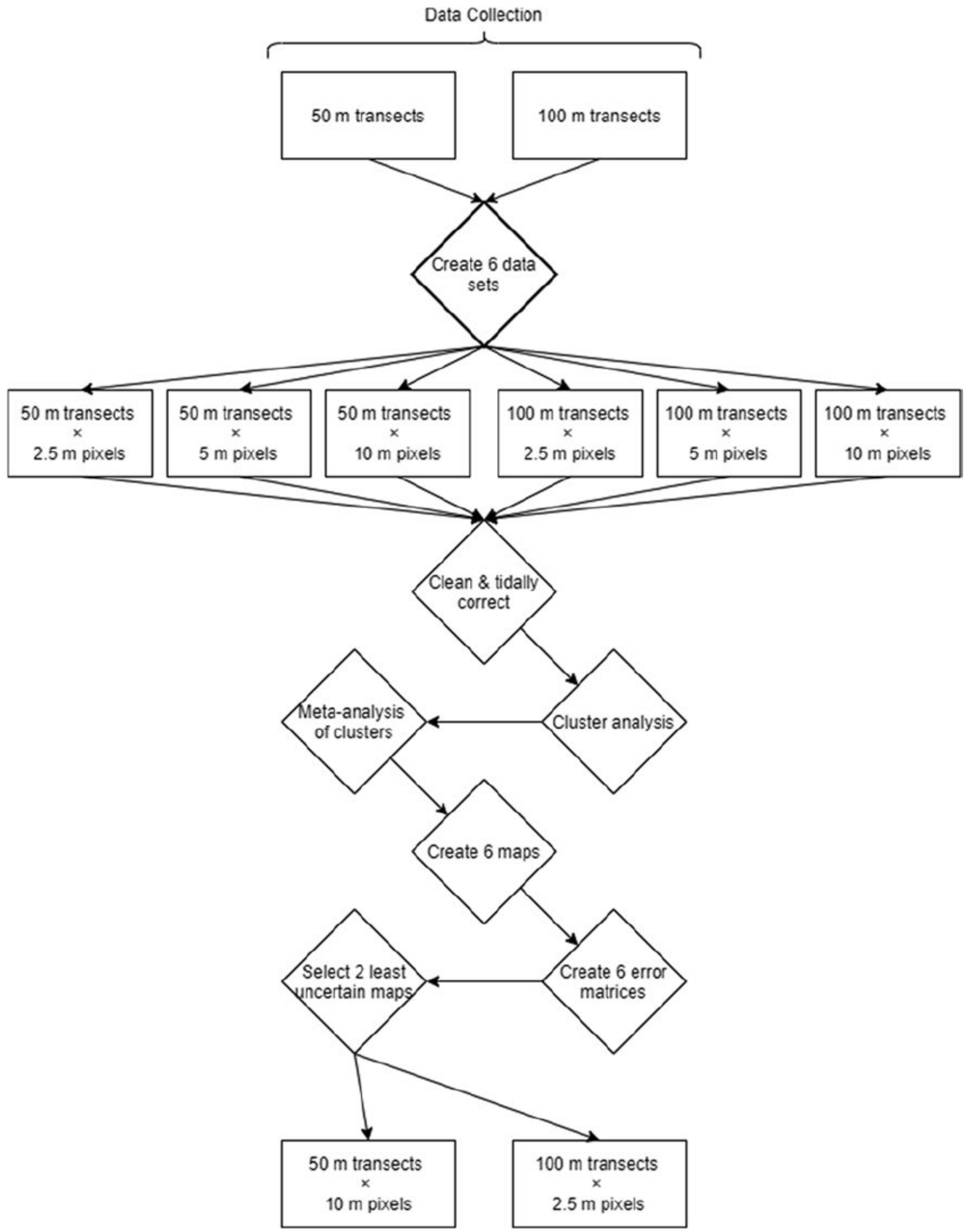
Acou tic data

Single-beam acou ic data were collected u ing a vertically oriented 204 8 kHz 8 6° beam angle tran ducer and a BioSonics Inc. MX aqua ic habi at echo sounder. This ystem i designed pecifically to detect, cla ify, and map sub trate in coastal areas. The local fi hing boat on which the echo ounder y tem was mounted was kept to a speed of 5 knots (2.6 m·s^{-1}) to minimize turbulence around the tran ducer and interference wi h lagging pings and to main ain consistent patial coverage in the along-transect direction. The ra e of acou tic ping produc ion wa 5 H , re ul ing in a equential distance b tween pings of ~0 5 m, which were georeferenced wi h Differen ial Global Positioning System with a po i ional accuracy of ~2 m. The data were collected over the course of 2 consecutive days in mid-November of 2016. Day 1 included roughly parallel east–we t ransec s separa ed by ~100 m (range 80–120 m; Fig 2A). Day 2 con i ted of parallel track po itioned midway b tween Day 1 ransec s, re ul ing in data coverage at ~50 m tran ect spacing (Fig 2B). Track separation dis ances were cho en ba ed on he size of he urvey areas and practicali ies of comple ion within a single day The area covered amoun ed to ~6 3 km^2, and 196 817 da a points (pings; covering ~1 54 km^2) were collec ed in total.

Ground-truth video data

Ground-truthing data for seafloor substrate were collected via a drop video camera (Seavi wer 950 Series, colour ver ion) and were later used in verification of the acoustic data. The videos were a igned to broad substra e categories, a described in the Sub tra e categories ection below, according to what ubstra e was vi ible in the footage. Videos were taken bo h on top of and between the acou ic transects, for a to al of 132 videos, each covering ~2–3 m^2 of seafloor and assigned according to the coarse t

Fig. 3. A flow chart depicting the method of creating the substrate maps.



ubs rate category vi ible, and were georeferenced wi h a GPS wi h a po i ional accuracy of ~2–3 m. The fir t set of videos were taken during the acous ic sampling, haphazardly and when logi - ically convenient, and then a second effort to collect videos wa made wi hout the re traint of acous ic sampling to fill in spatial gap wi hin the urveyed area.

Trap data

The lob ter fi hery in Liverpool Bay is part of Lob ter Fishing Area (LFA) 33, where the fi hing eason is open from the end of November to the end of May The loca ion of the lob ter trap buoys were used a a urrogate for the pre ence of lob ter based on fishers' experience in knowing where to deploy. Individual trap or trap tring are marked by di tinctive floats and no o her imilar buoys are pre ent in the bay The trap location data were collected u ing a DJI Phantom 4 aerial drone during 2 days wi hin the fi hing eason in May of 2017, flown wi hin the area covered by the acoustic data collection. The drone took 12.4 megapixel photo at a ra e of 0 2 Hz at an al itude of 90 m (2089 pho os) This created an overlap between the photo to en ure complete cover- age The drone was configured to always face north (gimbal yaw of 0°), such that the top of the resulting photographs would also correspond with north. The camera was configured to face straight down (gimbal pitch of 90°) to reduce unnecessary complexity in later analysis.

Data analysis and substrate map creation

Acoustic data

We created two substrate distribution maps to compare the effects of spatial data resolution on the display and interpretation of the data (Fig. 3). The acoustic data for these maps were selected from a larger pool of various spatially resolved datasets through a rigorous structured analysis that highlighted and compared the uncertainties associated with each dataset. The two datasets that had the least uncertainty were those where the data were collected on tracks 100 m apart (track resolution) and displayed as 2.5 m pixels (pixel resolution), known as Set A–Map A, and where the data had a track resolution of 50 m and a pixel resolution of 10 m, known as Set B–Map B.

The different pixel resolutions of Set A and Set B were created by binning consecutive acoustic data points at intervals of either 5 or 20 pings, respectively. As the pings were collected every 0.5 m, these bins respectively encompassed 2.5 m (Set A pixel resolution) and 10 m (Set B pixel resolution) lengths of transect. The bins were referred to as mean points (MPs) to differentiate from the use of "data point" for individual acoustic pings. We then converted these two acoustic datasets into substrate maps with the following methods.

Cluster analysis

To estimate the range of functional substrate categories in the surveyed section of the bay, a cluster analysis was performed. The data were cleaned by removing pings closer than 0.25 m to reduce wave- and bubble-induced sonic noise. A tidal correction based on the lower low water low tide (LLWLT) datum was applied, removing the influence of tidal level on depth over each survey's duration. The data were then initially analysed in Biosonics VisualHabitat version 2.0.1, which conducted an unsupervised fuzzy centroid means cluster analysis to group the MPs into clusters based on substrate characteristics captured at each MP. This analysis provided a cluster membership likelihood for each MP, indicating how well each MP fit the description of each cluster. The primary cluster memberships of the MPs were assigned to the clusters where they best fit. The analysis also reported the percentage of the total number of MPs that fit into each cluster, revealing which clusters were rare or potentially constructed of error characteristics. This information was then processed in Matlab to calculate the second-best-fitting cluster for each MP, providing a means by which to compare clusters — if two clusters shared many of the same MPs between their primary and secondary memberships, it is likely that the two clusters represented the same substrate and were combined into a single cluster. Since the cluster analysis was designed to deliberately overestimate the number of functional substrate clusters — as compared with the substrates identified by Tremblay et al. (2009; Table 1) — to avoid accidentally conflating potential substrates, this iterative paring down and combining of the clusters was an important step for classification accuracy. It was completed in tandem with visual inspection and interpretation of the echograms, using the metrics of acoustic strength (dB) and seafloor roughness. Three clusters were finalized for both Sets A and B.

