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Automated identification system for ships data as a proxy for marine vessel related stressors

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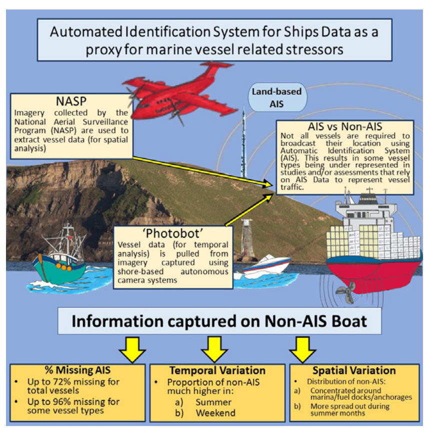
HIGHLIGHTS

- Automatic Identification System (AIS) increasingly used for marine conservation.
- Introduce 2 novel vessel traffic data collection systems complementary to AIS
- Quantify uncertainty using AIS to represent marine vessel associated threats
- Uncertainty quantified in space and time

GRAPHICAL ABSTRACT



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ABSTRACT

An increasing number of marine conservation initiatives rely on data from Automatic Identification System (AIS) to inform marine vessel traffic associated impact assessments and mitigation policy. However, a considerable proportion of vessel traffic is not captured by AIS in many regions of the world. Here we introduce two complementary techniques for collecting traffic data in the Canadian Salish Sea that rely on optical imagery. Vessel data pulled from imagery captured using a shore-based autonomous camera system ("Photobot") were used for temporal analyses, and data from imagery collected by the National Aerial Surveillance Program (NASP) were used for spatial analyses. The photobot imagery captured vessel passages through Boundary Pass every minute (Jan–Dec 2017), and NASP data collection occurred opportunistically across most of the Canadian Salish Sea (2017–2018). Based on photobot imagery data, we found that up to 72 % of total vessel passages through Boundary Pass were not broadcasting AIS, and in some vessel categories this proportion was much higher (i.e., 96 %). We fit negative binomial General Linearized Models to our photobot data and found a strong seasonal variation in non-AIS, and a weekend/weekday component that also varied by season (interaction term $p < 0.0001$). Non-AIS traffic was much higher during the summer (Apr–Sep) and during the weekend (Sat-Sun), reflecting patterns in recreational vessel traffic not obligated to broadcast AIS. Negative binomial General Additive Models based on the NASP data revealed strong spatial associations with distance from shore

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(up to 10 km) and non-AIS vessel traffic for both summer and winter seasons. There were also associations between non-AIS vessels and marina and anchorage densities, particularly during the winter, which again reflect seasonal recreational vessel traffic patterns. Overall, our GAMs explained 20–37 % of all vessel traffic during the summer and winter, and highlighted subregions where vessel traffic is under represented by AIS.

1. Introduction

Approximately 80 to 90 % of global trade relies on marine vessels, reaching an estimated 10.7 billion tons shipped in 2018, and with an estimated compound growth rate, shipping is expected to double in two decades (UNCTAD, 2018). There are a number of conservation challenges associated with marine traffic, but until recently high resolution spatial temporal information on marine vessels, and hence, associated maritime activity has been lacking (see Robards et al. (2016) for a review). Automatic Identification System for ships (AIS) was initially developed as a tool for vessel collision avoidance under the United Nations International Maritime Organizations (IMO) International Convention for the Safety Of Life At-Sea (SOLAS Regulation V/19: https://www.imo.org/en/OurWork/Safety/Pages/AIS.aspx). However, AIS also provides a rich dataset with high spatial and temporal resolution that can now be used to track and observe vessel activity anywhere in the world with clear applications in enhanced situational awareness (Lensu and Goerlandt, 2019). As well, marine conservation oriented researchers and managers increasingly utilize AIS to better understand threats and stressors associated with marine vessel traffic and mitigate against potential impacts from these threats. Indeed, there has been a sharp increase in the rate of research published in the last half a decade assessing threats to marine ecosystems associated with marine vessel traffic that are based at least partly, on AIS data. These recent publications have focused on threats such as illegal discharges of hydrocarbons and other pollutants (Bertazzon et al., 2014; Serra-Sogas et al., 2014; Rudebusch et al., 2020; Jalkanen et al., 2021; Liu et al., 2021b), ship strikes (Nichol et al., 2017; Blondin et al., 2020; Ebdon et al., 2020), invasive species (Iacarella et al., 2020a), air pollution emissions (Toscano et al., 2021), noise pollution (Erbe et al., 2012; Jones et al., 2017; Hermannsen et al., 2019; Cominelli et al., 2020), fisheries (McCauley et al., 2016), and physical impacts (i.e., anchoring: Deter et al. (2017). As well, AIS has been used as a basis for impact models producing generalized ecological stress indicators (Liu et al., 2021a), and to develop policy and mitigation strategies (McWhinnie et al., 2021).

Although AIS provides extremely useful information on marine vessel traffic, the system was not developed for marine conservation, and using these data for conservation purposes comes with some important challenges (see Robards et al. (2016) for a review). Probably the most important challenge is that not all vessels are required to carry and broadcast AIS, resulting in an uneven representation among vessel classes. In Canada, vessels over 300 t or 150 t with 12 or more passengers, with the exception of fishing vessels, were required by legislation concurrent with data collection for this study (2015–2017) to carry AIS (https://gazette.gc.ca/rp-pr/p2/2019/2019-05-01/html/sor-dors100-eng.html), whereas in the U.S., all commercial fishing vessels were required to carry AIS-B at least (https://www.navcen.uscg.gov/?pageName=AISRequirementsRev). These legal requirements have resulted in a large proportion of the fishing fleet and most of the recreational boats being underrepresented by AIS (Serra-Sogas et al., 2021).

Iacarella et al. (2020b) explored a variety of data sources that could be complementary to AIS. The Vessel Monitoring System (VMS) is an alternative vessel tracking data source to AIS that is used to track fishery vessels and monitor commercial fishing activity in Canada, but VMS is considered a closed system with highly restricted access (McCauley et al., 2016). This lack of access coupled with large inconsistencies in VMS requirements among regions within Canada (Iacarella et al., 2020b) makes this vessel tracking system a difficult tool to use for general conservation purposes. None of the dedicated systems available in Canada for monitoring vessel traffic (including AIS) sufficiently capture recreational and fishery vessel traffic in Canadian waters (Iacarella et al., 2020b), and because AIS carriage is largely voluntary in these vessel classes, it is difficult to estimate the proportion transmitting AIS. This lack of information on these vessel types is also noticeable at the global scale, as demonstrated in a recent publication by March et al. (2021). In lieu of consistent data from recreational and fishery vessel traffic, understanding and quantifying impacts from some threats such as noise (Hermannsen et al., 2019) and oil pollution (NRC, 2003; Fox et al., 2016) would suffer from imprecision, leading to inaccurate assessments, and therefore, conservation efforts aimed at managing and mitigating against these threats would be under-informed.

There is a comprehensive suite of available techniques for collecting data on vessel traffic activity from systems that are complementary to AIS. These techniques often involve the integration of AIS data (typically collected in situ) with vessel data extracted from AIS-independent sources, such as land-based radar (Barco et al., 2012), land-based radar coupled with optical imagery (Cope et al., 2020), satellite-based radar and optical imagery (Aiello et al., 2019), passive acoustics and land-based optical imagery (Merchant et al., 2014), and optical imagery collected from aerial surveillance aircraft (Serra-Sogas et al., 2021). Vessel data extracted from optical imagery captured with land-based camera systems have also been used to extend estimates of fishing activity data from either or both land-based questionnaire surveys and aerial surveys (Smallwood et al., 2012; Morrow et al., 2022); however, these studies typically do not integrate AIS as they focus on vessel traffic that is not required to carry AIS. Aerial survey techniques used to characterize vessel traffic in space and time were developed prior to the implementation of AIS (James et al., 1971; Ashton and Chubb, 1972), and more recently passive acoustics (Tesei et al., 2020) and survey questionnaires (Gray et al., 2011) have also been employed without integration of AIS data. Currently, aerial surveillance remains one of the best options for collecting data complementary to AIS and other traffic monitoring systems in Canada (Iacarella et al., 2020b), and a recent study introduced a novel technique that integrates AIS data and vessel data pulled from optical imagery collected by aircraft operated by Transport Canada's National Aerial Surveillance Program (NASP: Serra-Sogas et al., 2021).

