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Using a shore-based radar system to improve whale-vessel strike risk assessments at the entrance to San Francisco Bay

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Globally, vessel strike is a major cause of mortality for large whales, especially where whales are concentrated near busy seaports. Whale-vessel strike risk assessments depend upon a comprehensive understanding of local vessel activity. However, vessel traffic data used for these assessments are typically acquired from Automatic Identification System (AIS) broadcasts by ships, and many vessels do not transmit AIS. Here, we investigated the crucial data gap in these assessments by comparing patterns of AIS and non-AIS vessel activity. To accomplish this, we used an innovative shore-based technology package (ProtectedSeas Marine Monitor, or M2) that repurposed an off-the-shelf marine radar, AIS receiver, and camera to track all vessel traffic. The M2 system positioned at the mouth of the Golden Gate Strait, the entrance to a busy seaport region, San Francisco Bay, CA, USA, provided data for one year of analysis, and we found that 81% of all tracks analyzed were from vessels not transmitting AIS. Non-AIS vessel operation movements were generally more variable, and seasonal trends in non-AIS vessel traffic differed from AIS traffic. The highest speeds reached by non-AIS vessels in clear weather remained consistent even when operating in reduced visibility conditions, such as in dense fog. Our study demonstrated that exclusively using AIS data to model vessel-strike risk can lead to significant underestimations of vessel traffic activity. At the same time, the method used here points to a solution, as this accessible technology can be readily deployed onshore to provide more comprehensive vessel data to produce robust strike risk assessments in coastal or geographically constrained whale habitat.

KEYWORDS

automatic identification system (AIS), cetaceans, conservation, human impacts, large whales, marine radar, San Francisco Bay, vessel traffic

1 Introduction

Vessel strike is a leading cause of death for cetaceans wherever they overlap with intense human activity worldwide (Williams and O'Hara, 2010; Nisi et al., 2024). Vessel strikes can be challenging to quantify, and subsequently manage, since many factors cause them to go unreported and undetected (Rockwood et al., 2017). Only a small percentage of large whale carcasses are observed, as most carcasses sink or drift offshore and are unable to be recorded (Peltier et al., 2012; Reisdorf et al., 2012; Moore et al., 2020). Actual vessel strike deaths are likely much higher than stranding data suggest (Williams and O'Hara, 2010; Pace et al., 2021). Thus, successful mitigation efforts rely largely on estimates of risk through various modeling techniques that estimate the likelihood of vessel strike based on timing, location, and other variables (Williams and O'Hara, 2010; Nisi et al., 2024; Redfern et al., 2024; Blondin et al., 2025).

Methods for assessing whale-vessel strike risk require accurate data on whale distribution and vessel traffic patterns. For the latter, conventional strategies rely on the Automatic Identification System (AIS) to collect vessel traffic data (e.g., Redfern et al., 2013; Blondin et al., 2020; Smith et al., 2020; Nisi et al., 2024). AIS is an onboard broadcasting system created for navigational safety that sends data such as vessel information, speed, heading, and position to other vessels and to shore (International Maritime Organization, 2015). Globally, the International Maritime Organization requires that AIS be broadcast by all large commercial ships and passenger vessels with more than twelve passengers onboard (IMO Publishing, 2020), and individual countries may also adopt additional requirements. In U.S. waters, commercial vessels greater than 19.8 m (65 ft), towing vessels over 7.9 m (26 ft), and any vessel certified to carry over 150 passengers must transmit AIS (Federal Register, 2003). These data are openly available and have been utilized in a variety of environmental applications, including informing vessel strike risk assessments for whales (Robards et al., 2016). However, AIS was not designed with these applications in mind, thus limiting its capabilities. Vessels outside of these requirements may choose to transmit AIS, but because only a subset of vessels are required to do so, AIS does not provide a comprehensive census of actual vessel traffic, particularly for smaller vessels (Hague et al., 2025). Crucially, even small vessels that fall outside of the scope of mandated AIS transmission are capable of inflicting lethal amounts of force and have been documented to lethally strike whales (Kelley et al., 2021; Moore, 2022). Small vessels can also cause sublethal injuries which may result in reduced fitness (Van Waerebeek et al., 2007). While these vessels may have a lower likelihood of mortality in the case of a whale-vessel collision when compared to larger ships, they are more pervasive, have no restrictions in their areas of operation, and often lack targeted management efforts (Lane et al. in revision). The lack of inclusion of these types of vessels in strike risk assessments is a concern (Kelley et al., 2021; Mayaud et al., 2024).

One solution to comprehensively track vessel traffic is the use of marine radar, a navigation tool widely used by mariners to independently determine the location and activity of other vessels on the water regardless of their participation in AIS. Radar tracking systems produce high resolution data on vessel movements to

support collision avoidance (Bole et al., 2014), which also makes radar a useful tool for investigating these movements in relation to vessel strike risk for large whales (Cope et al., 2020; King et al., 2025). Shore-based radar systems have been used for monitoring non-AIS mandated and small-scale vessels in marine protected areas (MPAs) (e.g., Kemsley and Pukini, 2021; Cope et al., 2022), a context in which there is minimal use of AIS. For example, these radar configurations have been used to study vessel traffic across MPAs in southern California, USA and at Turneffe Atoll, Belize, and found that only 5% of vessels transmitted AIS (Cope et al., 2023). There are other methods to track non-AIS vessels, such as satellite-borne radar or optical imagery (e.g., Welch et al., 2022; Seguin et al., 2025). However, satellite systems typically capture single images of an area at each revisit which severely limits fine-scale analysis of vessel movements, although some work has been done to correlate satellite images of vessel wakes with vessel speeds (Kang and Kim, 2019; Wu et al., 2023).

We selected a busy seaport region, San Francisco Bay (SF Bay or the Bay), California, USA, to assess vessel traffic patterns using shore-based marine radar. This urban estuary is one of many worldwide where cetacean habitat and intense human activities overlap. SF Bay is the sole means of access for oil tankers, cargo ships, and other ocean-going vessels to reach six major and numerous other smaller seaports. SF Bay is also regularly trafficked by an array of other vessel types including commuter ferries, commercial fishing vessels, tourism vessels, and private recreational watercraft (Cope et al., 2020). Importantly, the Bay provides valuable habitat for many marine mammal species, including two particularly vulnerable large whales: gray whales (*Eschrichtius robustus*) and humpback whales (*Megaptera novaeangliae*). The co-occurrence of these species and vessels in and at the entrance to SF Bay poses a risk of collisions (Williams and O'Hara, 2010; Lane et al., in revision).

Humpback and gray whales have been observed seasonally every year at the entrance to and inside SF Bay since 2016 and 2018, respectively (Markowitz et al., 2024; Slaathaug et al., 2026). Humpback whales using the Bay as a feeding ground (as observed by Markowitz et al., 2024) are listed as endangered or threatened under the U.S. Endangered Species Act, depending on their breeding destination (National Oceanic and Atmospheric Administration, 2026). Prior to 2016, Rockwood et al. (2017) estimated that the number of vessel strikes of humpback whales off the west coast of the United States was at least double the Potential Biological Removal allowed by the Marine Mammal Protection Act. The same assessment determined that San Francisco was one of two locations along the west coast where mortality was highest. A more recent assessment identified SF Bay itself as high-risk for vessel strike for humpback whales (Lane et al. in revision).