Substrate categories

The assignment of substrate categories to clusters was based on four substrate categories developed for lobster habitat in southwestern Nova Scotia using the Wentworth scale (Tremblay et al. 2009) (Table 1). These categories and the method of creating them proved useful for the purposes of this work, but a number of changes were made to tailor the system to better suit the requirements of an acoustic dataset. A series of preliminary analyses indicated that the acoustic method was not sensitive enough to differentiate between BC (boulder, cobble) and CG (cobble, gravel) substrates and was unable to consistently and accurately cluster the MPs appropriately, so BC and CG were combined into a single category, rock (RK). This was determined through a series of meta-analyses of substrate cluster analyses, where the primary and secondary memberships of MPs were compared — the BC and CG substrate clusters were repeatedly populated with the same MPs switching between primary and secondary memberships, indicating no substantial difference in the characteristics required for membership in those clusters. Similarly, BG (boulder, gravel) was indistinguishable from either RK or soft sediment due to its inherent characteristics and was therefore not discovered through the acoustic data despite being present in the underwater videos. Additionally, because of its infrequent and sporadic nature, it was deemed unlikely to be an important category and was thus removed. The GS (gravel, sand) category was split into three categories: gravel (GV), sand (SA), and mud (MD). This expansion was done in part because adult lobsters display preferences among those categories and in part because the separate acoustic signals of GV, SA, and MD are distinct enough to differentiate — GV was similar to RK but smoother (less vertical change in the bottom line over horizontal distance), SA was smoother and hard (40 to 25 dB), and MD was smooth and soft (30 to 10 dB). The differences among GV, SA, and MD are also visible in the underwater video, such that GV was categorized according to the Wentworth scale (Table 1), and SA and MD were differentiated based on the presence and absence of sedimentary ripples, respectively (Whitlatch 1977). This allowed for confirmation of the acoustic data substrate categories. Mixed substrate, where more than one category was present within the scope of the video, was classified according to the coarsest substrate type present. The final substrate categories used in the further analysis were RK, GV, SA, and MD.

Table 1. (A) The grain sizes of the sediments and (B) the substrate categories used by Tremblay et al. (2009).

(A) Grain size	
Sediment	Size range (cm)
Sand	<0.4
Gravel	0.4 6
Cobble	6 26
Boulder	>26
(B) Substrate category	
Acronym	Sediments
BC	Boulder, cobble
BG	Boulder, gravel
CG	Cobble, gravel
GS	Gravel, sand

Ground-truth video data

These four substrate categories were then used to categorize the substrate visible on the underwater videos, which were sectioned into 132 individual video segments according to GPS location. Each of these segments, which each covered ~2–3 m^2 of seafloor, was visually examined and assigned the substrate category that best applied. To assign substrate categories to the acoustic clusters, we randomly selected a subsample of ~70% of the videos taken on top of the acoustic transects (25 videos of 36; 20% of the total 132 video segments) from the videos taken on top of the acoustic transects, so that the segments shared GPS

Table 2. An error matrix representing the nine possible outcomes of the comparison between the acoustic interpolation and the video segments.

Acoustic interpolation (prediction)	Video (ground truth) V_{RK}	V_{SA}	V_{GV}
A_{RK}	$V_{RK}A_{RK}$	$V_{SA}A_{RK}$	$V_{GV}A_{RK}$
A_{SA}	$V_{RK}A_{SA}$	$V_{SA}A_{SA}$	$V_{GV}A_{SA}$
A_{GV}	$V_{RK}A_{GV}$	$V_{SA}A_{GV}$	$V_{GV}A_{GV}$

Note: RK = rock, GV = gravel, SA = sand.

locations with acoustic data. This allowed the comparison of the substrate-assigned segments to the cluster-assigned MPs, connecting clusters with substrate categories through the shared location data. The mismatch among three acoustic clusters and four substrate categories was solved by the removal of MD as a category; only three of the video segments were assigned MD, which indicates that it is not a common substrate in the study area and likely would not have shown up in the cluster analysis.

Substrate distribution maps

Indicator kriging was used to predict the distribution of substrate categories within the surveyed area by quantifying the spatial autocorrelation of the acoustic data. The isotropic semivariograms were defined using a spherical model. The kriging interpolation produced raster map layers that displayed the probability of the grid cells belonging to each of the three substrate categories, and a single layer was created where the cells were assigned the substrate categories that had the highest probability. This process was completed using ArcMap version 10.5 in the WSG84 datum and converted Sets A and B into Maps A and B.

A bathymetric raster of the survey area was created through the interpolation of the depth data retrieved from the acoustic data. It was converted into 1 m depth contours, which were applied to the substrate distribution maps.

Validation and uncertainty

There were two major sources of quantifiable uncertainty in the above analyses: the interpolated data's agreement with ground-truth data (classification certainty) and the interpolation itself (modelling certainty). Both sources were resolved and examined to compare the relative accuracy of the two substrate maps.

Error matrices were used to determine the extent of the classification certainty for the two substrate distribution maps (adapted from Barrell et al. 2015). The ground-truth data, represented by the remaining 80% of the underwater video segments that were not used to assign substrate categories to clusters, were compared with the interpolated and classified acoustic data. The details of the agreements and disagreements between the two sets of data were laid out in an error matrix that tallied the number of occurrences of each of the nine possible outcomes (Table 2). These nine outcomes can be consolidated into four types relative to the substrate under consideration: (*i*) true positives (TP), where the ground-truth data (video; V) and the interpolated datasets (acoustic; A) agree on the presence of a particular substrate (i.e., $V_{RK}A_{RK}$ for RK); (*ii*) true negatives (TN), where the datasets agree on the absence of a particular substrate (i.e., when considering RK, $V_{SA}A_{SA}$, $V_{GV}A_{SA}$, $V_{SA}A_{GV}$, and $V_{GV}A_{GV}$); (*iii*) false positives (FP), or errors of commission, where the interpolation falsely predicts presence (i.e., for RK, $V_{SA}A_{RK}$ and $V_{GV}A_{RK}$); and (*iv*) false negatives (FN), or errors of omission, where the interpolation falsely predicts absence (i.e., for RK, $V_{RK}A_{SA}$ and $V_{RK}A_{GV}$). These outcomes were used to calculate five statistics for further investigation (Table 3). These statistics are highly correlated, since they are all derived from the outcomes of the error matrix, but they are useful in determining the relative accuracy of classification for each substrate category.

Table 3. Descriptions and equations of the statistics derived from the error matrices (adapted from Barrell et al. 2015).

Statistic	Equation	Description
Overall accuracy	$\frac{TP + TN}{n}$	Proportion of all predictions that were correct
Sensitivity	$\frac{TP}{TP + FN}$	Proportion of correctly prediction presences
Specificity	$\frac{TN}{TN + FP}$	Proportion of correctly predicted absences
Positive predictive value (PPV)	$\frac{TP}{TP + FP}$	Proportion of positive predictions that are TP
Negative predictive value (NPV)	$\frac{TN}{TN + FN}$	Proportion of negative predictions that are TN

Note: TP, true positive; TN, true negative; FN, false negative; FP, false positive.

The modelling certainty was described visually. In the creation of the maps, the substrate category for each cell was selected by choosing the category with the highest probability, which represented the certainty in the interpolation. The certainty was displayed as a map layer with the raster cells coloured to represent their percent certainty.

Trap data

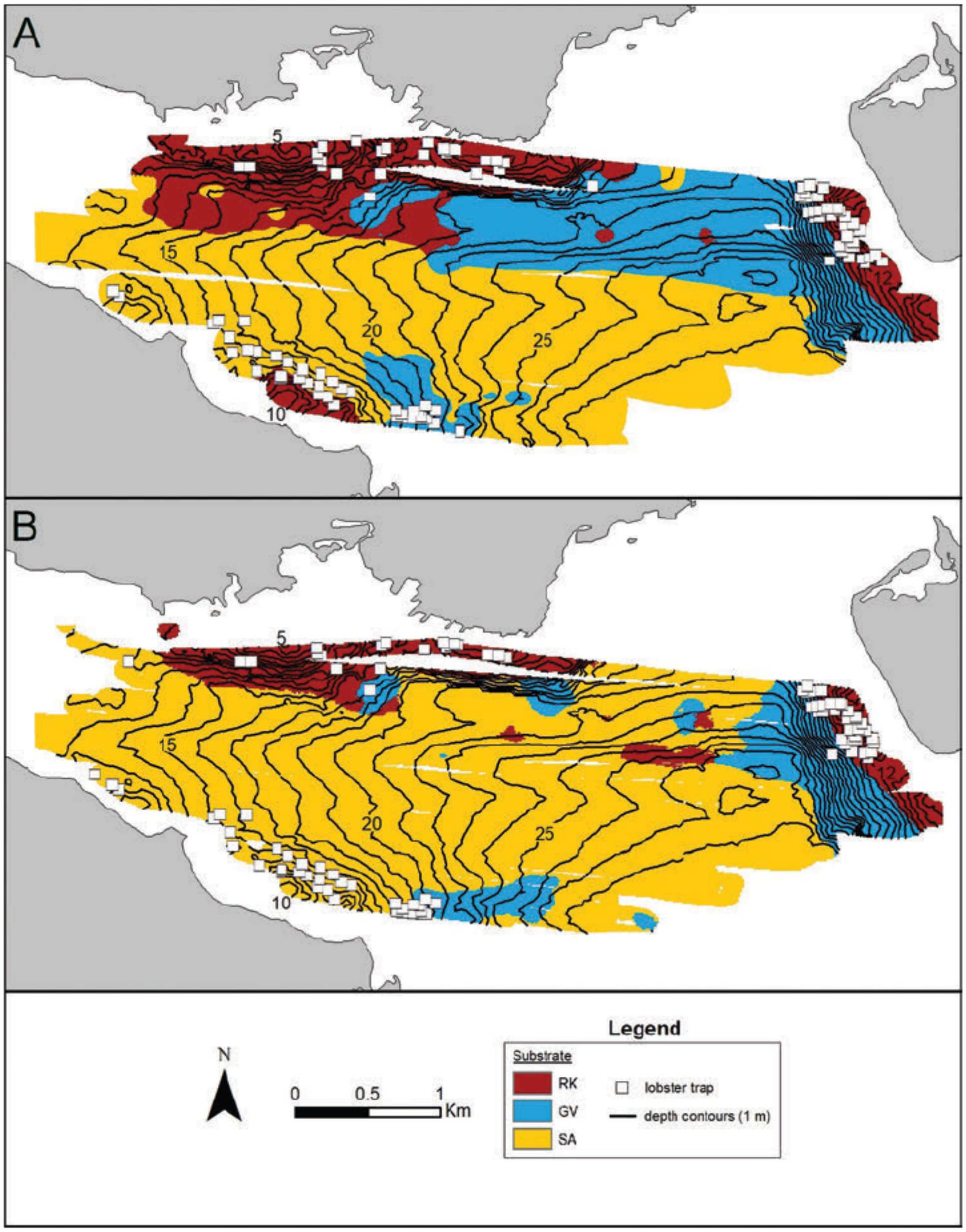
Using a combination of R version 3.4.1 and ArcMap version 10.5, the 2089 photos that comprised the lobster trap data were reduced in number through examination of image metadata. This included removing photos taken over land, at an oblique angle (i.e., gimbal pitch $< 88°$), from an altitude of lower than 85 m, or not facing within 10° of north. The photos were then further reduced by eliminating those that were redundant due to complete overlap. This left 168 photos efficiently covering the entire area flown by the drone. These photos were then visually inspected for lobster trap buoys. A corresponding data point was created and georeferenced at each buoy. If the rope connecting the buoy to the trap was visible through the water, the point was placed at the trap end to increase spatial precision. This created a dataset of lobster presence data that was later used in the presence-only maximum entropy analysis.