There are essentially three principal sources of uncertainty when using AIS as a proxy for a threat or stressor associated with marine vessels: 1) the proportion of vessel traffic captured by AIS (primary focus of this study); 2) the contribution of non-AIS traffic to the focal threat; and 3) accuracy of information contained in AIS data. Complementary marine vessel traffic data collected independently from AIS can be used to estimate the first uncertainty (proportion of vessel traffic missed by AIS), aiding in the interpretation of results from models estimating threat levels based entirely on AIS, including assessing their applicability to inform policy or conservation initiatives (Merchant et al., 2016). These data also can be critically important for directly informing policy makers and managers in marine spatial planning (Serra-Sogas et al., 2021), particularly in areas with intense recreational and fishery vessel traffic. Here we extend the technique developed by Serra-Sogas et al. (2021), by building separate spatial distributions for AIS and non-AIS vessels that extend across the Salish Sea fitting Generalized Additive Models (GAMs) based on AIS data and vessel information pulled from optical imagery collected by NASP. As well, we introduce a novel data collection technique using a semi-autonomous land-based optical camera system (referred to as Photobot from here on) that integrates AIS data collected in situ (on the same site) with vessel traffic data pulled from optical imagery collected in a navigationally restricted area of the Salish Sea (see Fig. 1: Boundary Pass). With both these techniques, we were able to

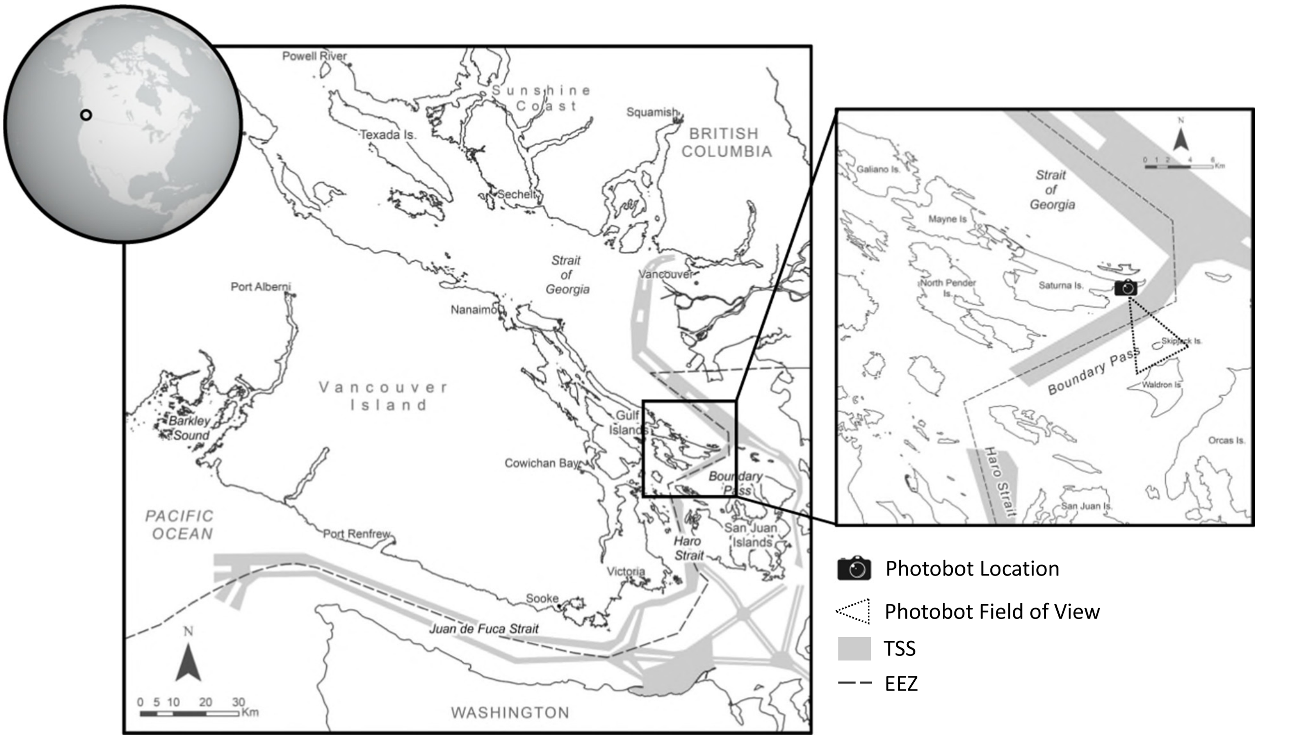

Fig. 1. Study region and location of AIS-Camera system ("Photobot") on south east point of Saturna Island. Field of View (FoV) of the Photobot is depicted as a triangle overlooking Boundary Pass from Saturna Island towards Waldron Island (right panel). TSS = Traffic Separation Scheme, EEZ = Exclusive Economic Zone.

build a more comprehensive understanding of vessel presence in the Salish Sea that allowed us to explore AIS representation among the different vessel classes across space and time, and discuss our results in terms of how they might help interpret AIS-based threat assessments, and affect policy informed by them.

2. Materials and method

2.1. Study area

NASP imagery covered most of the Canadian Salish Sea including Juan de Fuca Strait, Haro Strait, Boundary Pass, Gulf Islands and Strait of Georgia (Fig. 1). The POS imagery was collected overlooking Boundary Pass from the southwest tip of Saturna Island at a location that was approximately 25 m above sea-level (see inset: Fig. 1).

2.2. Temporal variability from Photobot system overlooking Boundary Pass

2.2.1. Imagery and AIS data collection

We developed our Photobot as a semi-autonomous system for integrating AIS with optical imagery collected using an off the shelf digital camera for collecting data on both AIS and non-AIS moving through navigational bottlenecks such as Boundary Pass in the Salish Sea (Fig. 1). The Photobot is centred around a single board computer (Raspberry Pi 3 or 4) and Python script developed to manage an array of optical cameras and an AIS receiver, as well as archive imagery and vessel traffic data on an external USB hard-drive. Everything is housed in a weather-proof enclosure with view ports for the cameras. It was designed to be installed in remote locations with solar power and an internet connection through an LTE router (a router capable of connecting to an LTE, "Long-Term Evolution" type of 4G mobile internet) or a satellite link to monitor system health and modify programming via remote access (for a full system description of hardware, capabilities, and available supporting software see Appendix A). At our study site, however, power and internet were provided by Saturna Island Marine Research and Education Society (SIMRES). Vessel traffic data presented here were pulled from imagery collected by a Canon Digital Single-Lens Reflex (SLR) camera tethered (i.e., connected by means of a USB cable) to the Raspberry pi (R-pi). The photobot was installed at around 35 m above sea-level, and the SLR camera was set with a field of view (FoV) horizontal angle of approximately 12 degrees (zoom lens with a focal length of approximately 45 mm) to capture vessel traffic moving through Boundary Pass (Fig. 1). We found that 35 m was ideal for the installation height at our location, which facilitated vessel classification (i.e., imagery of the sides of vessels) and prevented vessels in the foreground from obscuring vessels more distant from the camera. An FoV of 12 degrees was the best trade-off for us, reducing the likelihood of missing vessels passing through the FoV at high speed near the camera, while allowing us to identify small vessels in the background. Open-source applications and libraries such as gPhoto2 and libgphoto2 (http://www.gphoto.org/) were integrated into the Python script to communicate directly with the camera using Picture Transfer Protocol (PTP) specific to this brand and make of camera (see Appendix A).

The photobot camera image acquisition rate was set to a burst of three images per minute (i.e., set up using Raspberry pi python script described in the supplemental material), with images separated by 5 s intervals during each burst. Because the imagery was optical, acquisition occurred during daylight hours only (adjusted automatically to account for changing daylength). This acquisition rate resulted in approximately 2600 images captured per day, with digital storage sizes of 5-11 MB per image. A large external USB hard-drive (2 TB or larger) was used to house the imagery data archived by the R-pi script. We incorporated the burst of three image acquisition rate in part to conserve disk space, but also to facilitate the auto-detection software we developed to process the large number of images we collected during this and subsequent studies (see below). When visibility was fair or better (i.e., visibility of 5 km or more), the images provided sufficient resolution to detect even small vessels (i.e., 5–10 m in length) on the other side of Boundary Pass in our FoV, which is a distance of approximately seven kilometers (Le Baron, 2021). To ensure consistent unbiased sampling, we restricted our data collection and analyses to periods of time when visibility was sufficiently high to detect small vessels throughout the FoV. Nevertheless, we are far more likely to miss detecting non-AIS vessel traffic using this methodology, and we emphasize that our estimates of the proportion of non-AIS vessel traffic are conservative.

For this study, we relied on AIS data collected by the SIMRES AIS receiver that was located beside the camera enclosure and was made available to download through the Ocean Networks Canada Data Search portal (https://data.oceannetworks.ca/). It is important to note that AIS data collected through land-based receivers are limited to the field of view of the receiver, hence the need to collect in situ AIS data to couple with vessels detected in our imagery. Although we relied primarily on AIS data collected by SIMRES, AIS data from external yet proximate land-based receivers were sometimes required to fill temporal gaps due to periodic equipment failures at the study site. These externally sourced AIS data were provided by Ocean Networks Canada, via the Canadian Coast Guards land-based receivers that typically provide a greater field of view than most land-based receivers that are publicly hosted (i.e., the SIMRES receiver as an example). AIS data was decoded when necessary and geographically clipped to a geo-box encompassing the camera's field of view.