Gray whales entering SF Bay are not listed as endangered or threatened with their population currently estimated to be 17,750 (Lang et al., 2026), but during and subsequent to the recent 2019–2023 Unusual Mortality Event (UME), over half their population was lost, declining from 27,430 to 12,950 (Eguchi et al., 2025). Though the population has grown since the UME, in SF Bay, gray whales seem to be especially susceptible to vessel strike. Slaathaug et al. (2026) analyzed trends in gray whale mortality within and near

SF Bay, and found that 30 of 70 carcasses had indications of blunt or sharp force trauma indicating pre-mortem vessel strike. In the 11 cases where cause of death was able to be determined, vessel strike was the primary cause of death for nine of these individuals.

For this research, we utilized a mobile radar system, the ProtectedSeas Marine Monitor (M2), positioned at the entrance of SF Bay to 1) analyze the composition of AIS and non-AIS vessel traffic in the area, and 2) identify patterns of vessel activity, including seasonality, speed, and other movements. Understanding the true extent of vessel traffic in the area can inform more comprehensive and accurate vessel strike risk assessments, and thus support strategic and effective management actions to protect whales in urbanized waterways.

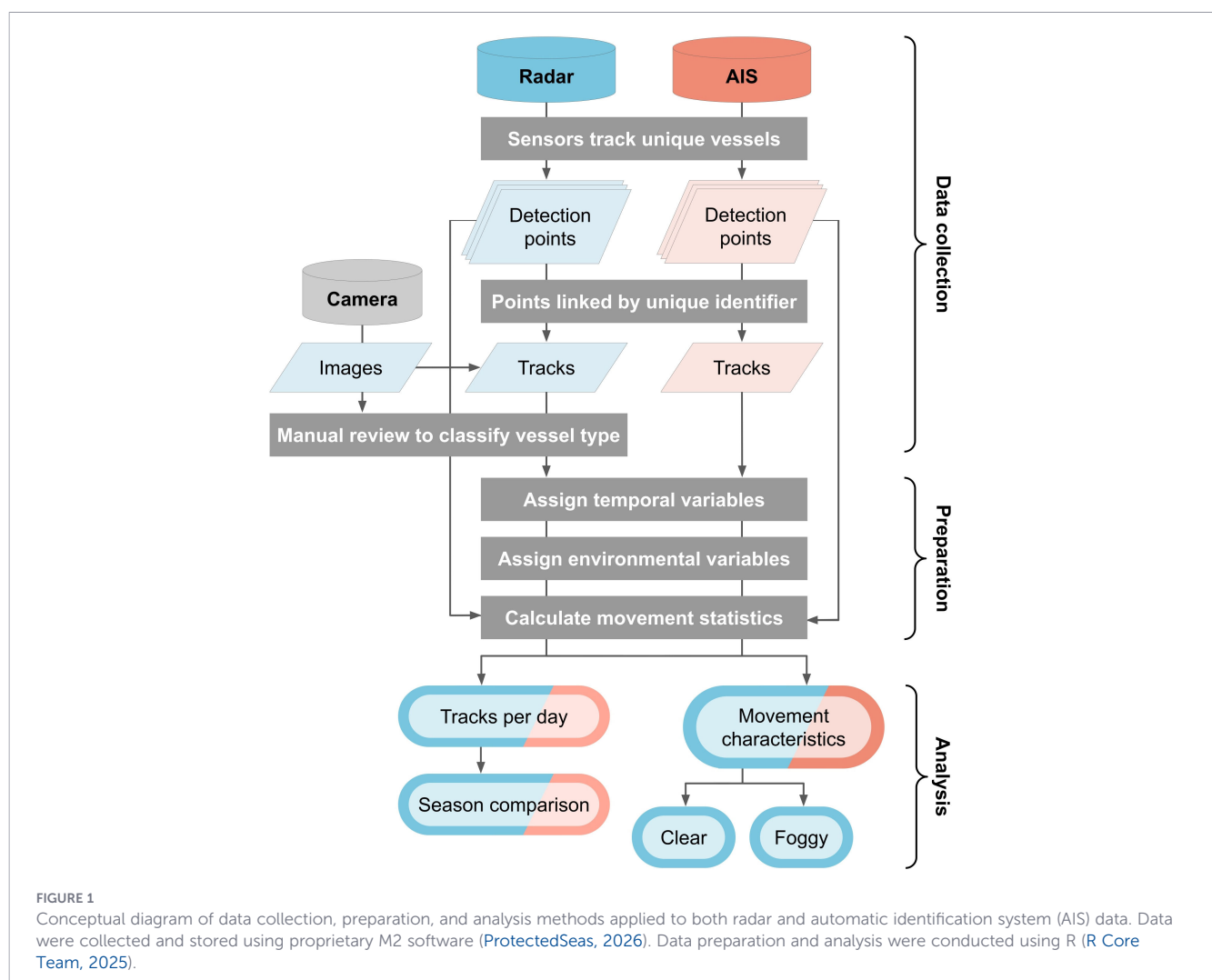
2 Methods

An overview of the data collection, preparation, and analysis methods is shown in Figure 1. The M2 system captured and integrated data from a radar system, camera, and AIS. We manually reviewed the data collected by the radar to classify vessel type for non-AIS vessels. Then we assigned temporal and environmental

variables relevant in the SF Bay Area and calculated vessel movement characteristics that could be relevant to strike risk. Finally, we analyzed how these variables and characteristics differed across AIS and non-AIS data.

2.1 Shore-based radar system

The M2 system deployed for this research is a shore-based technology package that autonomously detects, tracks, and collects data on nearshore vessels (Figure 2). The primary sensor is commercial off-the-shelf X-band marine radar, which generates electromagnetic pulses and uses pulse returns from solid objects to identify the geolocation and speed of targets on the water (Bole et al., 2014). Radar systems are widely used by boaters to safely navigate around obstructions and other vessels independent of their radar usage or participation in other tracking systems. The use of consumer grade radar made the system more cost-effective than military-grade or larger scale radar systems. Since radar depends on pulse transmission and reception, its tracking range is limited by obstructions between the radar antenna and the water's surface (i.e., line-of-sight), such as coastal topography and human-made structures, but is not limited by daylight or low-visibility conditions. The Furuno radar antenna used had a tracking range of 16 nautical



miles, although the effective range for this study was limited by elevated coastal bluffs. Within this range (2–3 nautical miles), the radar system tracked vessels of all sizes and provided tracking updates every 2–6 s.

In addition to radar tracking, the M2 system also collected AIS data. Participating vessels broadcasted their geolocation, speed, other dynamic data, and identification information across very-high-frequency (VHF) channels, and the M2 system collected the data using an AIS antenna and receiver. The range of AIS data reception is roughly limited to line-of-sight (Robards et al., 2016), although the effective range extended farther outside of the Strait and within the Bay than the radar range. The time interval between AIS broadcasts depends on vessel speed but ranges from 2–10 s for transiting vessels (International Maritime Organization, 2015).

A computer onboard the M2 system captured and stored data provided by both the radar system and AIS within an SQL database. M2 software used the vessel geolocations and other tracking information to dynamically direct a pan-tilt-zoom camera to autonomously capture images of unique vessels roughly every 2 min. Software was designed to zoom the camera according to the distance between the vessel and the camera, facilitating effective image capture across the full radar range. Unlike AIS, radar tracking does not provide the identity of vessels, so we manually reviewed vessel images to identify vessel type. All data and images were streamed to a cloud-based data management system and were accessible using an interactive browser-based user interface where we were able to review data selected for this study. The M2 system used was mobile, compact (4 m² footprint), powered by solar panels, and remotely operated. For a full description of radar tracking, AIS, and camera integration within the M2 platform, see Cope et al., 2023.