Maximum entropy modelling

Maps A and B were paired with the presence-only lobster trap data and LLWLT tidally corrected depth rasters and processed through MaxEnt, a species distribution and environmental niche modelling software that uses maximum entropy methods (Phillips et al. 2006). MaxEnt requires georeferenced presence-only species data (i.e., the lobster trap points) and independent environmental variable rasters (i.e., substrate maps and depth rasters). MaxEnt was used to develop four SDMs based on the data. MaxEnt also created receiver operating characteristic (ROC) curves, which plot the true positive rate against the false positive rate to evaluate the accuracy of the model, and histograms displaying the average species response to the different substrates.

The SDMs produced via MaxEnt come in four possible output formats, two of which were selected for the purposes of this work: "raw" and "cloglog". The raw output unit is relative occurrence rate (ROR), which is the relative likelihood of species presence in one raster cell as compared with another (Phillips et al. 2006). The unit for the cloglog output is probability of presence (POP), which is the absolute likelihood of species presence within a raster cell. These two formats were selected from the available four formats because the raw output adopts the fewest

Fig. 4. Substrate distribution maps for (A) Map A and (B) Map B with 1 m depth contours and lobster presence points. RK = rock, GV = gravel, SA = sand. Map creation information can be found in Materials and methods. [Colour online.]



assumption in it calculations of the output format , and the cloglog format produces the mo t u er-friendly and under tand-able unit.

Results

Trap survey

During he drone survey, 182 lob ter trap buoys were discovered and GPS-ref renced. Of hose, 86 raps were included within he extent of Map A, and 90 raps were within the extent of Map B (Fig. 4).

Substrate maps

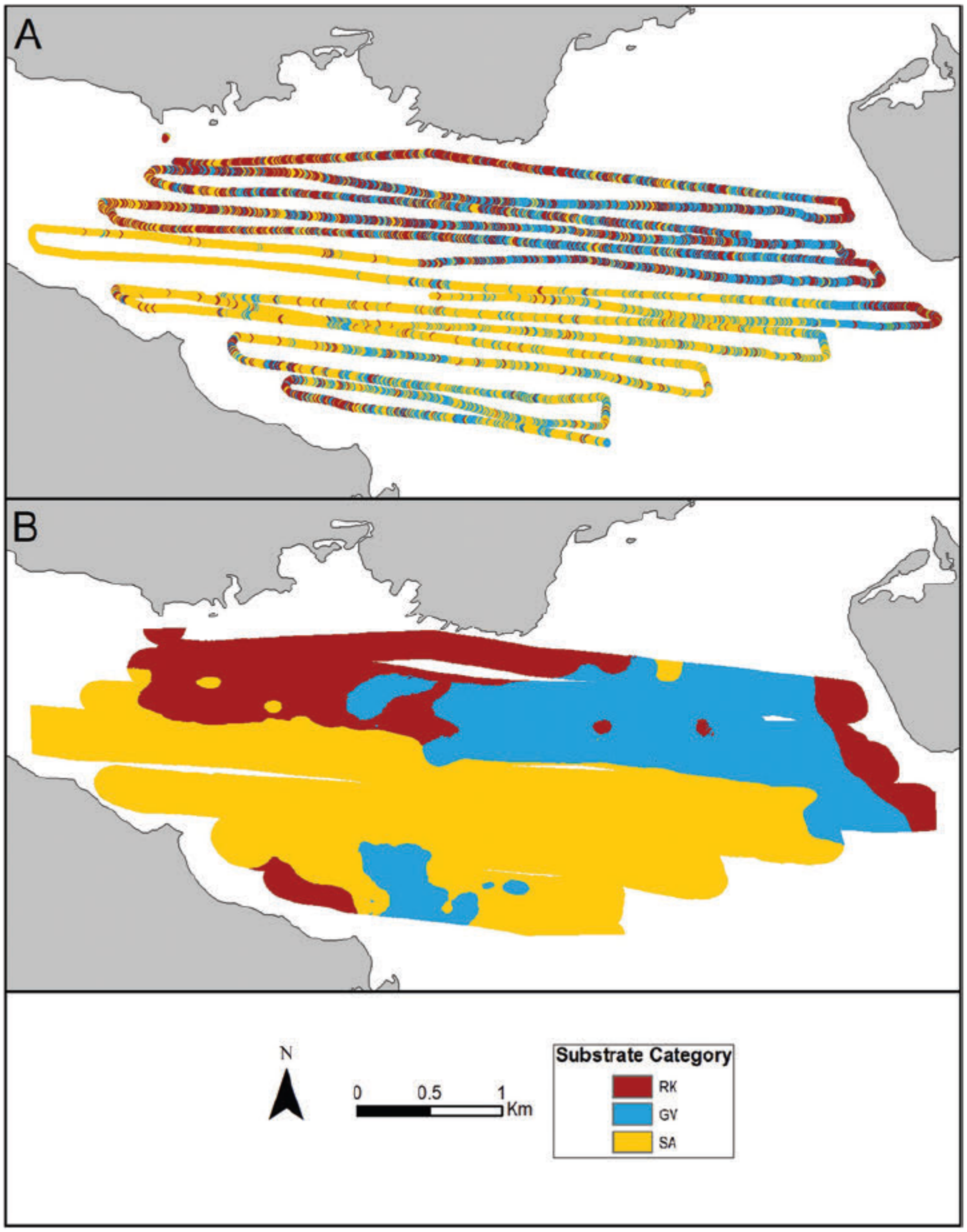
Depth

The 1 m dep h contour show a hallow gradient of increa ing dep h from we t to east through the bulk of the survey area, ranging from 4 3 to 29 2 m deep (Fig. 4) Near Coffin I land, the gradient is ubstantially steeper than the cen ral por ion, and it is relatively uniform in compari on with the gradient on the northern shore These steep gradient areas to the nor h and near the i land are also where both Map A (100 m track re olution, 2 5 m pixel re olution) and Map B (50 m rack re olution, 10 m pixel resolution) show di tribu ion of RK and GV The southern hore di plays a slightly steeper gradient than the cen ral channel, which corre pond to RK and GV in Map A

Map A

The ubs rate cla sification resulted in 9148 MPs cla sified a RK (23.1%), 19 6 0 as SA (49 6%) and 10 806 as GV (7 3%) for a grand to al of 39 574 MPs (Fig 5A). The majority of the SA MPs are located in the cen ral channel por ion of the bay, with RK and GV mo ly to he nor h and south RK MP are generally found along the coastal edges of the surveyed area, notably near Coffin I land and the northernmo t edge of the bay The bulk of the GV MPs are between the RK areas and the SA, particularly southwest of the i land. The northern half of the urveyed area appears to be

Fig. 5. Two representations of Map A: (A) acoustic data tracks with MPs classified into substrate categories; (B) interpolated data, completed via indicator kriging, showing the distribution of substrate category predictions. RK = rock, GV = gravel, SA = sand. Map r a ion information an be found in Ma erials and me hods. [Colour online.]



more he erogeneous, wi h he RK, GV, and SA MPs intermixed, than the cen ral SA-heavy ection.

The interpolation of the MPs produced a map with several small "i land " of ub tra e surrounded by a different sub tra e category, uch as he two areas of RK in the middle of the northea t ection of GV and the pa ches of SA in the northwe t wath of RK (Fig 5B) The cen ral channel SA majority shown in Fig 5A appears in the interpolation, with most of the southern half of the survey area predicted as SA. The northea tern extreme of the map, which ex ends to Coffin I land, predicts a trip of RK to the east hat then gives way to GV to the west and extending to approximately half of the northern ection. Notably, thi ection of GV prediction is located adjacent to the pas age between Coffin I land and the mainland and is further from land than the neighbouring ections where RK was predicted, which are generally near the hore

Map B

Substra e cla sification resul ed in 2535 MPs classified as RK (25 7%), 5365 a SA (54 5%), and 1951 a GV (19 8%), totalling 9851 MPs (Fig 6A). The cla sifications are le s homogeneous in compari on wi h hose of Map A, wi h he nor hern portion of the map con aining more SA MP and the cen ral channel area of the bay di playing a le s obvious trend towards SA than is vi ible in Map A. There are four tracks in the central channel section with segments that are decidedly classified as RK, in contrast with the tracks surrounding them, and are likely an artifact from the rough waves encountered during data collec ion. The sou hernmo t edge of the surveyed area has a trend towards GV, a does the northea tern edge before it tran itions to RK MPs near Coffin I land hese two ections are imilar to the ame area in Map A

Despite the diminished trend towards SA in the central channel rela ive to Map A, the interpolation still predict SA throughout

Fig. 6. Two representations of Map B: (A) acoustic data tracks with MPs classified into substrate categories; (B) interpolated data, completed via indicator kriging, showing the distribution of substrate category predictions. RK = rock, GV = gravel, SA = sand. Map r a ion information an be found in Ma erials and me hods. [Colour online.]