2.2.2. Processing imagery and linking vessel traffic data to AIS data

The first step in processing the imagery was to manually review and identify images with targets of interest. This was an intensive process requiring many person-hours because of the high number of images collected. Although we have developed an autodetection software (Marques et al., 2021) that greatly reduces processing time (Morrow et al., 2022; see Appendix A), all the imagery in this project was manually reviewed and images with targets were isolated for further data extraction. Once those images were identified and isolated, we used a second python tool (the AIS-Linker tool) that we developed to manually combine the AIS data with vessel traffic in the imagery (see Appendix A for more information). This script parsed the AIS data into subsets based on Maritime Mobile Service Identity (MMSI) used as a unique identifier, and linearly interpolated each subset of AIS positions into unique vessel tracks (associated with MMSI). Based on the interpolated positions and the time-stamp of an image, the script estimated the location of a vessel captured in an imagery and superimposed the position of this estimated location on the same image (Fig. A.2). The imagery time-stamp was assigned by the Pi computer with an internal time chip (Real Time Clock or RTC) that was synchronized with the internet. Imagery pixels are uniquely identified in the imagery (x,y coordinate within the image frame) and were georeferenced using known positions of land features in the FoV and interpolated pixel locations based on the optical characteristics of the camera lens.

Because linking AIS broadcasting vessels with vessels in the imagery relied on the time of image capture, the accurate interpolation of AIS positions, and the georeferencing of each of the imagery pixels, we included a margin of error depicted as a length of the track overlaid on the imagery on either side of the estimated current position (Fig. A.2). We then used this tool to go through these images, identify which of the observed vessels were broadcasting AIS, and link the information included in the AIS messages to the observed vessels broadcasting them. As well, this tool was developed to facilitate the manual documentation of non-AIS vessels, by including their vessel class and activity, as well as the vessel relative position within the imagery (pixel by pixel).

AIS tracks from broadcasting vessels were displayed where the vessel met the waterline, which is an indication that the imagery was well calibrated with this python tool. Although AIS locations were reported using the WGS84 geographic coordinate system, and our linker tool performed using NAD83, the difference in the base ellipsoids between the two coordinate systems apparently did not affect the positioning of target AIS vessels in our imagery. All contacts were recorded in the tool when they were first fully in frame and specific imagery pixels were labeled (using the software above) where the vessel met the waterline. In the case of non-AIS vessels, imagery pixels were labeled where the bow met the waterline and for AIS vessels, pixels were labeled at the waterline directly below where we estimated the AIS transmitter was located (Le Baron, 2021). AIS and non-AIS vessels were classified based on vessel class assigned by AIS or from manual classifications from the imagery as follows: cargo vessels, tanker, tug, passenger, government, fishing, ecotourism, sailboat, motor craft, and other. Motor craft included small vessels that were motorized only (i.e., not a sailboat or human propelled craft) that were largely recreational, but this class also included some small motorized vessels that were too distant to identify them as government or ecotourism. We also noted if AIS vessels were transmitting AIS-A (SOLAS compliant vessels) or AIS-B, which is a voluntarily implemented AIS transponder that is typically less expensive than AIS-A, and transmits at a lower power. We also identified wakes without target vessels as an indication of the number of vessels we missed in our FoV during our burst of three images captured per minute.

2.2.3. Mean daily vessel detection rates and proportion non-AIS vessel traffic, and analyses

We processed a total of 693,611 images captured in 2017, and split the vessel data into summer (Apr. - Sep.) and winter (Jan. - Mar. and Oct. - Dec.). The number of images processed was fairly consistent among days of the week (Table B.1), but varied by season because of the longer day length during the summer months. There were far fewer images processed during the month of April because equipment failure during that month resulted in fewer images captured. Because of the uneven distribution of images processed among months and seasons, we controlled for effort by using either mean daily detection rates (number of vessels detected per image per day) or mean daily proportion non-AIS (daily number of non-AIS vessels/daily total number of vessels detected). We fit a binomial Generalized Linear Model (GLM) to the observed vessel detection rates to test for the effect of weekend versus weekday and season using the statistical package R (version 4.1.1: R Core Team, 2021). Because we found an interaction between season and weekend versus weekday effect, we ran pairwise detection rate comparisons between weekend and weekdays within seasons, by estimating marginal means (*emmeans* function with the R package "emmeans") that control for the effect of season.

2.3. Spatial variability in AIS versus non-AIS vessel traffic from NASP data in the Salish Sea

2.3.1. Imagery collection and data processing

The National Aerial Surveillance Program (NASP) of Transport Canada conducted 74 aerial vessel surveys between August 13, 2015 and December 12, 2017 using a combination of visual and remote sensing surveillance. The NASP operates a maritime surveillance system that allows concurrent monitoring of AIS vessels on a moving map and a geopositioned, high resolution turret camera to investigate and document maritime activity. Crews were provided with the study area and requested to conduct surveys on a non-interference basis to their primary mission (pollution patrols). Surveys were conducted during good visual flying conditions at an average speed of 150 knots at altitudes ranging from 800 to 3500 f. depending on operational requirement. The surveys commenced with the console operator taking a picture of the map of the survey area with all AIS targets visible, marking the time and starting the video recording. The crew visually searched and called out all vessels observed while the console operator honed and focused on each vessel, cross referencing with the map to determine if it was transmitting AIS, and if it was not, zoomed the video in to capture high resolution imagery of the vessel along with its location. At the end of each survey, the recording was stopped and the operator captured a second map image showing the flight track through the survey area and updated positions of all AIS vessel targets. The operator also completed a survey form including the following data: survey date, mission number, start and end times of the survey, estimated surface wind speed, estimated swath visually covered, estimated percent of non-AIS vessels captured on the video and any other comments about the survey. Post flight, all survey data and imagery was compiled and shared with an analyst for post-processing data extraction and analysis (Serra-Sogas et al., 2021).

The video footage collected during each survey flight was reviewed manually and data compiled into a database for each non-AIS vessel sighted. The data compiled included the date, time, vessel position (latitude and longitude), vessel class and activity (e.g., fishing, sailing, motoring). The locations of AIS vessel targets were compiled from the console map images (jpeg), which were saved by the Surveillance Officer at the start and end of each survey. The AIS target ID was matched with the NASP Mission Report to acquire metadata on each AIS vessel detected by the aircraft AIS receiver, including: the MMSI number, vessel class, length and flag. This database was then imported to ArcGIS (version 10.6) to create a point shapefile of non-AIS vessel sightings. Vessels were classified similarly as above (see Serra-Sogas et al., 2021), but our spatial analyses (see below) were based on classifications aggregated into 2 groups only: AIS and non-AIS vessels. Unfortunately there were insufficient data to spatially model the NASP data at the vessel class resolution.

Distance sampling methods were used to estimate the area effectively surveyed by NASP or survey effort across the study area. First, the perpendicular distance from each non-AIS vessel sighted to its corresponding survey flight path was estimated and then used to fit the detection function with no other covariates. The detection function with the best-fit was used to estimate the Effective Side Width or area effectively searched by NASP when looking for non-AIS vessels. This value was then used to buffer each survey flight path. Finally, a grid of the study area (composed of 2.5 km $\times$ 2.5 km grid cells projected in BC Albers Equal Area) was used to estimate the aggregate area surveyed per cell (or NASP effort per cell) by summing the total area of overlapping flight path buffers contained within each cell. This distance sampling methodology was used to minimize bias that favored the detection of larger vessels.

Consistent with our Photobot system data collection period, we split NASP-based data into summer (Apr. - Sep.) and winter (Oct. - Mar.) seasons, and our analyses were based on detections for vessels that were underway.

2.3.2. Spatial modeling of NASP data

We fit negative binomial Generalized Additive Models (GAM, with gamma = 1.4; see package 'mgcv' in r documentation; Wood 2021) with a log link function to model the spatial distributions of non-AIS and AIS vessel detections by NASP, during the summer and winter. We chose to spatially model our NASP-based vessel data with GAMS as they are the most common technique for creating density surfaces based on survey data collected using distance sampling methods and processing (Thomas et al., 2010). Predictor variables were created by assigning each grid cell centroid with distance from shore, distance from recreational anchorages (from cell centroid), density of marinas, NASP effort (total area surveyed per season), and whether or not the centroid was located inside or outside of traffic lanes, which are part of the marine traffic schemes assigned by Canadian and US authorities. Both densities of marinas and locations of recreational anchorages come from spatial data provided by the British Columbia Marine Conservation (BCMCA: https://bcmca.ca/data/hu_tourismrec_marinas/ and https://bcmca.ca/data/hu_tourismrec_anchorages/). BCMCA classified "coastal ecotourism lodge, fishing lodge, floating fishing lodge, harbour authority/public wharf, harbour authority with marine fuel services, marina, marina with marine fuel services, marine fuel services, private marina/yacht club/yacht sales, Transport Canada public wharf and Transport Canada public wharf with marine fuel services" as marinas and coastal facilities, which we collectively refer to as marinas in this manuscript. Marina density in this study is simply the number of marinas identified by BCMCA per 6.25 km^2 (2.5 km $\times$ 2.5 km grid cell). We accounted for NASP effort as a log-transformed offset variable. We also included centroid location (in metres easting and northing) to capture spatial patterns not explained by the other variables as a bivariate spline in our GAMs, and we further structured this variable by location relative to the traffic separation schemes using the "by=" option in this bivariate spline. All other predictor variables were included as univariate splines in the GAMs (except for NASP effort), and we used AIC (Akaike Information Criterion) as a guide for number of smoothing knots (knots in a GAM not indicative of speed of a vessel) used in each of the spline curve variables including the bivariate spline (knots typically ranged between 10 and 20). We chose to fit the GAMs using a negative binomial distribution based on results from the r package "fitdistr", and from comparing quantile-quantile plots using the function "gam.check" in the r package "mgcv". We constrained our analyses only to grid cells with NASP survey effort during each season.