2.2 Data collection

Vessel data were collected from September 2021 through August 2022 using the M2 system positioned at Point Bonita, Marin County, California overlooking the Golden Gate Strait, the westernmost part of SF Bay (Figure 2). The M2 system was initially deployed to this location in 2016 and continues to monitor the area. We selected the specific year of data collection based on the timing of recently completed M2 system updates that improved camera functioning. We defined the study area as the effective range of the radar system, which was more restricted than the range of AIS data received. We extracted data collected during the selected time period from the M2 SQL database, and all analysis was conducted in R (R Core Team, 2025). Basic R computation and statistical functionalities were used unless otherwise noted.

2.2.1 Data formats

Geospatial data were provided by the M2 system in two formats: individual detection points and track lines. Detection points were captured from the M2 using both the AIS and radar systems and provided dynamic information, including a vessel's instantaneous speed and course over ground, date and time, and geolocation. Detection points from both the radar system and AIS provided a unique identification number that identified distinct targets from each other. For each unique target from both sources, M2 software generated track polylines (hereafter referred to as tracks) that chronologically connected detection points and identified summary information for the track record, including the start and end date and time. For vessels that transmitted AIS, AIS data also included their Maritime Mobile Service Identity (MMSI) and an AIS vessel type category (International Maritime Organization, 2015).

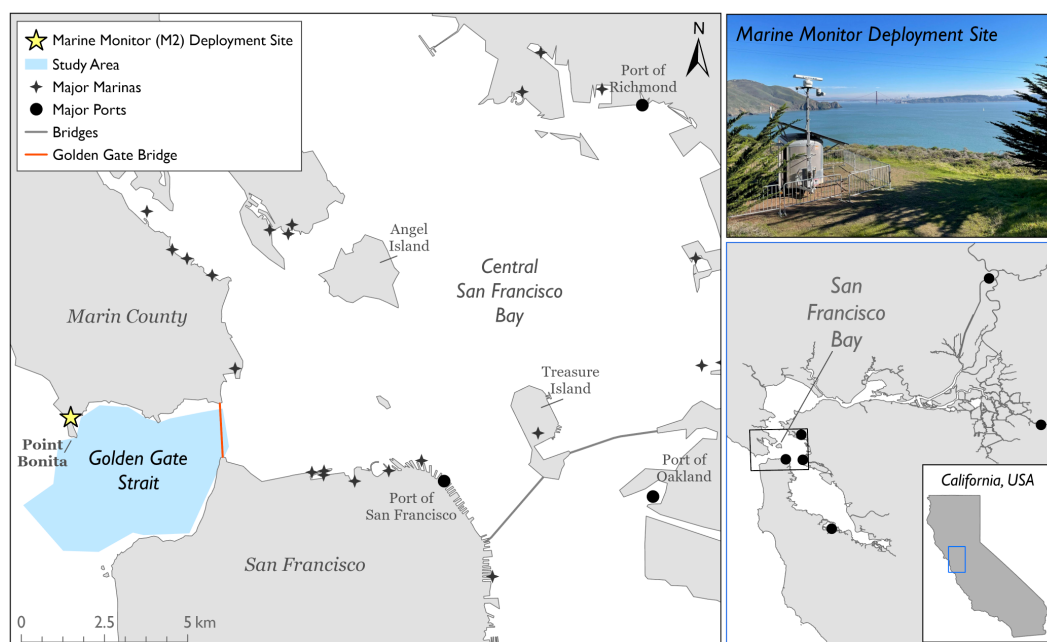


FIGURE 2

Study area, defined by the effective radar range, in relation to highly trafficked central San Francisco Bay. Image at upper right shows the M2 system deployed at Point Bonita.

The radar system tracked all vessels regardless of whether or not they transmitted AIS. Therefore, there were both radar and AIS records for vessels that transmitted AIS. M2 software linked these records using coincident radar and AIS detection points. As recommended by [Kazimierski and Stateczny \(2015\)](#), radar and AIS detections that occurred in similar space and time with similar movements were associated if they met all of the following criteria:

- detections were within 100 m in geolocation,
- detections occurred within 15 s,
- detections had a difference in speed less than 1.5 knots (0.77 m/s), and
- detections had a difference in course less than 10 degrees.

The M2 system recognized radar and AIS tracks as associated when there were more than 20 coincident detection point pairs that met the association criteria. Since our intent was to analyze the composition of AIS versus non-AIS, radar track records associated with AIS tracks were excluded from analysis. Therefore, tracks detected by radar hereafter refers to vessels tracked exclusively by radar meaning they were non-AIS tracks. Occasional errors in either radar or AIS tracking (discussed in subsequent sections) could have inhibited successful track association, so we manually reviewed all non-associated radar tracks and removed any that were found to duplicate an AIS track.

2.2.2 Data selection

Given the substantial time required to review every record from a full year, we selected to review a stratified random sample of four days per month. A random number was assigned to each date in a month according to the number of days in the month. The dates were then ranked based on their assigned number and classification was done in numerical order of the first four ranked days in each month. For a day when the M2 system underwent maintenance, the next ranked day for the given month was used in its place.

2.2.3 Vessel track classification

Unlike AIS, commercial marine radar systems do not provide identifying information on vessels. Therefore, track records and images of non-AIS transmitting vessels were manually reviewed and classified by vessel type. Images of AIS transmitting vessels were not reviewed since vessel type is reported by AIS. Using track images, we classified radar tracks as one of the following non-AIS transmitting vessel classes:

- recreational (small or large)
- sailing vessel
- commercial (small or large)
- commercial fishing
- other (small or large)
- unknown (small or large)

We used these classes to capture as much detail as possible from track images, and classes were subsequently grouped into categories for analysis. We defined the classification schema as follows: vessels

were classified as small when they had a single level and as large when they had multiple stories, see [Supplementary Figure 1](#) for examples. Vessels were classified as other when details of the vessel were distinguishable, but the vessel type was not appropriate under any other class (e.g., law enforcement and military). Vessels were classified as unknown when details of the vessel were indistinguishable, typically due to partial obstructions or low image quality (e.g., blurry). Other and unknown vessels were grouped together for subsequent analysis. Other issues arose in image review, including occasional erroneous radar tracking caused by sea clutter and weather events, a common issue with data collected via marine radar ([Bole et al., 2014](#)). All tracks were given a rating based on track and image quality, and we used additional classifications to note issues so they could be appropriately handled in analysis. Vessel class examples and the track classification rubric are available in [Supplementary Materials \(Supplementary Figure 1; Supplementary Table 1\)](#).