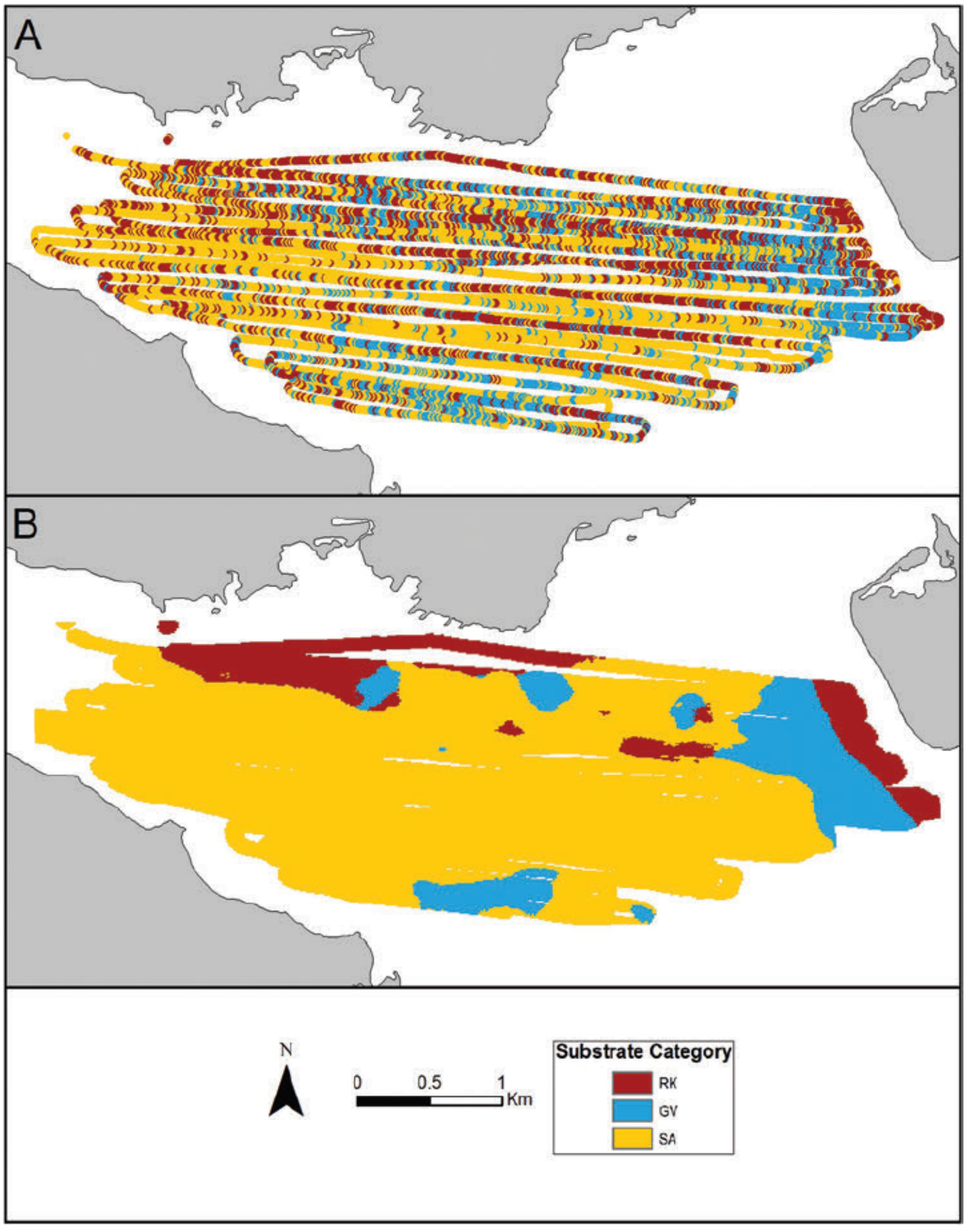


Table 4. Error matrix for Map A representing the comparison between the acoustic interpolation pr di tion and the und rwat r video.

Acoustic interpolation (predi tion)	Video (ground tru h) RK	SA	GV
RK	15	17	3
SA	7	3	8
GV	17	15	6

Note: RK = rock, GV = gravel, SA = sand.

Table 5. The error statistics for the Map A map as a function of substrate type.

Sub tra e	Overall accuracy	Sensitivity	Specificity	PPV	NPV
RK	0.5165	0.3846	0.6154	0.4286	0.5714
SA	.48	0.0857	0.7321	.1667	0.5616
GV	. 27	0.3529	0.5676	0.1579	0.7925

Note: RK = rock, GV = gravel, SA = sand, PPV = positive predictive value, NPV = negative predictive value.

the en ire middle ection of the map (Fig. 6B) SA dominates thi interpolation, encompa ing much of the northern half of the map in addition to the central channel. The section adjacent to the passage between Coffin I land and the mainland is predicted a majority SA, wi h some patches of both RK and GV wi hin i . The rip of RK and then GV by Coffin I land is predicted in a imilar manner to hat in Map A, but the GV tran ition into SA at a much clo er point to the i land. RK is absent from the ou hern half of the predictions, occurring only near the shore on the

Fig. 7. Modelling certainty maps derived from the probability remainder of the interpolated data: (A) Map A, (B) Map B. Map creation information can be found in Materials and methods.

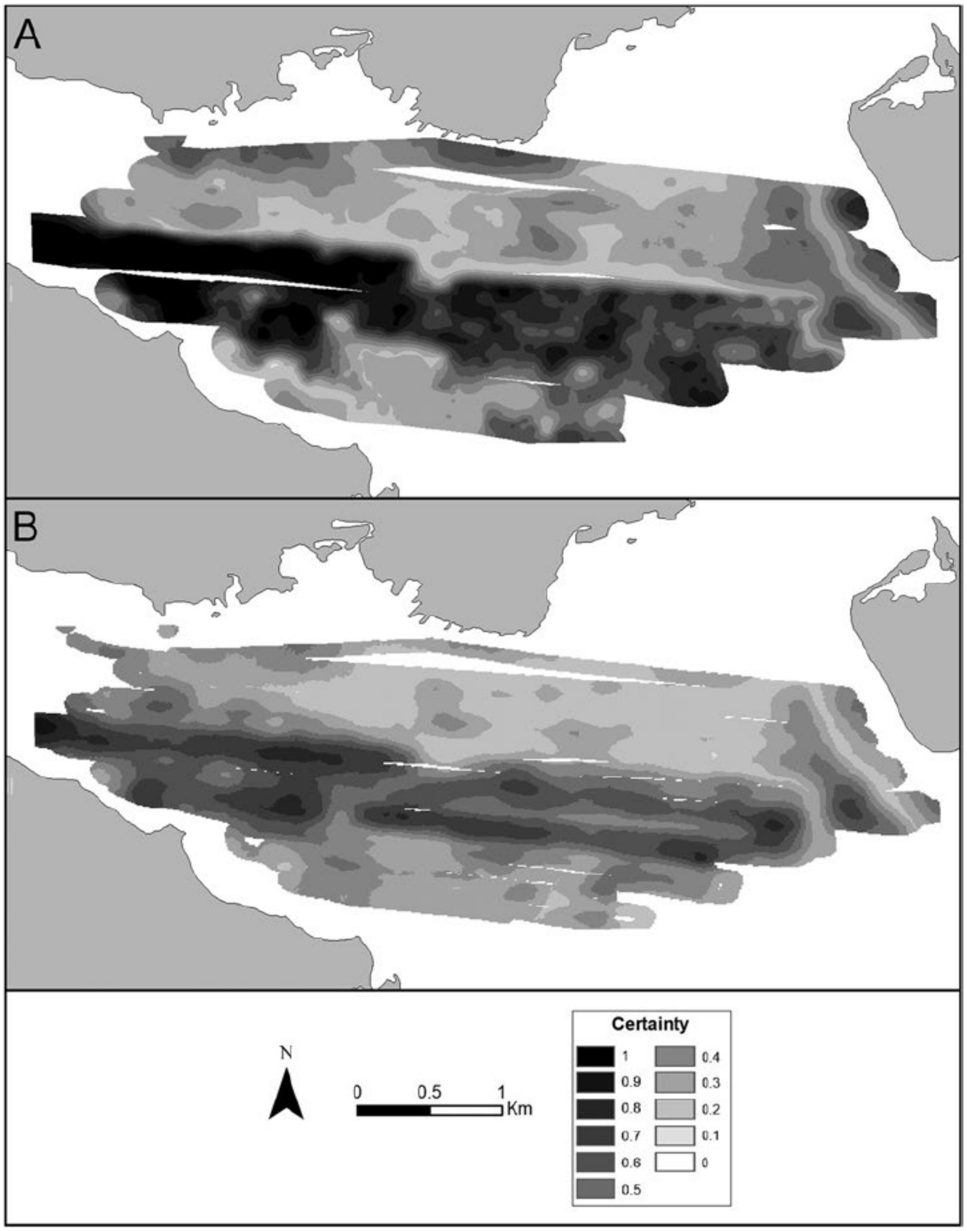


Table 6. Error ma rix for Map B repre enting he omparison be ween he a ou ti interpolation predi ions and he underwa er video.