Using the best fit GAM for each season, we predicted both AIS and non-AIS vessel traffic predictions onto the same 2.5 $\times$ 2.5 km grid we used for the GAM analyses above, using a spatially even effort of 1 km^2 among these grid cells. Because our GAMs were constrained to include only the cells with NASP survey effort, our GAM predictions varied in extent among seasons (Figs. 3 & 4). For example, NASP effort extended across the Juan de Fuca to include the US territorial waters during the winter but not during the summer. The proportion of non-AIS vessel traffic was estimated by dividing the GAM predicted non-AIS vessel traffic by the sum of the predicted non-AIS traffic and AIS traffic.

3. Results

3.1. Temporal variability from Photobot system overlooking Boundary Pass

Overall, we detected and characterized 9475 vessels passing through Boundary Pass during the calendar year 2017 (summer $n = 8059$; winter $n = 1416$), based on either or both visual assessments of optical imagery and AIS data collected in situ (Fig. 2 & Table 1). Overall, a considerable proportion of marine traffic travelling through Boundary Pass was not captured by AIS, ranging from 25 % non-AIS tracked vessels in the winter (October to February) to 72 % in the summer (May to September). Cargo, Tanker, and Tug vessels were consistently and comprehensively captured by our in-situ AIS receiver, particularly during the summer (only one Tug out of 113 not captured by AIS). There were a few notable exceptions during the winter, with 22 Cargo vessels out of 834 (3 %), four Tanker vessels out of 70 (6 %), and 11 Tugs out of 65 (17 %) not captured with our in-situ AIS receiver. AIS failed to capture a considerable proportion of the remaining vessel classes with non-AIS vessels representing as high as 96 % of vessels detected. The most under-represented classes were identified as Fishing, Ecotourism, Sailboat and Motor Craft vessels ranging from 67 to 96 % non-AIS.

Based on mean daily detection rates (number of vessels detected/images processed/day), the proportion of non-AIS vessel traffic was much higher during the summer (Fig. 3 & Table 2: 71–74 %) than during the winter (Fig. 3 & Table 2: 18–38 %). The strong seasonal variation was due largely to an increase by an order of magnitude in smaller recreational vessel traffic detected in both the Sailboat and Motor Craft classes during the summer (Fig. 2). These classes included the highest number of vessel detections overall, and had the lowest proportion of vessels transmitting AIS. The proportion of non-AIS vessel traffic also varied significantly from weekday to weekend, but this variability was somewhat inconsistent between summer and winter (Fig. 3 & Table 2). In general, there was an increase in the proportion of non-AIS vessel traffic on the weekends, but the greatest proportional increase occurred in the winter when non-AIS traffic nearly doubled.

It is important to note that not all vessels broadcasting AIS are legally obligated to do so. Many vessels detected using our system are voluntarily transmitting the lower power transmission AIS-B, and hence, tracking these vessels using AIS is less reliable than for tracking vessels obligated to transmit AIS-A. All of the commercial vessels in the Cargo, Tanker, and Tug classes are transmitting AIS-A, whereas most of the vessels transmitting AIS in the Ecotourism, Sailboat, and Motor Craft classes are broadcasting AIS-B (Table 1). Vessels broadcasting AIS in the Fishing class vary seasonally in terms of broadcasting AIS-A or AIS-B, as many commercial fishing vessels are not required to carry AIS in Canada opting to broadcast using AIS-A or AIS-B (or neither).

Wake detections indicate the passage of a vessel that was not captured in the imagery, and hence, could not be classified visually. Because we programmed the system to capture images every minute in a burst of 3 photos separated by 5 s, we may have missed vessels in our imagery. Fast-moving vessels passing close to the camera where the field of view is the narrowest

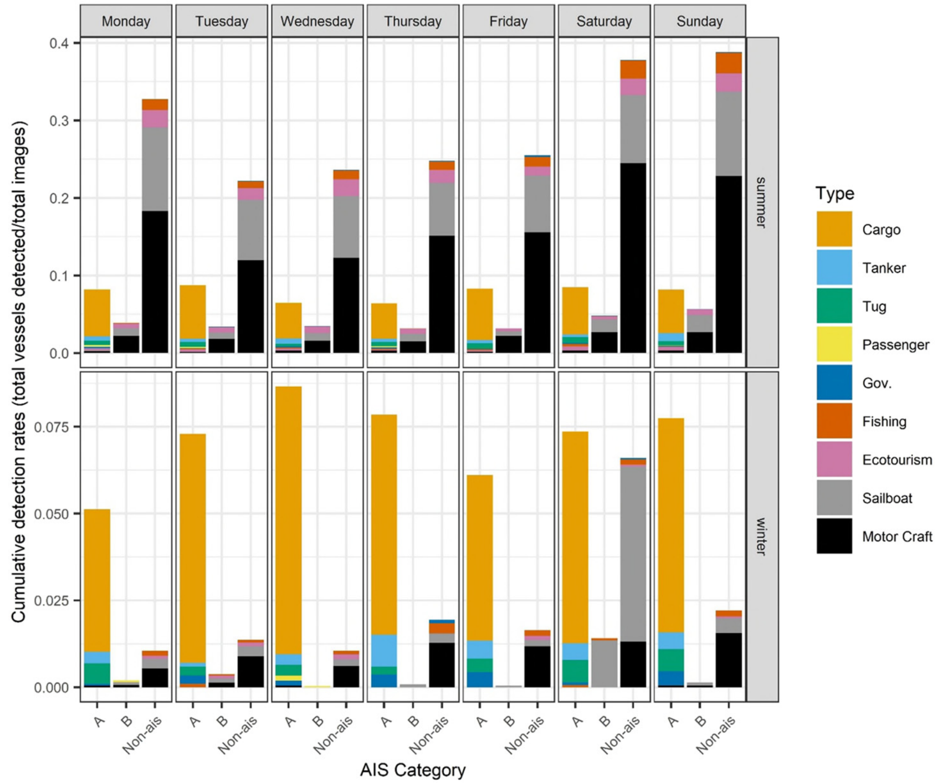

Fig. 2. Variability in total detections by vessel class across the week and by season for January to December 2017 (summer = April – September; winter = January – March, October – December). Note that the Cumulative Detection Rates differ by an order of magnitude between seasons, driven mostly by Non-AIS traffic variability.

were most likely not captured in our imagery. We used wake as a means of estimating the proportion of vessels missed in this way, and none of the wakes captured by our imagery could be linked to a vessel broadcasting AIS. This indicates that using this methodology, we may have underestimated vessels not broadcasting AIS but this probability was relatively low. The total number of vessels detected as wake only was 259 (Table 1), which represents 2.7 % of all vessels detected (259/9475), with a much higher number of missed vessels in the summer (n = 257) than the winter (n = 2), presumably because nearshore recreational activity was much higher during the summer.

Table 1
Vessel detections based on optical image assessments and AIS data collected in situ during Winter (Oct. – Dec. and Jan. – Mar. 2017) and Summer (Apr. – Sep. 2017). Cargo includes all types of cargo vessels including bulk carrier, container, and tanker vessels. Passenger includes ferries and cruise ships. Number of images processed: summer = 157,878, winter = 268,325. 3 % of vessels detected in winter could not be identified as AIS or non-AIS.

	Summer				Winter			
	AIS class				AIS class			
		A	B	Non-AIS		A	B	Non-AIS
Type	Total detected	%	%	%	Total detected	%	%	%
Cargo	1055	100	0	0	807	97	0	0
Tanker	104	100	0	0	66	94	0	0
Tug	114	98	0	1	64	84	0	0
Passenger	19	89	11	0	5	60	40	0
Gov.	47	51	13	34	38	89	0	8
Fishing	315	8	1	91	29	10	7	83
Ecotourism	543	10	22	67	16	0	12	88
Sailboat	1856	0	12	88	161	0	21	79
Motor Craft	3721	1	11	88	172	2	2	96
Other	56	64	23	12	7	29	0	43
Wake	257	0	0	100	2	0	0	100
All	8108	19	9	72	1367	69	3	25

3.2. Spatial variability in AIS versus non-AIS vessel traffic from NASP data in the Salish Sea

Our GAMs performed moderately well, explaining 20 to 37 % of the spatial variability in detection rates of generalized (i.e., pooled among categories) non-AIS and AIS vessel traffic during the summer and winter (Table 3: Deviance Explained) and based on data extracted from imagery collected by NASP. Unfortunately we had insufficient data to model vessel classes separately, hence our GAMs were constrained in their precision. All predictor variables significantly explained spatial variability in AIS and Non-AIS vessel traffic except for Density of Anchorages for AIS vessels in both seasons. Significant spatial patterns or aggregations of traffic intensities that were not associated with our predictor variables (Table 3: lat. and lon. bivariate splines) existed inside and outside designated traffic lanes (Traffic Separation Scheme) for both non-AIS and AIS vessels for both seasons, except for non-AIS vessels inside lanes during the summer. These unexplained spatial aggregations played a bigger role in determining model outcomes during the summer than during the winter (except for non-AIS traffic inside the shipping lanes).