2.3 Data preparation

The accuracy of AIS data depends on vessel operator input and standard functioning of onboard equipment, and errors have been well documented (summarized by [Emmens et al., 2021](#)). Therefore, we used the following steps to prepare the data for analysis. We removed AIS tracks with maximum speeds greater than 50 knots ($n = 3$; 0.3% of AIS tracks) as this uncommon high speed could indicate equipment error. We also removed any AIS track with an invalid MMSI or AIS vessel type category ($n = 13$; 1.4% of AIS tracks) as this could indicate operator error installing the device. Removal of this small number of tracks should not significantly impact overall results. To account for AIS transmission disruptions and avoid double counting these vessels, we removed any AIS tracks with a MMSI that had also been detected within the previous three hours (e.g., if a vessel left the study area but returned within three hours, it was counted as a single transit), similar to the time-gap thresholding strategy described by [Sinni and Kyriazanos \(2025\)](#). The three-hour threshold was based on the approximate revisit times of tug and tow vessels assisting ships through the Strait, which we identified as unique transits. Lastly, since the range of AIS data was spatially larger than that of the radar-limited study area, we clipped AIS detection points to the study area and identified the new track start and end date and time.

2.3.1 Temporal variables

We assigned a season attribute to each track based on its start date (January, February, March = winter; April, May, June = spring; July, August, September = summer; October, November, December = autumn) similar to previous studies in the region ([Jensen et al., 2015](#); [Cope et al., 2020](#); Lane et al., in revision). We assigned a day/night attribute to each track based on its start time and sunrise/sunset times at the location using the StreamMetabolism R package ([Sefick, 2023](#)). Since images of non-AIS vessels captured at night could not be classified, we only retained tracks that started during the day for analysis.

2.3.2 Environmental variables

Given that the SF Bay area is subject to dense seasonal fog ([Oliphant et al., 2021](#)), several of the study days consisted of a large

quantity of tracks with an image quality rating of full obstruction. Fog does not limit radar tracking, so we sought to retain tracks from these days for analysis when possible. We identified analysis days when there were more than 30% of tracks with the image quality rating of full obstruction and considered these days as having heavy fog. After a detailed review of tracks from these days ($n = 6$ days), we were unable to successfully discriminate between AIS and non-AIS transmitting vessels on one of these days (24 October 2021) so they were removed from analysis.

2.3.3 Movement characteristics

We calculated additional track statistics to provide more insight on the movement characteristics of vessels. First, we determined the duration of each track using the difference between the start and end times. We ignored any track with a duration less than one minute. Then, we calculated movement statistics for each unique track using the speed and course over ground reported at detection points. There is a well-established relationship between vessel speed and the lethality of collisions (Vanderlaan and Taggart, 2007; Kelley et al., 2021), so we identified the maximum speed reported for each track. Along with maximum speed, we also identified maximum acceleration and deceleration by calculating the change in speed per second between each consecutive detection. We also captured vessel course deviation, i.e., the level of variation in a vessel's direction of travel, by calculating the standard deviation of the course across its detection points (King et al., 2025) using the circular R package (Lund et al., 2022). Acceleration, deceleration, and course variation are critical estimates of how predictable a vessel's movements were. Strike risk assessments and vessel encounter models do not typically consider these additional variables (e.g., Rockwood et al., 2017), likely because larger vessels, such as commercial ships, have limited maneuverability compared to smaller vessels (King et al., 2025). However, unpredictable movements have been associated with disruption of behaviors, such as foraging (Nowacek et al., 2001, 2007). These variables can also demonstrate the vessel's capacity to maneuver effectively to avoid collision, further discussed in Section 4. Radar tracking accuracy can be reduced during initial target acquisition (Bole et al., 2014), so we ignored the first minute of detection points when calculating movement statistics of non-AIS tracks.

2.4 Data analysis

2.4.1 AIS vs. non-AIS traffic

Tracks were considered unique events, and the analysis was conducted primarily by counting tracks per day, with the exception of comparing the overall number of tracks by source (AIS versus non-AIS) and summarizing movement characteristics per track. Tracks represented voyages by the classified vessel type through the study area. Most of the classes that we used to categorize non-AIS transmitting vessels were more descriptive than AIS vessel types defined by the International Telecommunication Union (2014). Therefore, in order to compare AIS and non-AIS data, we grouped both AIS vessel types and non-AIS mandated vessel types into overall categories according to Table 1. We counted the total

number of AIS and non-AIS tracks within each overall category for each day of analysis and across the entire study period. We also calculated the percentage of non-AIS tracks in relation to the total number of tracks.

2.4.2 Non-AIS traffic

To further summarize non-AIS traffic while retaining more descriptive classes, we grouped similar non-AIS classes according to Table 2. Sailing vessels remained their own category since they are not typically powered by motor and operate differently than motorized vessels. We divided all motorized vessels into large or small motorized classes and also included a separate recreational class that captured only motorized vessels that could clearly be distinguished as such (e.g., speed boats, cruisers, center console boats, yachts, skiffs, dinghies). Since recreational vessels are not required to use AIS and are less regulated, we sought to identify and analyze these vessels as a group when possible. Note that motorized vessels could be grouped in the large or small motorized classes and the motorized recreational class. Class categories were treated as unique in analysis. We counted the total number of non-AIS tracks within each grouped class for each day of analysis.

2.4.3 Seasonal presence

We compared daily activity across seasons, including the daily AIS and non-AIS track counts and daily percentages of non-AIS tracks. Daily AIS track counts were normally distributed and had homogeneity of variance within each season, so we performed parametric ANOVA and *post hoc* comparisons across pairs of consecutive seasons. Daily non-AIS tracks and percentages were not normally distributed within all seasons but had few outliers. Therefore, we applied the non-parametric Kruskal-Wallis test. Since there were some seasons with a normal distribution, which makes the Kruskal-Wallis test less powerful, we defined a conservative

TABLE 1 Vessel classes used for AIS vs. non-AIS analysis. AIS vessel types defined by International Telecommunication Union (2014).

Overall category	AIS vessel types	Non-AIS classes
Cargo	AIS vessel types 70-79	None observed
Tanker	AIS vessel types 80-89	None observed
Tug tow	AIS vessel types 21, 22, 31, 32, & 52	None observed
Commercial fishing	AIS vessel type 30	Commercial fishing
Pleasure craft	AIS vessel types 36 & 37	Sailing or recreational
Other	All other AIS vessel types	Commercial, other, or unknown
Unidentified	None observed	Tracks with image quality of partial obstruction or full obstruction and no vessel class identified

significance threshold of $p < 0.01$ to avoid misclassifying differences in non-AIS activity across seasons.

We performed a seasonal analysis for each track category (Tables 1 and 2) independently using the daily track counts of AIS and non-AIS vessels. When daily track counts of a class were normally distributed with homogeneity of variance in each season, we performed a parametric ANOVA test and *post hoc* comparisons across pairs of consecutive seasons with a significance threshold of $p < 0.05$. The large motorized and sailing vessel categories met these requirements after performing a square-root transformation and were analyzed similarly. For categories that could not be transformed to achieve a normal distribution but had minimal outliers, we applied a non-parametric Kruskal-Wallis test and *post hoc* comparisons of daily track counts across consecutive seasons. The daily track counts of these categories were normally distributed in some seasons, so we defined a conservative significance threshold of $p < 0.01$.