A ou ti in erpolation (predi tion)	Video (ground tru h) RK	SA	GV
RK	6	8	0
SA	27	24	10
GV	4	3	4

Note: RK = rock, GV = gravel, SA = sand.

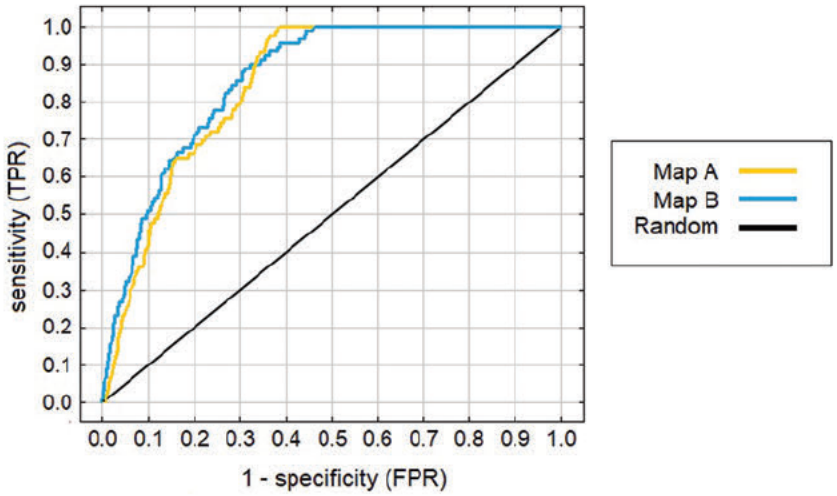
Table 7. The rror tatis ics for he Map B as a fun ion of sub trate type.

Sub tra e	Overall accuracy	Sensitivi y	Specifici y	PPV	NPV
RK	0.5465	0.1622	0.8367	0.4286	0.5694
SA	0.4419	0.6857	0.2745	0.3934	0.5600
GV	0.8023	0.2857	0.9028	0.3636	0.8667

Note: RK = rock, GV = gravel, SA = sand, PPV = positive predictive value, NPV = negative predictive value.

northern edge and near Coffin I land. The varia ion vi ible in the noninterpolated da a, par icularly in the cen ral channel and the southern shore, was largely made uniform by the interpolation, and this was likely due to the smoothing factor Since indicator kriging tend to crea e artificially harp boundarie between neighbourhoods, we applied a smoothing factor to reduce he effect of the mathema ical artifacts However, the moothing al o removed some of the varia ion in the da a, creating unexpectedly homogeneous predictions. While there was moothing in bo h Map A and Map B, it is more evident in Map B due to the higher variance in the noninterpolated da a.

Fig. 8. Receiver operating characteristic (ROC) curves for both Map A and Map B. Curves that exist above the theoretical model at 1:1 (area under the curve, AUC = 0.5) are considered better than random. Map A has an AUC of 0.846, and Map B has an AUC of 0.860. TPR, true positive rate; FPR, false positive rate. [Colour online.]



Validation and uncertainty

Map A

The classification error matrix and statistics for Map A (Tables 4 and 5) showed that RK was incorrectly predicted as GV for 43.59% of the predictions. This model tended to err on the side of RK or GV, meaning that it was about three times more likely that SA points were incorrectly predicted as either RK or GV compared with RK or GV points incorrectly predicted as SA. For example, the sensitivity value for SA, which is the number of actual SA points that were correctly predicted as SA, is only 8.57%, a much lower value than the sensitivity of RK (38.46%) or GV (35.29%), indicating that many actual SA points were predicted to be another category. Seventy-three percent of the classification errors (FN and FP) for Map A are due to these two trends.

The positive predictive value (PPV), which is the percentage of positive predictions that were TP, is 42.85% for RK, 16.67% for SA, and 15.79% for GV, suggesting that this model is best at finding RK in comparison with the other two substrate categories. The overall accuracy for each of the substrate categories in this map is ~50%. For all three categories, the overall accuracy was mostly the result of TNs than TPs.

The modelling certainty map showed high certainty in the centre of the bay and along most of the extreme edges of the survey area near the shore (Fig. 7A), indicating that the substrate is likely more homogeneous in these locations. The northern third of the map had a lower certainty, as did a small section to the south. Lower certainty coincided with higher heterogeneity (Fig. 5A). The vast majority (34 of 44) of the RK classification errors uncovered in the matrix are located within the southern patch of low certainty.

Map B

The error matrix and statistics for Map B (Tables 6 and 7) showed an opposite trend compared with Map A, where instead of erring on the side of the more complex substrate, it erred on the side of SA. Both RK and GV were ~3.3 times more likely to be incorrectly predicted as SA than the other way around. The sensitivity of SA is 68.57%, compared with RK at 16.21% and GV at 28.57%, meaning that there were a much higher number of SA points correctly predicted as SA than RK as RK or GV as GV. Similarly, the specificity (or percentage of correctly predicted absences) is relatively high for RK (83.67%) and GV (90.27%) in comparison with SA (27.45%); SA is over-predicted for presence and therefore results in fewer correctly predicted absences. This over-prediction is visually depicted in the difference in variation between the noninterpolated data, which shows heterogeneity across much of the map, and the interpolated data, which displays large sections of homogeneous SA (Fig. 6).

The PPV for RK is the same as for Map A at 42.85%. While it is higher than the SA and GV categories (39.34% and 36.36%, respectively), the difference is not substantial. This indicates that the ability of this model to distinguish one category over another is approximately equal among the categories. The overall accuracies for the categories were 54.65% for RK, 44.18% for SA, and 80.23% for GV, all of which were mostly the result of TNs.

The modelling certainty map is similar in structure to that of Map A but with a trend of lower certainty throughout the entire bay (Fig. 7B). The northern portion of the bay and a section on the southern shore show particularly low certainty, which coincided with higher heterogeneity (Fig. 6A).

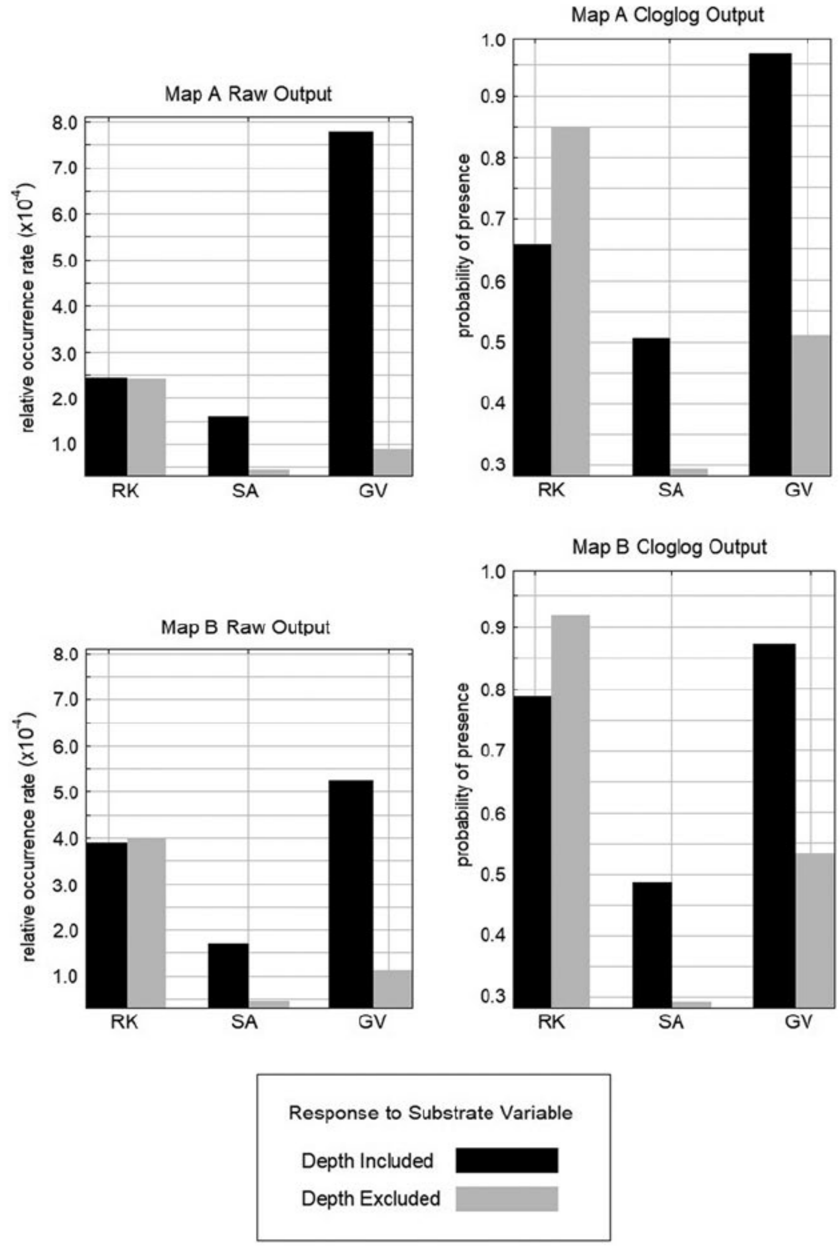
MaxEnt SDMs

Map A

The areas under the curve (AUC) of the ROC curves are identical for both the raw and cloglog Map A model output formats (Fig. 8) at 0.846. This is a measure of how well the model performs and is compared with the results of a theoretical model based on randomly distributed predictions (AUC = 0.5).