The relationship between distance to shore and vessel detection likely drives much of the spatial patterns we see mapped as GAM outputs (see Figs. 4 & 5), where non-AIS vessel traffic and consequently, proportion non-AIS, tends to occur closer to shore. Distance to shore was one of the most important variables explaining spatial patterns in non-AIS vessels traffic for both seasons, and was more important for predicting AIS traffic patterns during the winter than for the summer (Table 3). Distance to shore was particularly important for explaining vessel traffic variability within a coastal strip that extended five to 15 km from shore (Fig. 5: there was dramatic increase in confidence intervals for trends beyond this point), except non-AIS traffic during the winter where vessel traffic intensity continued to decline with distance from shore beyond this coastal strip (Fig. 5). All declines in predicted densities with distance from shore were similarly steep up to five to 10 km, except for AIS vessel traffic in the summer. Beyond 10 km there was either no relation (non-AIS) with shore or a slightly

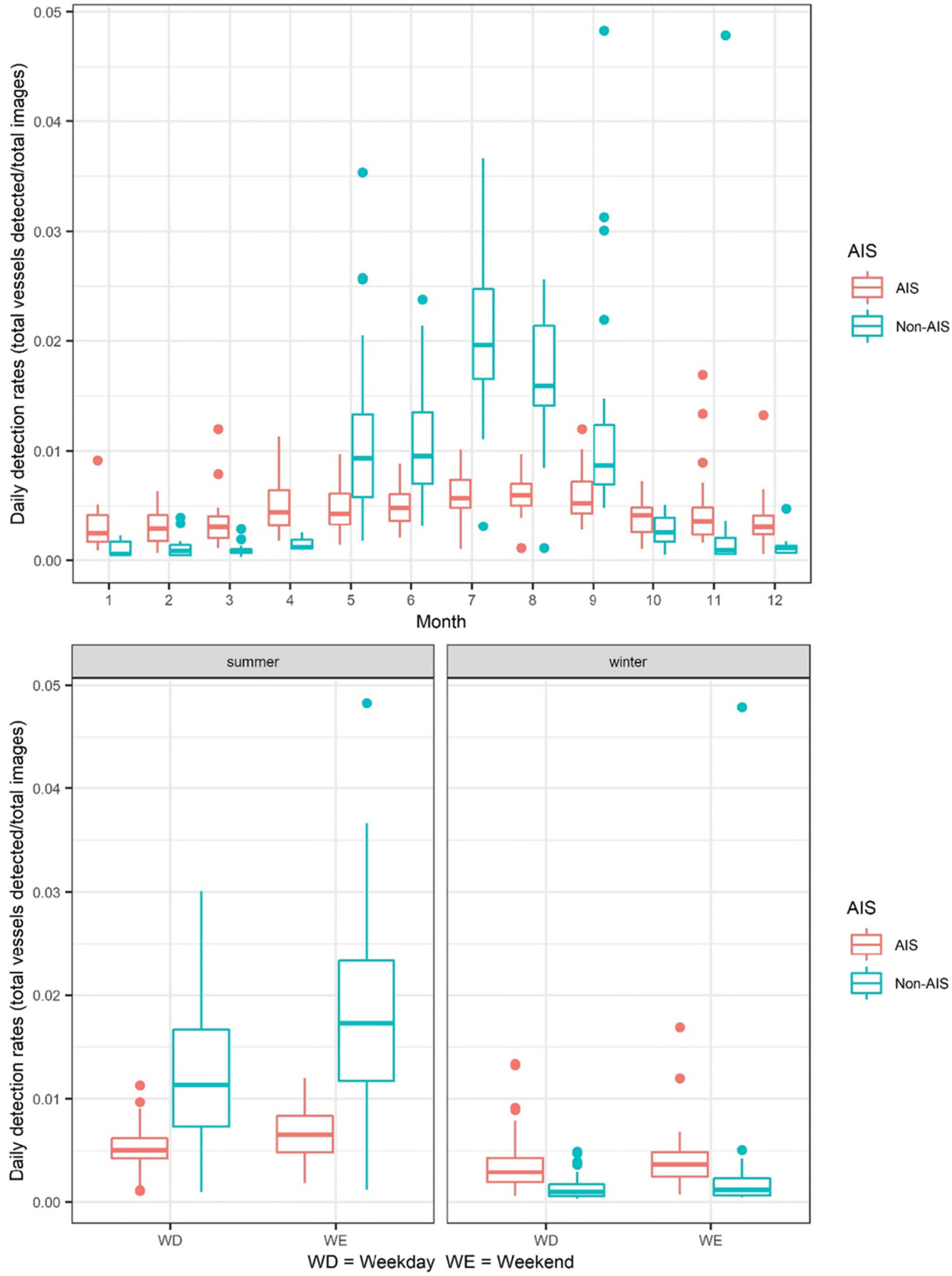

Fig. 3. Median daily detection rates (total vessels detected/total images taken per day) for AIS and Non-AIS vessels based on data pulled from Photobot imagery and AIS receiver. Upper panel depicts mean daily detection rates by month and lower panel depicts detection rates for weekdays (Mon-Fri) versus weekends (Sat-Sun). Mid line = median, box = 25/75 percentile, whiskers = 5/95 percentile, with outlier values as dots.

increasing density (AIS). This shift in trends may indicate sub-groups of AIS vessels with movement patterns that are not strongly affected by distance from shore or may be intentionally moving away from coastal features.

Density of marinas was strongly associated with non-AIS and AIS traffic patterns in both summer and winter (Table 3), though it was somewhat less important during the summer than the winter for non-AIS traffic. Oddly, density of marinas partially predicts increasing non-AIS traffic in the summer to a point, then falls off rapidly to no relationship, while in winter the relationship is strongly positive throughout the range of marina densities (Fig. 5), suggesting that non-AIS traffic movement patterns are more tightly linked to marina locations during the winter than during the summer. The unexpected relationship between marina density and AIS vessel traffic in the winter (Fig. 5), given that marinas refer to facilities supporting mostly recreational and smaller fishing vessels, may either or both reflect vessel classes within winter AIS traffic with movement patterns that relate to marina densities at different spatial scales. It is unclear why this pattern is not consistent between seasons.

Density of anchorages, which also support mostly recreational vessels, was strongly associated with summer non-AIS traffic patterns, less so for winter patterns, and AIS traffic showed no association with anchorages in

Table 2
Summary of Generalized Additive Models (GAMs) for spatial distributions of vessel detection probability based on imagery collected by NASP. NS: non-significant ($p > 0.05$); '*' $0.05 > p > 0.01$; '**' $0.01 > p > 0.0001$; '***' $p < 0.0001$.

Spline (predictor variable)	Summer		Winter	
	Non-AIS	AIS	Non-AIS	AIS
Lat., Long. (outside lanes)	***	***	*	*
Lat., Long. (inside lanes)	NS	***	*	*
Distance to shore	***	*	***	***
Density of marinas	*	**	**	**
Density of anchorages	***	NS	*	NS
Deviance explained	29.1 %	21.5 %	36.7 %	20.0 %

Table 3
Summary of Generalized Additive Models (GAMs) for spatial distributions of vessel detection probability based on imagery collected by NASP. NS: non-significant ($p > 0.05$); '*' $0.05 > p > 0.01$; '**' $0.01 > p > 0.0001$; '***' $p < 0.0001$.

	Summer		Winter	
Spline (predictor variable)	Non-AIS	AIS	Non-AIS	AIS
Lat., Long. (outside lanes)	***	***	*	*
Lat., Long. (inside lanes)	NS	***	*	*
Distance to shore	***	*	***	***
Density of marinas	*	**	**	**
Density of anchorages	***	NS	*	NS
Deviance explained	29.1 %	21.5 %	36.7 %	20.0 %

either season (Table 3 and Fig. 5),. During the summer there appears to be two distinct groups of non-AIS vessel traffic that are associated with density of anchorages at different spatial scales.