2.4.4 Movement characteristics

We observed five movement characteristics of both AIS and non-AIS vessel track records: 1) duration of time spent within the study area; 2) maximum speed traveled; 3) maximum acceleration; 4) maximum deceleration; and 5) course deviation. Tracks with any erroneous portions caused by sea clutter and weather events were not included in this analysis. These tracks were identified by irregular and unrealistic track shape and classified during manual review (see [Supplementary Table 1](#) for classification rubric). Since higher speeds pose greater risk of vessel strike ([Vanderlaan and Taggart, 2007](#)), the speeds at which movements occur could indicate different movement patterns that are potentially relevant to risk assessments. Therefore, we also compared maximum speeds with duration, acceleration and deceleration, and course deviation. Given the occasional presence of fog in the study area, we also compared these movement characteristics across foggy and clear conditions. Since fog presence varies throughout the day ([Oliphant et al., 2021](#)), we compared distinct tracks that occurred during foggy versus clear conditions. Non-AIS tracks with images fully obstructed by fog were considered to occur during foggy conditions, and non-AIS tracks with a classified vessel type from image tagging were considered to occur during clear conditions. Since we did not

review images of AIS vessels, we excluded them from this portion of the analysis.

We compared the histograms of track counts by each movement characteristic during clear conditions with those of track counts during foggy conditions. To evaluate differences in each movement characteristic across the two conditions, we applied the non-parametric exact two-sample quantile test ([Brown and Mood, 1951](#); [Johnson et al., 1987](#)) using the EnvStats R package ([Millard, 2013](#)) where both the median ($q = 0.5$) and 90th percentile ($q = 0.9$) values under each condition were compared. We selected the median to evaluate a general shift in behavior from clear to foggy conditions and the 90th percentile to evaluate the behavior change at the most extreme values. We used a significance threshold of $p < 0.05$ to identify significant differences.

3 Results

3.1 AIS vs. non-AIS traffic

Across 47 days of analysis, we manually classified a total of 3,297 non-AIS vessel track records. During manual review, we identified invalid tracks ($n = 127$) and non-AIS tracks that duplicated AIS tracks not initially captured by the association criteria ($n = 140$). After removing these 267 tracks, 3,030 non-AIS tracks remained for analysis. These non-AIS tracks made up 81% of all daytime vessel tracks ($n = 3,749$) in the Golden Gate Strait during the study period ([Figure 3](#)). We were able to classify 2,313 of these tracks with a non-AIS category. No commercial fishing vessels broadcasted AIS, as they were exclusively tracked by radar, and most pleasure craft (98%) and other vessel types (82%) were non-AIS vessels. In contrast, all cargo, tanker, and tug and tow vessels used AIS.

3.2 Non-AIS traffic

Overall, the majority of daytime non-AIS vessel tracks were recreational (i.e., associated with the AIS pleasure craft class; [Figure 4](#)). Small motorized vessels were the most common non-AIS category during the study period ($n = 1,428$ tracks). Of these tracks, 44% were recreational. A much smaller share of large motorized tracks were recreational (16%).

3.3 Seasonal presence

Daily track counts of AIS vessels remained more consistent across seasons than the track counts of non-AIS vessels ([Figure 5](#)). There was a significant decrease in daily AIS tracks from autumn to winter ($p < 0.05$), but the median daily count remained between 10 and 20 vessels in every season. There was a significant increase in daily non-AIS tracks from spring to summer ($p < 0.01$), and summer had the highest median and maximum daily count of all seasons ($n = 111$ and $n = 232$, respectively).

The daily percentage of non-AIS tracks was also significantly greater in summer compared to spring ($p < 0.01$) when there were roughly similar numbers of AIS and non-AIS tracks each day.

TABLE 2 Classes used for non-AIS-only analysis. Unidentified tracks were not included in this analysis.

Non-AIS category	Non-AIS classes
Commercial fishing	Tracks classified as commercial fishing
Large motorized	Tracks classified as large commercial, recreational, other, or unknown
Small motorized	Tracks classified as small commercial, recreational, other, or unknown
Motorized recreational	Tracks classified as small or large recreational
Sailing vessel	Tracks classified as sailing vessel

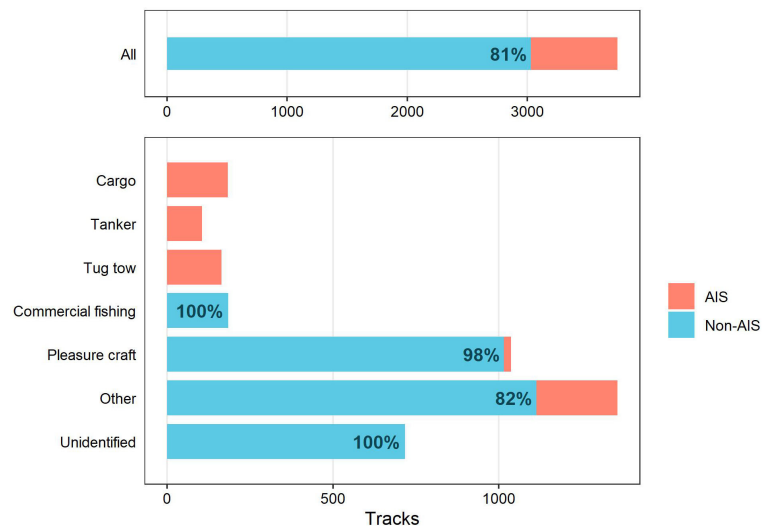


FIGURE 3

The total number of tracks by source. Different x-axis scales are used to show detail of track counts for the overall categories. Percent values indicate the percentage of non-AIS tracks.

During summer, non-AIS tracks made up 95% of all tracks on the day of peak non-AIS activity. The daily percentages of non-AIS tracks in autumn and winter were generally lower than in summer, however more than half of all vessel tracks were non-AIS on the majority of days in these seasons. The *p*-values for all seasonal comparisons are noted in Table 3.

AIS vessel classes demonstrated different seasonal patterns (Figure 6). Daily track counts of tanker ships and other AIS vessels significantly decreased from autumn to winter ($p < 0.01$). Daily track counts of tug and tow vessels were generally lower in winter compared to the other seasons, likely because they typically assist the larger vessels, but the difference was not significant. The maximum number of cargo ship tracks per day occurred in spring, while the few AIS broadcasting pleasure craft tracks peaked in summer and autumn.

Daily track counts of the non-AIS motorized classes, including commercial fishing, were generally higher in summer (Figure 6).

The class with the highest daily track count in summer was motorized recreational craft ($n = 85$), and differences in track counts across seasons were not significant. The daily track counts of both large and small motorized vessels were significantly higher in summer compared to spring and autumn, and the daily track count of commercial fishing vessels was significantly higher in summer compared to autumn. There were no significant differences in daily sailing vessel tracks across seasons.

3.4 Movement characteristics

Based solely on the average of all combined tracks, AIS vessels spent more time in the study area than non-AIS vessels, although this was a result of the anomalously long durations of tug and tow tracks (Figure 7). Tug and tow vessels spent 43 minutes in and moving through the study area on average, while all other AIS vessel categories spent an average of 16 minutes or less. Sailing vessels

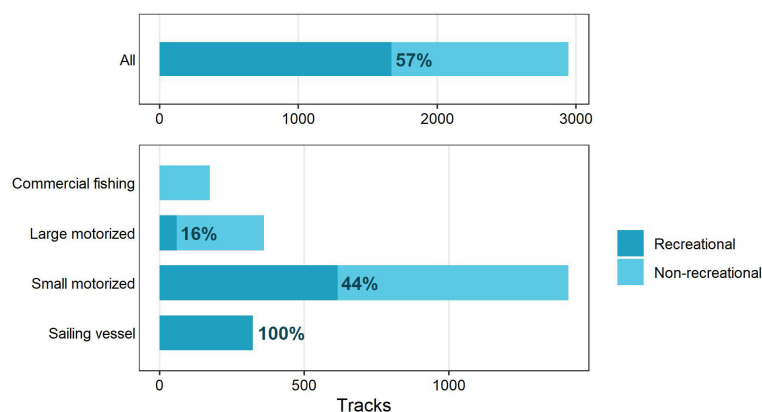


FIGURE 4

The total number of tracks in each non-AIS category. Different x-axis scales are used to show detail of track counts for the non-AIS categories. Non-AIS recreational vessel types, including those that coincide with the AIS pleasure craft class, are identified in dark blue. Percent values indicate the proportion of recreational vessel tracks.