The species response graphs, which plot response (i.e., ROR, POP) against the variable in question, illustrate a correlation between depth and substrate category (Fig. 9). The substantial change in response when depth was excluded as a secondary variable indicates that depth and substrate do not occur independently of one another. Depth has a larger effect on the overall species response than does substrate category; the MaxEnt environmental variable contribution statistics demonstrate that depth contributed 85.7% to the model and substrate category only 14.3%. For both the raw (relative likelihood of species presence in one raster cell as compared with another) and the cloglog (absolute probability of species presence in a raster cell) output models, the response to substrate category (with depth excluded) is strongest in RK (respectively: 2.42×10^{-4}, 0.847), followed by GV (9.40×10^{-5}, 0.518), and SA (4.38×10^{-5}, 0.288). This pattern coincides with the recognized relationship between adult lobsters and their habitat selection, where lobsters prefer shelter-forming substrates over sand.

Fig. 9. Species response to substrate categories. Black bars show the marginal response to the substrate variable with the depth variable included; grey bars show the response to the substrate variable without the depth variable. RK = rock, GV = gravel, SA = sand.



The raw output hows high ROR along the shoreline , particularly against Coffin Island (Fig. 10A). The bulk of the centre and the southeast corner contain substantially lower RORs, particularly as the bay opens to the ocean. The ROR along the outhern edge, near the hore, are generally lower than hose at the other two clu ter of lob ter trap (i e., the northern and Coffin I land hores) The we tern ection of the cen ral channel has relatively high RORs de pi e the absence of lob ter trap , which implie ano her unmea ured variable may have an effect on lob ter trap placement in thi area

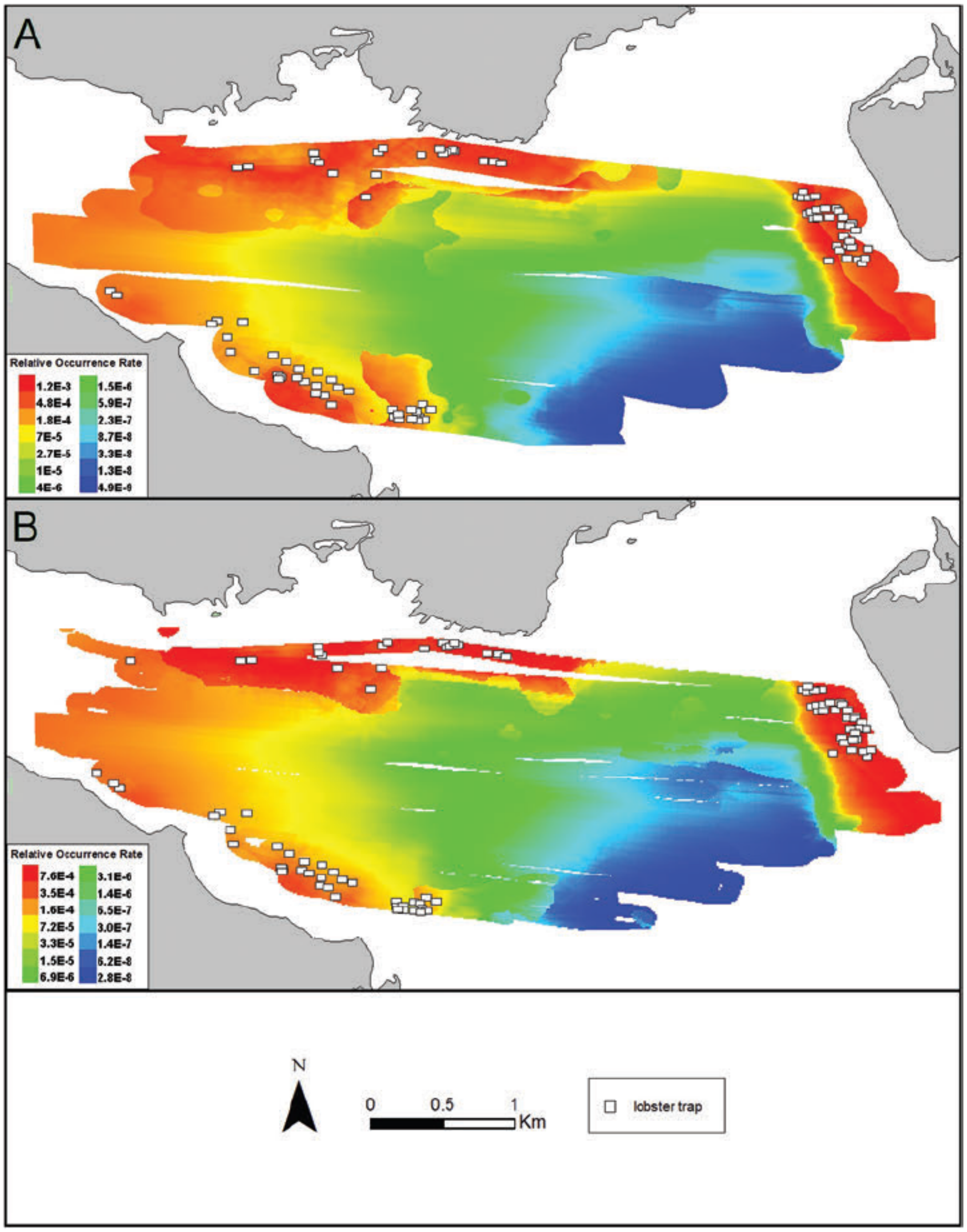
The cloglog model ou put prediction are similar to tho e of the raw model with high POP values in the same areas (i e., coa tal par icularly along Coffin I land) and low POP values in the central and ou heastern ections (Fig. 11A) While not direc ly comparable, the cloglog ou put appears to label more area a less uitable than does the raw model.

Map B

As for Map A, the AUC for the ROC curves are identical for both Map B model output format (Fig 8) at 0 860 This AUC is not ub an ially different from the Map A AUC value of 0.846

The specie re ponse graphs reveal the same confounding relationship between substrate and depth as in Map A, where the ub rate category variable is not independent from the dep h variable (Fig. 9) The dependence is skewed in a imilar manner to hat of Map A, where the change in response of the ub rate ca egory variable with or without depth is much larger than the change in re ponse of the dep h variable wi h or wi hout the ub rate category variable This implie that the dep h variable has more weight in the model, a conclu ion hat i supported by the environmental variable contribu ion s a i tic indicating that depth con ributed 71 4% to the model and subs rate category con ributed 28.6%. Again, both the raw and the cloglog output

Fig. 10. Raw output species distribution models (SDMs), with white rectangles indicating the location of the lobster traps: (A) Map A, (B) Map B. Note the difference in the colour scales. Map creation information can be found in Materials and methods. [Colour online.]



re ponded ronge t to sub trate (dep h excluded) in RK (re pectively: 4 00 $\times$ 10^{-4} 0.929), then GV (1 15 $\times$ 10^{-4} 0 533) and finally SA (4.97 $\times$ 10^{-5}, 0.280).

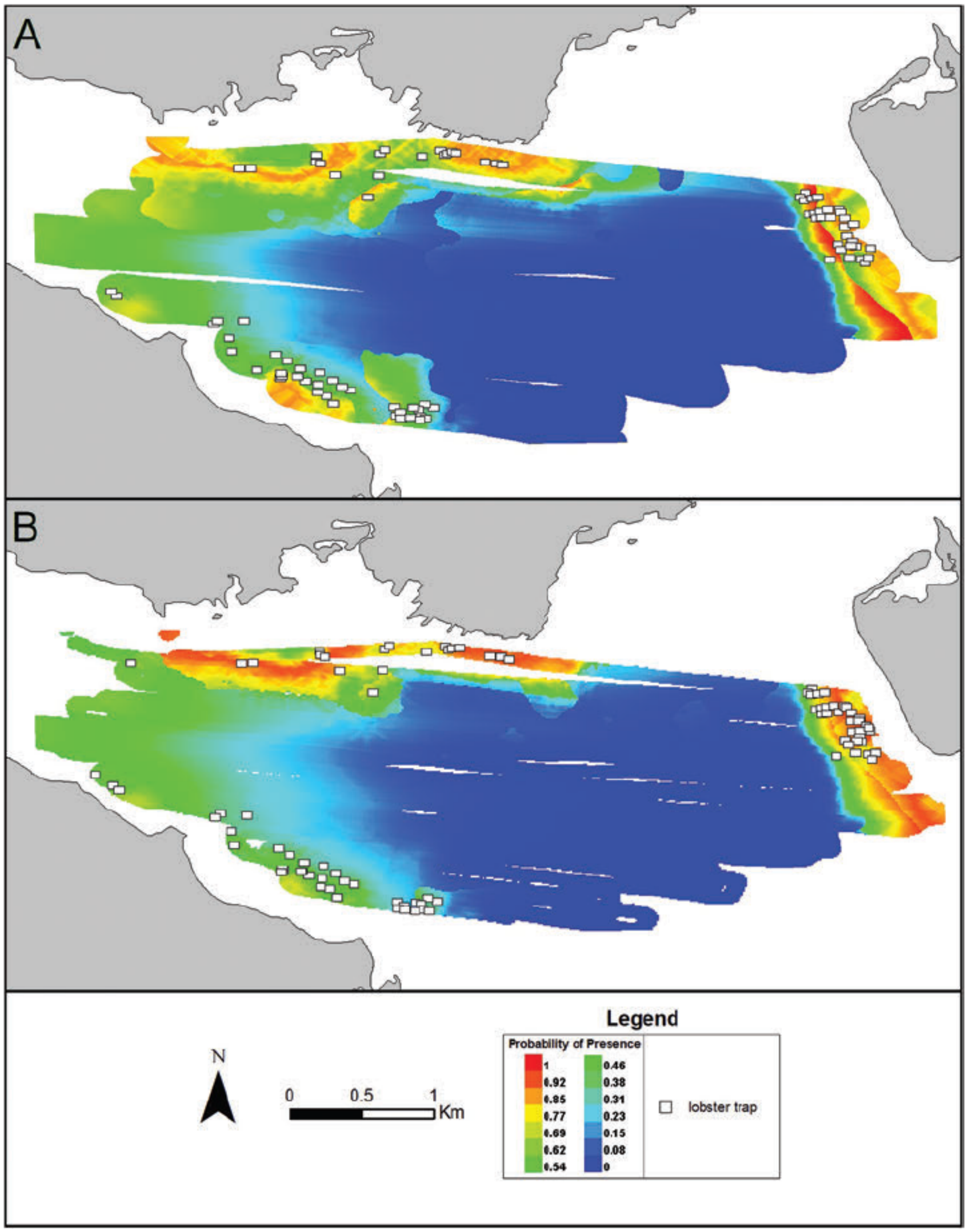
Much like Map A the raw output for Map B displays high ROR values near the three coastlines (Fig 10B) Near Coffin I land, the RORs are almo t uniformly extremely high. The sou hern coastline has lower RORs than the equivalent area in the Map A raw model. Again, the western section has relatively high RORs con idering the ab ence of traps