When we combine GAM output layers for AIS and non-AIS vessel traffic (Fig. 4: Proportion Non-AIS), there is a considerable shift in the predicted proportion non-AIS from summer to winter, with a greater number of 2.5. km x 2.5 km grid cells estimated with a higher proportion non-AIS during the summer. Predicted proportion of non-AIS summer traffic tend to dominate cells close to shore, particularly in the Strait of Juan de Fuca and the Southern Gulf Islands, but also extends out into the middle Strait of Georgia from Vancouver Island (between Nanaimo and Courtenay) towards Texada Island (Fig. 4). Non-AIS vessels tend to avoid traffic separation lanes, which is clearly seen in the Strait of Juan de Fuca. Similar patterns occur during the winter (Fig. 4), with higher proportions of non-AIS vessels near the coast, particularly in the Strait of Juan de Fuca near Sooke, and extending out from mid Vancouver Island towards Texada Island. However, there was a noticeably disproportionate increase in non-AIS traffic in central Strait of Georgia. As well, the proportion of non-AIS traffic is considerably lower inside the traffic separation scheme lanes for both seasons, particularly in the Juan de Fuca.

Density surfaces from the GAMs based on NASP collected data indicate that there are a higher number of output grid cells (2.5 × 2.5 km) with a higher proportion of non-AIS vessels during the summer than winter (Fig. B.1). During the summer, over 50 % of grid cells are estimated to have 73 % non-AIS vessel traffic or higher (median), and 20 % of cells with 92 % non-AIS or higher (80th percentile). Distribution of cell frequency is much more even across the range of proportion non-AIS estimates for the winter GAM, where the median (50th percentile) occurs much closer to 50 % non-AIS (Fig. B.1), and the 80th percentile occurring near 80 % non-AIS.

3.3. NASP estimates within Photobot's field of view (FoV) overlooking Boundary Pass

There were six GAM prediction nodes (separated by 1 km) located within the FoV of the Photobot system overlooking Boundary Pass. Models based on summer NASP data predicted 53–68 % non-AIS traffic for each of

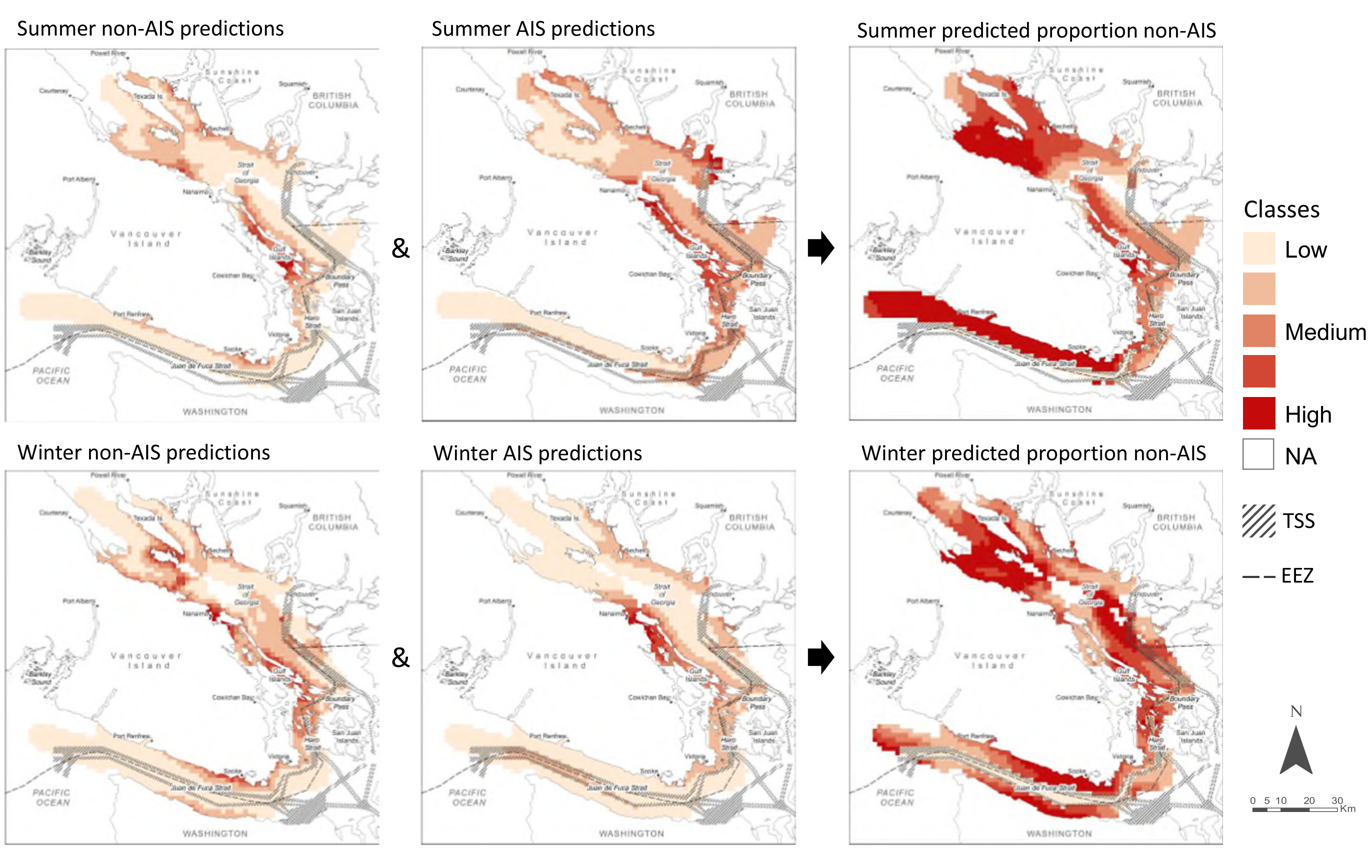

Fig. 4. Summer (top row) and winter (bottom row) AIS and non-AIS predicted, and the proportion non-AIS tracked vessel traffic. GAM density surfaces based on data collected from NASP imagery.

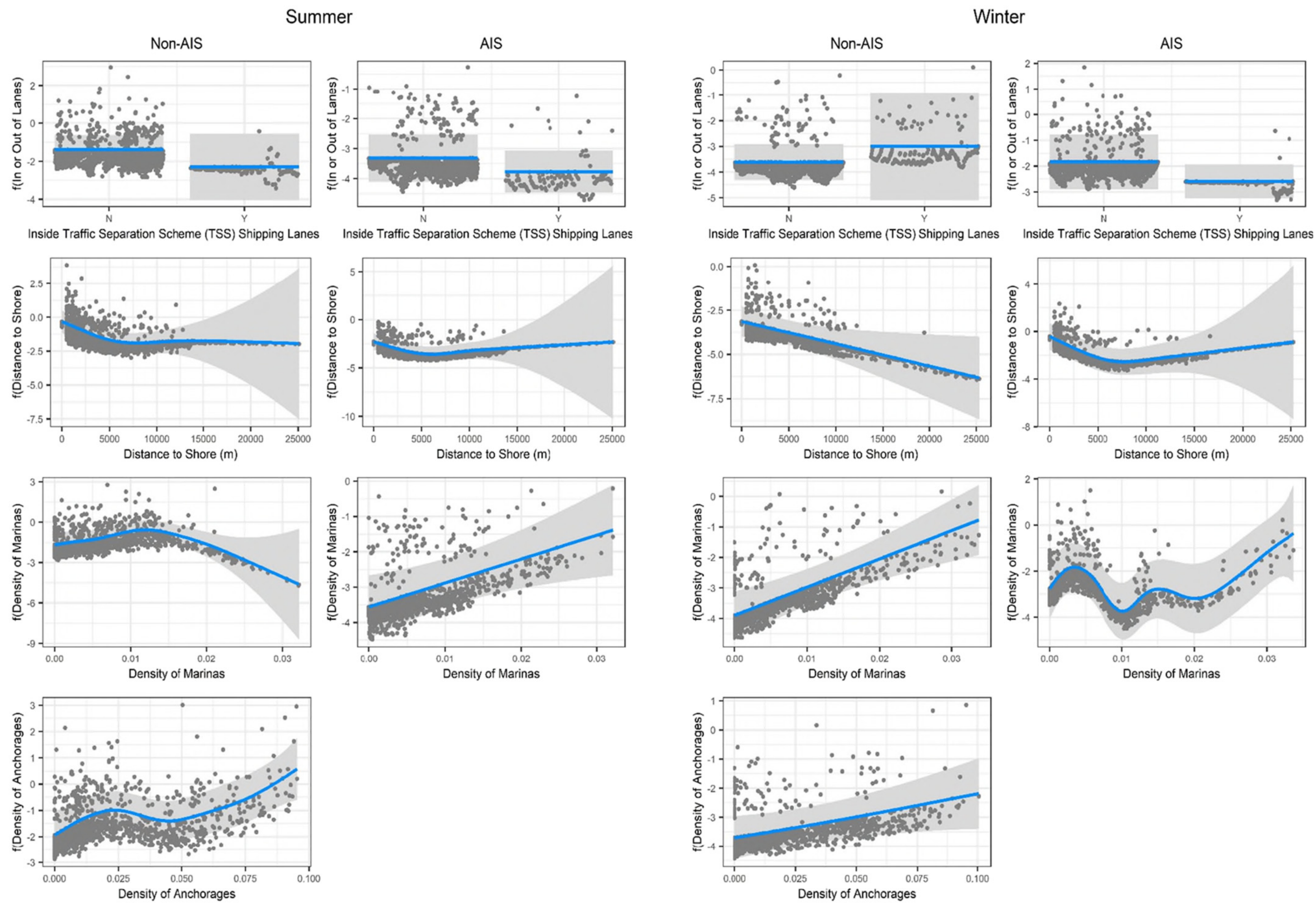

Fig. 5. Partial prediction plots from summer and winter best-fit GAMs.

the nodes, and models based on winter data predicted 38 % to 66 % non-AIS traffic. This suggests that our GAMs underpredicted the non-AIS proportion of vessel traffic during the summer (Table 1: 72 % observed total non-AIS vessel traffic) and overpredicted this proportion traffic during the winter (Table 1: 25 % total observed non-AIS).