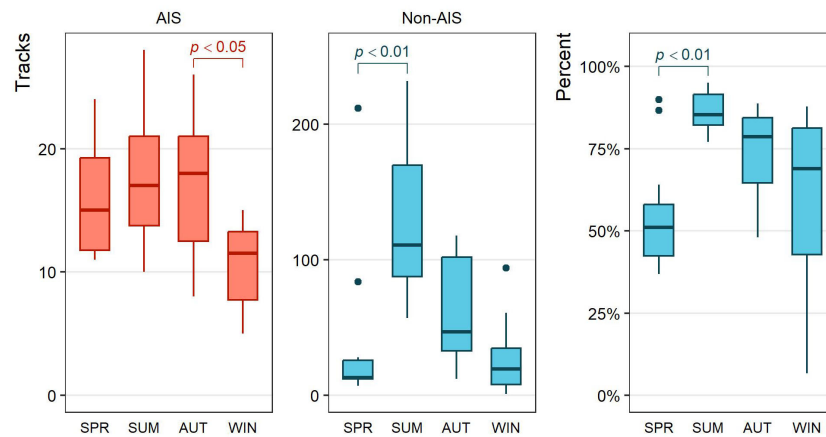


FIGURE 5

Count of daily AIS and non-AIS tracks and the daily percentage of non-AIS tracks in each season (spring (SPR): $n = 12$ days, summer (SUM): $n = 12$ days, autumn (AUT): $n = 11$ days, winter (WIN): $n = 12$ days). Consecutive seasons with a statistically significant difference are notated with brackets and the significance level.

spent 27 minutes on average, and all other non-AIS vessel categories also spent 16 minutes or less, although the standard deviation in these categories was generally greater than that of AIS vessel categories.

Non-AIS vessels reached higher maximum speeds on average than AIS vessels with small motorized and motorized recreational classes reaching 19.4 and 18.1 knots on average, respectively. Cargo ships and other AIS vessels had the highest maximum speeds of AIS vessels on average at 14.7 and 14.6 knots, respectively. Non-AIS vessels also reached higher maximum acceleration and deceleration rates on average than AIS vessels, although the standard deviation of tug and tow and other vessels was greater than that of other AIS vessel classes and showed a similar range of values to non-AIS vessel classes (Figure 7). Small motorized vessels had the highest maximum acceleration and deceleration rates of 0.45 and 0.42 knots/s on average, respectively.

Tug and tow vessels had the highest course deviation on average at 48.9 degrees. Non-AIS sailing vessels and AIS other vessels also had relatively high course deviation on average at 41.8 and 33.2 degrees, respectively. The course deviation of AIS pleasure craft and non-AIS motorized recreational vessels was similar, likely due to similar vessel types included in the classes. Results demonstrated expected patterns when comparing maximum speed with duration and course deviation: vessel classes with faster maximum speeds (e.g., small and large motorized) spent less time in the area and changed course less often. But these non-AIS vessel classes also had the highest rates of acceleration and deceleration.

When comparing movement characteristics of vessel tracks across clear and foggy conditions ($n = 991$ and $n = 346$, respectively), we found that maximum speed and acceleration and deceleration rates remained similar (Figure 8). The median values of maximum speed and deceleration were significantly lower when

TABLE 3 Significance (p -values) of the differences in seasonal activity of vessel classes. The p -values in bold identify those that met the significance threshold level.

Vessel class	Significance level	Spring vs. summer	Summer vs. autumn	Autumn vs. winter	Winter vs. spring
AIS	$p < 0.05$	0.77	0.97	0.02	0.06
Cargo	$p < 0.05$	0.25	0.67	0.89	0.11
Tanker	$p < 0.01$	1.00	1.00	<0.01	<0.01
Tug tow	$p < 0.05$	0.55	0.98	0.24	0.73
Pleasure craft	$p < 0.01$	1.00	1.00	0.81	1.00
Other	$p < 0.05$	0.07	0.99	<0.01	0.65
Non-AIS	$p < 0.01$	<0.01	0.06	0.06	1.00
Commercial fishing	$p < 0.01$	0.03	<0.01	1.00	1.00
Large motorized	$p < 0.05$	<0.001	<0.01	0.60	0.80
Small motorized	$p < 0.01$	<0.01	<0.01	0.23	1.00
Motorized recreational	$p < 0.01$	0.01	0.04	0.57	1.00
Sailing vessel	$p < 0.05$	0.75	0.91	0.99	1.00
Non-AIS percent	$p < 0.01$	<0.01	0.11	1.00	1.00

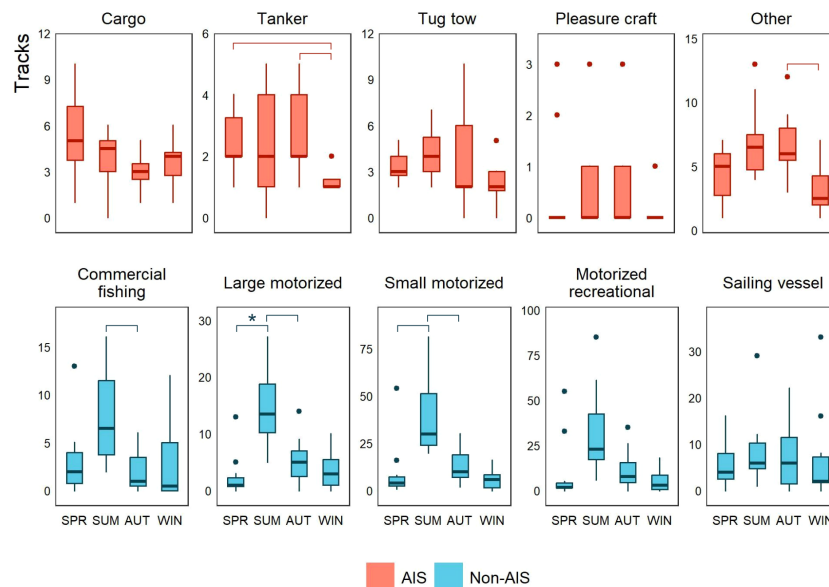


FIGURE 6

Count of daily AIS and non-AIS tracks within each overall class in each season (spring (SPR): $n = 12$ days, summer (SUM): $n = 12$ days, autumn (AUT): $n = 11$ days, winter (WIN): $n = 12$ days). Consecutive seasons with a statistically significant difference ($p < 0.01$) are notated with brackets. Bracket with asterisk indicates significance level of $p < 0.001$. Note different y-axis scales used.

it was foggy, but the difference in value was minimal (0.9 knots and 0.05 knots/s, respectively). Further, the 90th percentile values were not significantly different across conditions indicating that the most extreme speeds and changes in speed did not change in foggy conditions. The 90th percentile values of duration and course deviation were significantly lower when it was foggy.