The cloglog output for Map B is visibly less patchy in compari on wi h the cloglog output of Map A, wi h moother ran i ion in notable areas (e g , Coffin Island; Fig. 11B) The nor hern hore clu ter of high POPs is higher in his model han in Map A. There are some barely vi ible patche of higher POP value in the northea tern quadrant of the bay, contrasted against the zero value POPs that encompass most of hat area; the e patches corre pond to GV and RK patche on the ubs rate map.

Discussion

Reliable habitat maps u eful in marine pa ial planning are dependent on the quality of mapped environmen al variable . For lob ter, ubs rate is a cri ical determinant of habitat, o we con ider variation in ubstra e designation ari ing from acous ic data and its subsequent analysis. Most previous marine studies of habi at mapping and SDM do not con ider the fine pa ial cales and re olu ion we have examined, namely due to a lack of suitable data (Brown et al. 2011; Lecours et al 2015) Similarly, few studies include even ba ic assessmen s of error and uncer ainty in their SDMs, let alone more in-depth analyses (Robinson et al 017) In this study, we explored the relationship between habitat heterogeneity and the patial re olu ion of the input da a, explicitly te ted the effec s of pa ial re olu ion on SDM output, and inve igated the uncer ainty of the SDM , all of which are important steps in the further development of the use of SB-AGDS and other remote ensing technologies for MSP.

Fig. 11. Cloglog output SDMs, with white rectangles indicating the location of the lobster traps: (A) Map A, (B) Map B. Map creation information can be found in Materials and methods. [Colour online.]



While the overall re ult of the maps crea ed from Map A and Map B are similar, both demons ra ing higher lob ter response along Coffin I land, the northern hore, and to a les er extent the ou hern shore, there are di tinct difference between the maps requiring examination to develop an appropriate interpretation. These con idera ion are impor ant to future application of acou tic habi at mapping for use in SDM

Resolution and track eparation

The selection of the track resolutions and pixel re olutions for use in the tudy was surpri ingly difficult. Despi e the fact that patial re olu ion can have rong implications for the outcome of the map layers (Brown et al 2011), there i no tandard for choice of values in studies of this type, due in large part to site-specific differences in habitat heterogeneity. There is a large variety of rack resolutions found in the literature for urveys of similar scales, depths and nearshore locations as in our work (Freitas et al 2011; Ander on et al. 2002; Brown et al. 2005; Foster-Smi h et al. 2004) Given that the footprint diam ter of the acous ic pings collected in Liverpool are very mall (0.45–5.4 m depending on dep h) in compari on wi h mo t of the literature examples of track resolu ion (70 m – 2 km), the interpolation b tween the pings on epara e track would be spar ely informed if hose literature values were adopted. The relatively small size of Liverpool Bay allowed the choice of ighter track spacing (Brown et al 005). However, effort is inversely proportional to track resolution, and rack resolutions were chosen to balance hese two conflic ing components while examining the consequences of patial re olu ion on SDM output

The literature provide di cu sion of the pixel re olu ion limitations of optical data (Schweizer et al 005), but SB AGDS studies tend to avoid the matter (Lecours et al. 2015) The elec ion of overly coarse pixel resolu ion can lead to what is commonly known a the “mixed pixel problem”, where the value of a pixel is the result of a combination of signals from different reflective groups (Schweizer et al. 2005; Jones and Sirault 2014). However, too small pixel resolution allows for "noise", or spurious detail in the form of microscale substrate patchiness to be collected and recorded as valid, habitat-level variation.

The effects of the different spatial resolutions resulted in the differences in substrate distribution between Maps A and B in the northeastern quadrant. The low modelling accuracy in the area indicates that interpolation was not effective, suggesting high heterogeneity in the substrate. This heterogeneity can lead to differences in binned averages if the bin sizes vary, reflected in subsequent pixel construction. As indicated above, Map A errs on the side of RK and GV, which has the risk of overestimating lobster habitat. However, Map B results err on the side of SA and could be considered to underestimate lobster habitat. These trends are most easily observed in the interpolated substrate maps (Figs. 5 and 6). This discrepancy highlights the necessity of considering spatial scale with respect to habitat heterogeneity when evaluating both the input layers and the results of SDMs, with particular implications for decisions made within the context of MSP.

Substrate categories

Despite the confounding nature of depth on substrate category, the switch in response rankings between RK and GV in reaction to the exclusion of the depth variable does not substantially alter the final map interpretation because RK and GV were likely confounded themselves. Descriptive resolution is a term first coined by Green et al. (1996) to encompass the varying breadth and detail of substrate category descriptions revealed by remote sensors. The descriptive resolution of the SB-AGDS in this study is quite coarse, revealing the substrate categories RK, GV, and SA. This coarseness has created broad substrate categories, and given that RK and GV can be relatively similar in physical structure, especially when contrasted with SA, there is a high probability that (*i*) they share some characteristic acoustic features and (*ii*) they were often confounded during the cluster analysis, before the interpolation stage. This is in essence a more abstract version of the mixed pixel problem explained above. If the SB-AGDS were able to define narrower substrate categories, the assignment of substrates into those categories would likely be more precise, have less potential overlap, and display a clearer relationship between substrate and lobster response.

The effect of depth changed the magnitude and ranking of the substrate categories (Fig. 9). In all four model outputs (raw and cloglog for Map A and Map B), lobsters were most strongly associated with GV and second-most with RK when depth was included, but those positions reversed when depth was removed from the analysis; and lobsters associated with SA the least, though with a change in magnitude following the removal of depth. Areas categorized as GV span a wide range of depths, from ~8 to 27 m, and most of the lobster presence points found in GV areas are located in the shallower sections, particularly along the shore of Coffin Island. Therefore, the relationship between the species response and GV when depth is included is expected; shallow GV has a high lobster presence. When depth is removed as a variable, there are very few presence points on the large patches of deeper GV, and species response averages out to much lower values. The lack of lobster presence points in deep GV areas is likely due to the increased distance from RK areas, which is the more preferred substrate. Because there is less variance in depth in the areas categorized as RK (roughly 4 to 14 m), the removal of depth has a lesser but opposite effect on RK. Despite this explanation of the interdependency between depth and substrate, removing depth from consideration entirely and using only substrate to predict species occurrence would be inappropriate. Even when confounded with other variables, depth has a substantial effect on habitat suitability because the best lobster habitats in coastal areas tend to be found in shallower water (Lawton and Lavalli 1995).

Differences in descriptive resolution were the rationale behind altering the substrate categories compared with Tremblay et al. (2009; Table 1). The video system in their study was able to detect the difference between boulders and cobbles, but our acoustic system was not. Tremblay et al. (2009) found fewer lobsters on cobble substrate than among boulders, meaning that the combination of the two categories in this study could have skewed predictions depending on the actual ratio of cobble to boulder in the RK areas. Similarly, Tremblay et al. (2009) found very few lobsters on GV substrate, and in our study the relatively high response to GV may be a result of the proximity of GV to RK (Figs. 10 and 11; particularly near Coffin Island). However, the landscape context of the lobster habitats was not explored in either study and may have had an undetermined effect on the outcome (Mazerolle and Villard 1999).

Depth

Bathymetry is one of the most readily available and useful data layers for marine geospatial studies, especially when obtained at high resolution through remote sensing. Depth was the main contributing variable in both Map A (85.7%) and Map B (71.4%), meaning that depth had a stronger influence on the responses of both models than the substrate categories. Depth was included in the modelling process because it is a standard oceanographic variable and is temporally stable at similar scales to substrate distribution. However, the entire depth range of the surveyed area is well within the habitable range for the American lobster (Holthuis 1991). If depth is a major causative variable, the western section of the surveyed area, which is both shallow and sandy (Fig. 4), would have likely had more lobster traps. This is an indication that the depth variable is not the main contributing factor to species response. Instead, the pattern that is detected by the model through the depth variable appears to be more closely related to distance from shore (Fig. 10 and 11; the southern shore has high probability of presence despite relatively deep water). Distance from shore is highly correlated with substrate type, as substrates are generally coarse near shore and grow finer with distance, which indicates that the high suitability on the shorelines is likely to be the result of substrate and not depth.