4. Discussion

In this study, we introduce and develop novel systems and methodology for acquiring and analyzing marine vessel traffic data pulled from optical imagery, and compare these data with vessel data collected using in-situ AIS receivers. Our systems and methodology provide complementary measures of uncertainty (i.e., proportion of vessel traffic not captured by AIS) in that vessel data collected using our Photobot provide high temporal resolution in a restricted area (within the camera FoV), and our analyses based on NASP data provide high spatial resolution that extends across our study region in the Salish Sea. As well, our Photobot system provided sufficient data over a short time span, allowing us to break down temporal patterns among our various vessel classes.

Based on Photobot data collected during 2017, 72 % of all traffic moving through Boundary Pass during the summer is not captured by AIS. These vessels are mostly recreational, with peak traffic occurring during July and August. During the winter, the proportion of non-AIS vessels drops to around 25 %. As well, the proportion of non-AIS traffic increases during the weekend for both seasons, but the increase during the winter is disproportionately higher during the weekend probably because recreational boating likely occurs over longer periods during the summer (i.e., extends beyond weekend activities). Furthermore, we found that vessel classes are unequally represented by AIS data. Cargo, tanker, tug, and passenger vessels are nearly 100 % detected using AIS data collected by receivers in situ (Table 1), resulting in a high degree of certainty when using AIS to indicate threat levels associated with these vessel classes. There was a wide range of uncertainty for the remaining classes that ranged from 34 to 91 % non-AIS traffic in summer and 8–96 % in the winter, with non-AIS traffic dominating recreational vessels (Sailboat and Motorcraft), as well as some of the smaller commercial vessel classes (Ecotourism and Fishing).

Based on NASP data, the highest uncertainty with AIS based threat estimates is concentrated mid Strait of Georgia (Fig. 4 coastal Vancouver Island between Nanaimo and Courtenay), southern Gulf Islands, and the north shore of Juan de Fuca where recreational traffic would be highest. This pattern is consistent between seasons, though the clusters are more tightly associated with important marinas during the winter found in Sooke harbour (Juan De Fuca), on or close to the Southern Gulf Islands, and mid Strait of Georgia. As well, non-AIS traffic tends to occur closer to shore than AIS traffic, and this association is much stronger during the winter than during the summer (Figs. 4 & 5). The close association of non-AIS traffic with marinas and shorelines during the winter probably reflects avoidance of bad winter weather. During the long stretches of favorable weather during the summer, non-AIS vessels are more likely to travel farther from marinas and shorelines. Seasonally our NASP data based GAMs predicted that 50 % of grid cells contained 61 % or higher non-AIS traffic during the winter, and 72 % non-AIS traffic or higher during the summer (Fig. B.1).

At this point, it is important to note that effort was not heterogeneous for either Photobot or NASP data collections. There was a possibility that we missed vessels in our Photobot imagery. In particular smaller non-AIS vessels tended to travel faster and closer to shore, where the FoV is narrower. However, our wake analyses indicate that our rates of missed detections were quite low (2.7 % or less). As well, the NASP effort was low or non-existent over some areas proximate to high densities of marinas, such as south and west of Vancouver or northern Haro Strait (see Fig. 4 - Serra-Sogas et al., 2021). NASP provided imagery and AIS data that were collected opportunistically, and flight paths reflected operational requirements unrelated to our pilot study (see Serra Sogas et al., 2021). Including data collected from these areas with high densities of marinas, likely would have emphasized these areas as relatively high proportion of non-AIS, and de-emphasized other areas we have currently identified in this study.

Furthermore, our NASP data-based GAMs accounted for only 20–37 % of the observed variability in vessel detections for non-AIS and AIS tracked vessels during the winter and summer (Table 3: Deviance Explained). We expect our GAM performances would improve with sufficient data to model vessel classes separately, which in turn would allow us to statistically eliminate unassociated predictor variables and increase the precision of our models. These improvements in GAM performance would have likely resulted in FoV located GAM nodes predicting a proportion of non-AIS traffic closer to what was estimated based on data collected by the Photobot. However, we emphasize that the GAMs were predicting non-AIS proportions over the entirety of the Salish Sea and their precision would be limited at smaller scales (such as the FoV). Alternative modeling approaches such as those based on machine learning algorithms may work better for predicting non-AIS traffic at both larger and smaller scales. As well, we expect that there are important drivers for some of the vessel classes that we did not include in our models such as proximity to urban centres. Nevertheless, since we categorized our GAM results into quantiles (reduced precision), our GAMs help improve our understanding of the relative spatial distribution of AIS and non-AIS traffic, and our maps with proportional categories of non-AIS provide solid information for interpreting how well AIS represents traffic seen in various sub-regions of the Salish Sea.

Both photobot and NASP rely on optical sensors or cameras that can be hampered by visibility, and hence our vessel data collection periods were constrained to conditions favoring small vessel traffic (i.e., daytime and calm conditions). Radar-based systems would be better for quantifying vessel traffic in absolute terms. However, because AIS does not perfectly capture marine traffic even for vessels required to carry AIS (for example see (Zhang et al., 2019, Liang et al., 2021), our optical techniques have some advantages over radar based systems in that at least some of the AIS information can be verified. In particular, vessel traffic can be categorized more precisely by vessel type for both AIS and non-AIS traffic using optical imagery. Nevertheless, some of the AIS-based error in our study could not be resolved with the optical imagery. This source of error occurred primarily during the winter when some vessels identified in the imagery as legally obligated to carry AIS were apparently not broadcasting AIS (Table 1). As well, there was a small proportion of vessels (3 %, Table 1) that could not be identified as requiring AIS or not. Comprehensive techniques such as the Multi-View Feature Fusion Network (MVFFNet; Zhang et al., 2019) should help resolve these outstanding errors introduced by AIS, and we propose that our novel vessel traffic data collection techniques based on optical imagery may in turn, help learning based systems such MVFFNet improve their performances.

4.1. Uncertainty assessing marine vessel associated threats based on AIS

We have introduced novel data collection and analytical techniques for temporally and spatially estimating the first uncertainty described in the introduction for using AIS as a proxy for vessel associated threats; the proportion of vessels not captured by AIS. In the following section we discuss this uncertainty in terms of how it relates to threats often indicated using AIS.

Based on our results, AIS can serve reliably as a proxy for threats from larger vessel traffic such as ship strike (risk from smaller vessels notwithstanding) in the Salish Sea. AIS data have been used in the Canadian Pacific Region as an index of risk exposure to ship-strikes for large whale species in regions dominated by larger vessel traffic (i.e., Cargo, Tanker, and large Passenger vessels such as cruise ships) (Nichol et al., 2017), which are vessels classes that we have shown are well represented by AIS in our study region. AIS data also allow for improved predictions of likely interactions between vessels and cetaceans with better estimates of potential impacts (Blondin et al., 2020). Speed of vessel is an important factor determining lethality of a ship-strike (Vanderlaan and Taggart, 2009), and care must be taken when integrating speed from AIS data (Simard et al., 2014; Nichol et al., 2017). Speed of vessel can be associated with the third uncertainty we described above; "accuracy of integrated information in AIS data".

Ship-strike is considered one of the most important challenges to conservation and recovery of large whales (DFO, 2017a) and clearly a concern SRKW as well (DFO, 2017b). Increasing observations of large whale species (primarily Humpback Whales – *Megaptera novaeangliae* as well as Gray Whales - *Eschrichtius robustus*) (Calambokidis et al., 2018) coupled with increasing large vessel traffic is resulting in an increased risk of ship-strike in our study region. A voluntary vessel slow down initiative stewarded by the Port of Vancouver Authority (ECHO – Enhanced Cetacean Habitat and Observation program: https://www.portvancouver.com/environmental-protection-at-the-port-of-vancouver/maintaining-healthy-ecosystems-throughout-our-jurisdiction/echo-program/) may be mitigating this risk, and AIS (coupled with acoustic data) has been used to test the effectiveness of these measures (Joy et al., 2019). AIS proved essential for testing the effectiveness of similar voluntary vessel slow-downs initiatives implemented in New Zealand (Ebdon et al., 2020) and the US (Redfern et al., 2019).