4 Discussion

This study characterized vessel activity with respect to vessel strike risk, an opportune use of the M2 system. Our focus was due to the growing conservation concerns for humpback and gray whales that face an increased vessel strike risk in SF Bay (Lane et al. in revision; Slaathaug et al., 2026). However, the M2's ability to continuously and independently monitor vessel traffic has other applications valuable for marine mammal conservation science. Both small and large cetaceans have been documented to exhibit varying acoustic, behavioral, and physiological responses in the presence of vessel traffic. Though sublethal, these responses can drain energy reserves, interrupt feeding behavior, displace animals, and interfere with communication (Lusseau, 2005; Hatch et al., 2012; Blair et al., 2016; Marley et al., 2017; Sprong et al., 2020; Ferrari et al., 2026). The M2 system provides a means to collect comprehensive vessel data to evaluate varying vessel characteristics, including those analyzed here (e.g., acceleration and deceleration rates, course deviation, etc.), and subsequently investigate their impacts on small and large cetaceans.

Here, we demonstrate that high resolution vessel tracking by marine radar can be used to bridge the AIS vessel traffic data gap, which allows for a more comprehensive understanding of vessel

traffic in urbanized waterways that also serve as valuable habitat for large whales. The M2 system provided continuous data collection across 47 days of analysis, plus additional days that were not selected for manual review. During the study period, only 19% of vessel tracks detected at the entrance of SF Bay were transmitting AIS. This represents a greater disparity than that identified by an M2 system positioned farther east into SF Bay where 66.1% of vessel traffic was transmitting AIS (Cope et al., 2020). In that study, the M2 was stationed in an area of particularly high commercial ferry activity, which likely resulted in the higher number of AIS vessel tracks. Globally, scientists have analyzed the rate of AIS-transmission in vessel traffic through radar, visual observations from land and sea (including through theodolites), and acoustic detection. The percentage of AIS transmitting vessel traffic varied widely depending on location, ranging from up to 72% in the Boundary Pass, Canada/USA, 43% year-round in coastal Scotland, 32% in the San Juan Islands, USA, and 17% in Denmark (Barco et al., 2012; Hermannsen et al., 2019; Magnier and Gervaise, 2020; Lo et al., 2022; O'Hara et al., 2023; Hague et al., 2025). These comparisons reveal that the entrance of SF Bay has a low rate of transmission of AIS relative to other areas. It also highlights notable variation in coverage by area when it comes to risk assessments using AIS as a sole data source for vessel distribution. The proportion of vessels transmitting AIS in this study was low likely due to two factors. First, SF Bay lies within a metropolitan area where recreational boat use is common, comprising the majority of non-AIS transmitting vessel usage in this study. Second, we only analyzed daytime activity. Many smaller vessels are limited in their operational capabilities at night while large ships transit to port at all hours. The inclusion of vessel activity at night should produce an overall higher AIS transmission rate.

No commercial fishing vessels, 2% of pleasure craft, and only 18% of other vessels were transmitting AIS. There is an optional

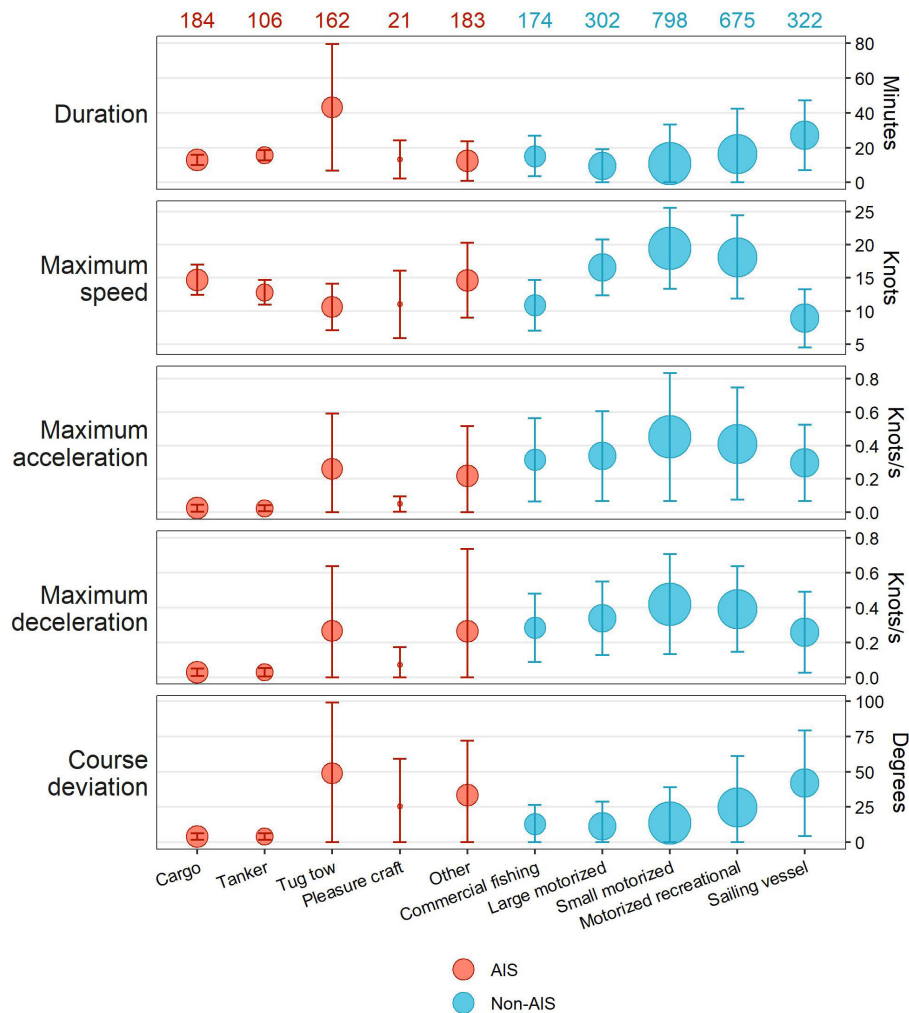


FIGURE 7

Average and standard deviation of movement characteristics of AIS and non-AIS vessel tracks. Values are available in [Supplementary Table 2](#). Point size indicates the relative count of tracks, with the number of tracks for each vessel denoted above the top panel.

version of AIS for smaller vessels not required to use it, called Class B, that boaters can choose to outfit their vessel with for enhanced navigational safety (Robards et al., 2016). However, the small percentage of vessels transmitting AIS in these other classes suggests that if a vessel in this region is not required by law to broadcast AIS, it likely will not. This is of note when it comes to accurate reporting of vessel strike risk because while large ships have been primarily considered to be the most lethal to whales (Laist et al., 2001; Garrison et al., 2025), vessels of any size are capable of inflicting lethal amounts of force (Kelley et al., 2021; Mayaud et al., 2024).

The majority of non-AIS transmitting vessels were recreational vessels, which do not fall under the current regulations for AIS. Yet in urban areas such as SF Bay, small recreational vessels are among the most numerous vessel types (Hatch et al., 2012; Hermannsen et al., 2019). Even with several large commercial ports located within SF Bay, our data indicated that recreational vessel traffic remains predominant. Aside from volume, recreational vessels may also pose higher risk due to their pilot's relative lack of experience and formal training compared to commercial vessels. Additionally, recreational vessels cover a wider portion of the Bay and other coastal waters compared to commercial vessels (Laist et al., 2001;

Cope et al., 2020; Rudebusch et al., 2020; Lane et al., in revision) and have been documented to approach cetaceans at closer distances (Nowacek et al., 2007). Example from SF Bay shown in [Supplementary Figure 2](#). This highlights the value of outreach strategies targeted specifically to recreational boaters.