Even a cursory examination of lobster presence overlaid on substrate maps shows a clear preference for coarser substrate. Nonetheless, we are left with an overall accuracy of 44.19% 80.23%, which may be close to random on the lower end. This occurs due to the interaction of depth and substrate. We suggest that some of the interaction of our variables is a consequence of the small area over which the SDM was applied. Small areas inherently contain a reduced range of the values of environmental variables. While we investigated the effect of sampling scale on substrate maps, the overall study area is fixed and resolution is high in both cases. Lobsters are not fished over the entirety of the study site but undoubtedly occur throughout the study area even if at low density. The relatively shallow bathymetry of the entire bay is well within lobster depth range, so a depth preference in itself is less likely. Instead, greater depths incorporate coarser substrate and thus more apparent habitat. In applying SDM to marine species, it is important to consider the context of range of variables. While the benthic substrate ranges from MD to RK, the full spectrum of this variable, depth does not have enough variation to be important as a predictor. This statement highlights the notion that marine environmental variables should be evaluated critically in the context of information value when considering inclusion in models. Regardless of indicator value, bathymetry is usually incorporated into SDM, since it is the most widely available spatial variable.

Lobster traps

Collecting precisely geolocated lobster presence data in Nova Scotia was challenging. A scientific trapping license is difficult to obtain, as are GPS records for traps deployed by fishing boats. No records of geolocated lobsters were found for Liverpool Bay at a suitable scale; government records of landings are binned in grid cells of ~18.5 km × 18.5 km (Coffen-Smout et al. 2013). Accompanying a lobster fisher on their boat as they retrieved traps would have required considerable financial compensation for their time. Additionally, lobster fishers can be extremely protective of their trap placements, as the knowledge of prime trapping spots is valuable (Acheson 2003). However, given the level of detailed knowledge on lobster behaviour and preferred habitat that most lobster fishers have (Acheson 2003), it is reasonable to assume that the presence of a trap buoy is associated with lobster presence. Therefore, the strength of the local fishers' knowledge of adult lobster movement was considered reliable enough that the traps they deployed could be used as presence indicators in the model.

Since we used lobster traps as an indicator of presence, our SDM does not cover all phases of the lobster life cycle and instead targets catchable adults. For example, fishers may deliberately avoid areas or substrate types known to be frequently populated by berried females (Campbell 1990; Chang et al. 2010). For a migratory benthic species, one would not expect a single substrate type to characterize the entire life cycle. Our species distribution model is thus somewhat finely tuned to the fishery. However, our focus was on MSP aspects of lobsters with respect to fish farming, and a central component of that context is the fishery. Our additional work on lobster–substrate relations involves the occurrence of juveniles on soft substrates (McKee 2018). The sampling requirements for surveying juvenile lobsters is a major research effort (Dinning and Rochette 2019), and it would not be routine in an MSP context. This difference within the lobster life cycle highlights the utility of SDM applied to MSP. A model adapted to juvenile *H. americanus* for a given location may eventually have broader applicability, which would avoid the impractical task of quantifying juvenile abundance for each location.

One of the major assumptions in using MaxEnt is that the modelled area has been thoroughly sampled (Elith et al. 2011). This assumption was met, since the fishers have sampled the modelled area over an extended temporal scale, using decades of experimentation, trial and error, and shared information. Some change in the location and borders of the known lobster habitat is to be expected over so long a period, but MaxEnt's boundary modelling is already limited in its precision.

Conclusions

To avoid user–user conflict between the lobster fishery and the salmon aquaculture industry in Liverpool, new salmon pens could be placed near the centre of the surveyed area, particularly in the green sections of the SDMs. This area is not particularly suitable for lobsters and would satisfy the basic requirements of the net pens, which include shelter from the open ocean and at least 15 m depth. However, other aspects of coastal activity would need to be considered, as it is possible that that area has high traffic or experiences other environmental concerns that would negatively affect its suitability to aquaculture, and lobster trap locations do not capture every aspect of lobster habitat. Similarly, avoiding co-location does not address every concern regarding their interaction with aquaculture. Our primary goal with this study was to avoid siting of fish farms in lobster fishing areas so that the removal of fishable bottom is minimized. At present, there is little evidence that fish farm effluents are generally affecting lobster fisheries (Grant et al. 2016, 2019).

More generally, this study has shown that the use of SB-AGDS is effective in creating fine-scale lobster habitat suitability maps, despite a number of caveats for their use and interpretation. The indistinct boundaries between substrate patches and the relative nature of the raw suitability distribution values suggest that the maps would be best used as qualitative models for use in MSP, with scales of high and low suitability. The difficulties in obtaining lobster presence data remain but could be mitigated with the formation of strong relationships between local fishers and researchers. Because of their fine scale, local relevance, and species-specific design, the maps created using the above described method are suitable for use as the data layers required in a marine spatial planning exercise designed to manage the user–user conflict between the local lobster fishery and the net-pen aquaculture industry. We emphasize that this study was conducted at such a local scale because the planning decisions are made at the same scale; if this scale of work is repeated in different geographic areas, then larger-scale patterns may emerge that could prove informative in future planning work. Appropriate data layers are often lacking in MSP, and the use of primary data defining resource use is an important input to planning efforts. We therefore propose that this method could be used in similar future bay-scale marine spatial planning ventures.

This study also supports the argument that spatial resolution is a critical aspect of benthic habitat mapping studies and that the effects of scale and resolution should be explicitly discussed and analysed along with consideration of uncertainty, especially given the relative lack of focus on these issues in the literature (Robinson et al. 2017). The substantial differences in the two final maps is a direct result of experimenting with spatial resolution and serves as an important reminder to interpret spatial models and map layers with a discerning eye.

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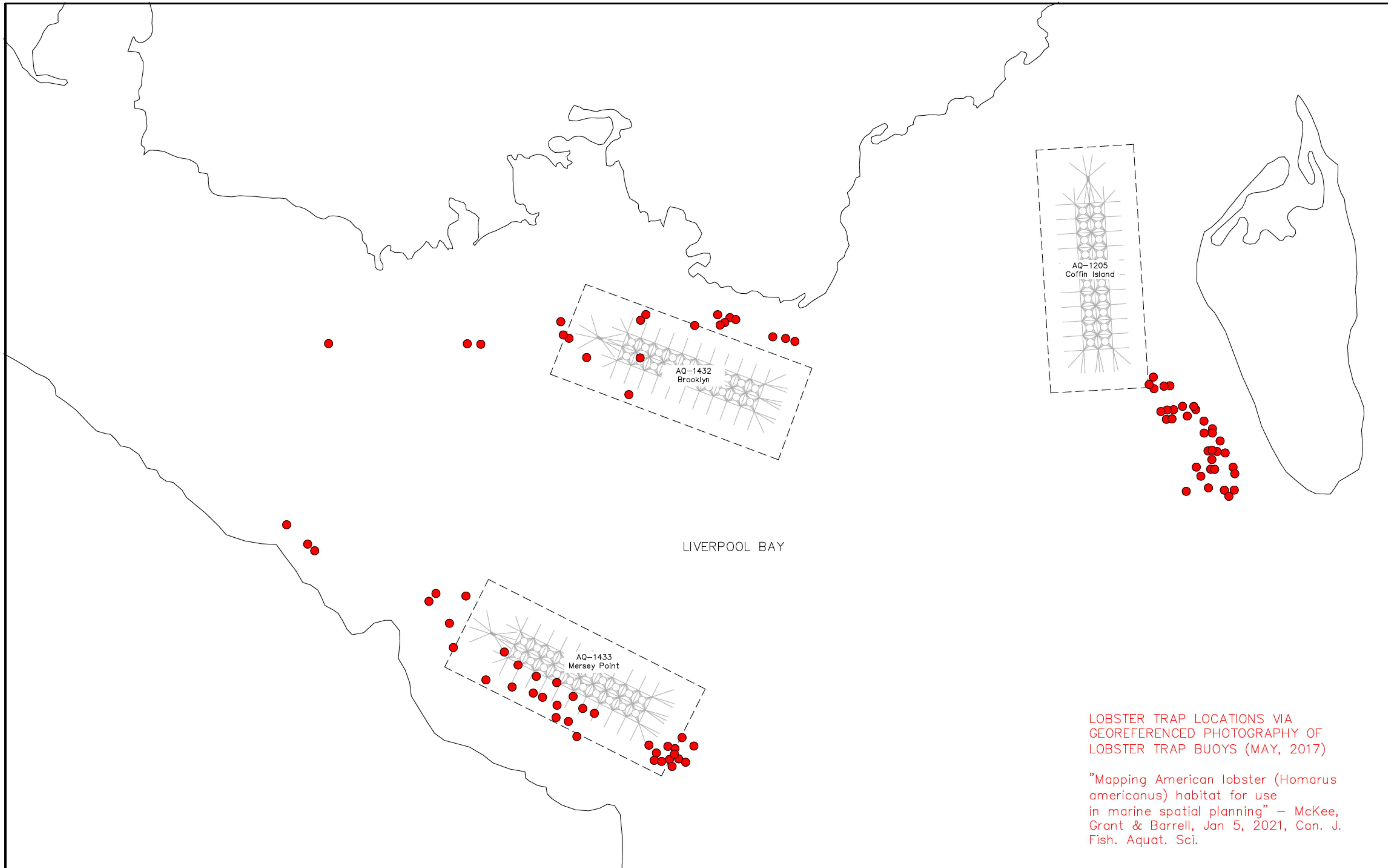
KCS Application re AQ#1205X, AQ#1432, AQ#1433 in Liverpool Bay, Queens County

This is **Exhibit B** referred to in the Affidavit of Adam Turner, affirmed before me on February 16, 2024.

[redacted]

New Brunswick Commissioner of Oaths


AQ–1205
Coffin Island
AQ–1432
Brooklyn
LIVERPOOL BAY
AQ–1433
Mersey Point
LOBSTER TRAP LOCATIONS VIA GEOREFERENCED PHOTOGRAPHY OF LOBSTER TRAP BUOYS (MAY, 2017)
"Mapping American lobster (Homarus americanus) habitat for use in marine spatial planning" – McKee, Grant & Barrell, Jan 5, 2021, Can. J. Fish. Aquat. Sci.