Although the risk of ship-strike from smaller vessels, which are very under-represented by AIS data, for these large cetacean species has never been assessed in our study area, a few studies have shown that even small vessels can cause fatal injury particularly when travelling at high speed (Kelley et al., 2020; Schoeman et al., 2020). Furthermore, small-vessel-strike risk is likely increasing with the increase in the abundance of small vessels, particularly recreational vessels, and cetaceans in near shore areas. As well, collisions with smaller vessels could play a much bigger role challenging the conservation or recovery of smaller organisms such as sea otters (Rudebusch et al., 2020), which are currently expanding their distribution in British Columbia (Nichol et al., 2020).

The effects of anthropogenic disturbance on aquatic birds in coastal and freshwater habitats in general is well documented (for a review see Carney and Sydeman, 1999, Steven et al., 2011, Fliessbach et al., 2019). A number of studies have focused on potential impacts from vessel traffic by measuring flight initiation distances (FID) as an indication of sensitivity to vessel presence or using spatial distributions to indicate whether or not marine bird species are avoiding regions with higher intensity of vessel traffic (Kaiser et al., 2006; Schwemmer et al., 2011). Some of these studies focused on interactions with smaller vessels that are much less likely to be tracked by AIS (Rodgers and Schwikert, 2002; McFadden et al., 2017) including canoes (Glover et al., 2015). Boat speed and type are important factors contributing to disturbance (Burger, 1998; Ronconi and St. Clair, 2002; Burger et al., 2019).

There has been a considerable amount of research documenting impacts from recreational boating on fish (Whitfield and Becker, 2014). Similarly, vessel presence has been shown to negatively impact marine mammals behavior. For example, boat presence has been shown to reduce foraging activity of SRKW in the Salish Sea (Lusseau et al., 2009) and bottlenose dolphins in Scotland (*Tursiops truncatus;* Pirotta et al., 2015), and elicit short-term responses in bottlenose dolphins (*Tursiops* sp.) in Australia (Bejder et al., 2006a) that can lead to longer term declines in abundance (Bejder et al., 2006b). Disturbance from vessel presence (including noise) has been recognized as one of the principal impediments to the recovery of the SRKW in Salish Sea (Ferrara et al., 2017), particularly when coupled with low prey abundance (Murray et al., 2021). However, much of this concern focuses on smaller and typically tourist vessels (for example see Seely et al., 2017), which are unevenly represented by AIS in our region at the time of this study. A recently conducted research project, Whale-watching AIS Vessel movement Evaluation (www.waveproject.ca), utilized AIS (installed voluntarily by participating organizations) for the classification of whale-watching vessel movement through agent-based modeling (Nesdoly, 2021). The results from this probabilistic state-based classification model provide information on when and where whale-watching vessels were likely observing wildlife. As a proxy for cetacean location, this information can inform marine policy decisions, and has the potential to be used as a regulation compliance tool.

There is a growing body of literature describing noise impacts on marine taxa and their ecosystem (Duarte et al., 2021), including important prey species of fish (Ivanova et al., 2020). Coastal waters are key habitats for many marine species, but these shallower areas are also prone to underestimations of vessel noise levels by those models that utilize AIS data because these are the areas where smaller boats (e.g. recreational vessels) that are less likely to broadcast AIS dominate (Pine et al., 2016; Hermannsen et al., 2019). The under-representation of vessel traffic in shallow ecosystems closer to shore is consistent with results from our study. Additionally, shallower waters effectively act as high pass filters (Forrest et al., 1993) and as such significantly increase the transmission loss of low-frequency sound, including those low-frequency components of vessel noise. Consequently, while low frequency noises (such as those produced by larger, distant vessels) may not pose a notable concern within coastal areas, mid-high frequency noise from closer sources, produced by smaller, non-AIS boats may represent a significant impact to local soundscapes (Hermannsen et al., 2019). This will result in negative impacts on species that rely on these areas to carry out vital life functions such as foraging, breeding and resting (Putland et al., 2018; Wisniewska et al., 2018; Sprogis et al., 2020).

Large scale catastrophic oil spill risk assessments and prevention policies rely on marine vessel traffic metrics and typically focus on larger vessels that either transport crude oils and refined products or store large quantities of oil products as fuels. Traffic metrics for these assessments have been effectively based on AIS for over a decade (Eide et al., 2007). However, it has been estimated that smaller chronic oil pollution represents a much larger contribution of oil input into the marine environment, and earlier assessments pegged recreational vessels and activities largely responsible for this input when 2-stroke outboard engines were prevalent (NRC, 2003). Recent estimates attribute less input to recreational vessel traffic per se, given the recent shift to predominately 4-cycle outboard motors, yet input from this category of vessel traffic remains considerable (GESAMP, 2007). Furthermore, in Canada's Pacific Region, approximately 90 % of oil pollution observations observed by Transport Canada's National Aerial Surveillance Program are associated with marinas (Serra-Sogas et al., 2014; Berry et al., 2018). Hence, AIS used as a proxy would represent only a fraction of actual oil input and this fraction would vary across regions and over time.

Larger vessels, which are well represented by AIS in our region, are important contributors to damage to marine habitats caused by anchoring (Deter et al., 2017; Watson et al., 2022) and are important vectors for introduced invasive species (Herborg et al., 2009). Both Deter et al. (2017) and Herborg et al. (2009), as well as Carreño and Lloret (2021), emphasize the important role that smaller vessels (i.e., recreational) may play in terms of anchor damage and introduced species, and recognize the lack of information available for this category of vessels. Recent work assessing and identifying recreational vessels as important vectors for invasive species relied on questionnaires to collect traffic information rather than utilizing AIS (Simard et al., 2017). Similarly, threats from fishing are not well represented by AIS in Canada, with recent studies relying on alternative sources of information on fishing activities (Fox et al., 2021; Morrow et al., 2022).

Here we provide some measure of uncertainty that can help correct impact assessments based on AIS, and improve interpretations of these assessments potentially improving science-based policy. Our results can inform further studies assessing these threats and identify where and when we need to improve our understanding of vessel traffic and associated stressors. Uncertainty still remains with respect to how much non-AIS vessel traffic contributes to the various threats we have discussed here, which requires further research. Also AIS-B continues to be implemented voluntarily, and may prove to be a useful data source for improving our understanding of recreational vessels and others currently not required to broadcast AIS, but uncertainty must be similarly characterized as AIS-B transducers broadcast with lower power and are unevenly implemented across vessel classes.

5. Conclusion

We believe that our methodology is transferable to other regions of the world and could provide useful data on vessel traffic that is otherwise unreflected in threat models based on AIS alone. The camera system has been developed to be very autonomous with solar power and connectivity via a cellular or satellite networks, and hence, can be installed anywhere there is a concentration of vessel traffic within optical range of a land feature. Ideally, these locations would also be subject to aerial surveillance programmes with crew that were willing to collect AIS and opportunistic video of vessel traffic (see Serra-Sogas et al., 2021). These surveillance programmes could be military based or pollution specific such as the aerial surveillance programmes in Europe in support of multinational agreements covering shared seas such as the North Sea (the Bonn Agreement: https://www.bonnagreement.org/activities/aerial-surveillance) and the Baltic Sea (HELCOM: https://helcom.fi/aerial-surveillance-and-regional-cooperation-remain-key-in-detecting-oil-spills-in-the-baltic-sea/).

Quantifying the proportion of vessels not captured by AIS is an important first step for improving assessments of threats associated with vessel traffic when basing these assessments on AIS. We believe this is the most comprehensive assessment of how well AIS represents vessel traffic in a region, with alternative novel methodology that are highly complementary. The GLMs based on data pulled from imagery collected using our land-based AIS-camera systems identifying strong temporal trends (weekends and seasons) in terms of AIS vs non-AIS traffic, and the GAMs based on NASP collected imagery provided spatially explicit estimates of AIS and non-AIS traffic.

However, recreational vessel traffic is considerably under-represented by AIS throughout the Salish Sea, and the proportion of non-AIS traffic is inconsistent among subregions and over time. For some marine traffic associated threats such as noise, smaller non-AIS vessel traffic can play a dominant role impacting marine ecosystems, and impact assessment based on AIS that do not account for this uncertainty can result in unacceptably low estimates.

CRediT authorship contribution statement

Patrick D. O'Hara: Conceptualization, Data curation, Formal analysis, Methodology, Supervision, Writing – original draft. **Norma Serra-Sogas:** Conceptualization, Methodology, Project administration, Writing – review & editing. **Lauren McWhinnie:** Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review & editing. **Kim Pearce:** Methodology, Data curation, Resources, Supervision, Validation, Writing – review & editing. **Nicole Le Baron:** Investigation, Data curation, Writing – review & editing. **Gregory O'Hagan:** Software, Writing – review & editing. **Andrea Nesdoly:** Conceptualization, Data curation, Methodology, Writing – review & editing. **Tunai Marques:** Software, Writing – review & editing. **Rosaline Canessa:** Funding acquisition, Project administration, Supervision.

Data availability

The authors do not have permission to share data.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendices A & B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2022.160987.

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