Seasonal patterns showed that AIS vessels were less varied during daily track counts across seasons than non-AIS vessels. Capturing seasonal variations is especially important in risk assessments, as whale presence is often seasonal. Non-AIS vessel traffic, including that of commercial fishing and recreational vessels, was highest in summer compared to all other seasons, similar to other studies globally (Mazzotta et al., 2022; Baitalik and Bhattacharjee, 2023). Summer is when humpback whales most often enter SF Bay to feed (Markowitz et al., 2024). This heightened seasonal vessel use is missed when evaluating vessel-related risk using only AIS data (Lane et al., in revision).

We analyzed a series of movement characteristics (duration, maximum speed, maximum acceleration, maximum deceleration, and course deviation) to evaluate differences in how each vessel type utilizes the study area, which could influence their risk of colliding with a whale. We observed that these movement characteristics were

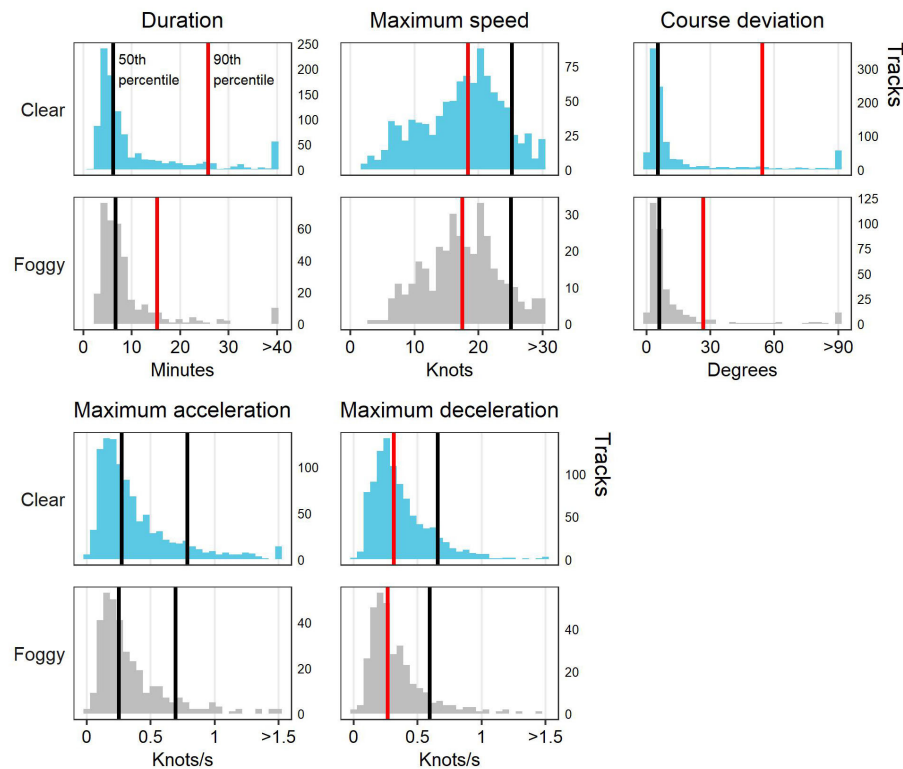


FIGURE 8

Non-AIS track distributions based on vessel duration, maximum speed, course deviation, and maximum acceleration and deceleration under clear and foggy conditions. Vertical lines indicate the 50th percentile (leftmost) and 90th percentile (rightmost) values. Red lines indicate a value in foggy conditions that was significantly different ($p < 0.05$) from the respective value in clear conditions.

inherently interrelated. For instance, a vessel's speed may impact its duration in the area or the complexity of its course deviation. For example, a slow moving or adrift vessel may be more affected by passive forces like wind, waves, and currents than a faster vessel (Wijaya and Nakamura, 2024). A statistical analysis of the relationships between all the characteristics was outside the scope of this work, but we provide a comparison of vessel speed with the other characteristics for each AIS and non-AIS category in [Supplementary Figure 3](#). Higher speeds are strongly associated with higher probabilities of collision between vessels and whales, including increased probability of lethal collisions (Vanderlaan and Taggart, 2007; Kelley et al., 2021), and thus the relationship between speed and the other movement characteristics evaluated here should be carefully considered when interpreting their possible influence on vessel strike risk.

Generally, while our assessment of course deviation gives a quantitative measure of variation in trajectory, this metric does not necessarily serve as a proxy for vessel maneuverability. Vessels simply transiting through the area are less likely to deviate course during their more brief time observed, regardless of capability, whereas slower moving vessels engaged in idling or fishing are far more likely to stay in the area longer and result in higher course deviation. The variability in course deviation of vessel categories shown in [Figure 7](#) suggests which can more easily or quickly maneuver, but more research is needed to address the specific question of maneuvering capability.

Non-AIS vessels, especially small motorized and motorized recreational vessels, were observed to reach higher maximum

speeds and maximum acceleration and deceleration rates on average than AIS vessels. These characteristics necessitate a much faster reaction time from the operator to avoid a whale surfacing ahead of the vessel (Busby, 2023; Barić et al., 2025). Higher acceleration/deceleration rates may also make these vessels less predictable to whales, and thus harder for them to avoid while engaging in other behaviors, such as foraging (Nowacek et al., 2001, 2007). At the same time, the ability to quickly accelerate or decelerate may also make these vessels better able to change heading and maneuver quickly to avoid collisions with wildlife (Schoeman et al., 2020). However, if a whale is detected within a close distance by a vessel moving at high speed, that vessel's ability to maneuver does not ensure that a collision will not occur (Wiley et al., 2016).

AIS vessels spent longer in the study area on average than non-AIS vessels, though this was skewed by the presence of tug and tow vessels. Because of the challenging bathymetry and navigational considerations within SF Bay, tug and tow vessels are required to wait within the Golden Gate Strait before oil tankers arrive for escort in and out of port (California Department of Fish and Wildlife, 2006). During this holding pattern, tug and tow vessels typically remain stationary, so duration may not be a pertinent factor in determining potential risk in this case. Relatedly, tug and tow vessels had the highest course deviation on average, though this is likely related to the same circumstances as duration if tug and tow vessels are being partially carried by tides and currents while awaiting tankers in the study area or repositioning as they approach ships. This explanation is supported by their low maximum speed relative to other vessels. Thus,



FIGURE 9

In the presence of fog, a whale's blow can be difficult to detect (left). In contrast, a blow can be seen at a distance in clear ambient light (right). Photos: (left) P. Rodriguez/TMMC under NMFS permit # 26532; (right) W. Keener/TMMC under NMFS permit # 20386.

in the case of tug and tow vessels, longer average duration and higher course deviation, in combination with their low maximum speeds, likely indicate lower collision risk by these vessels.

Marine radar is an essential tool for mariners navigating in fog which is especially relevant for coastal locations like San Francisco. Our analysis revealed that non-AIS vessels did not significantly change certain movement patterns during reduced visibility (Figure 8). It is likely that mariners rely on their own radar to navigate safely around vessels and structures in foggy conditions. But because fog reduces the range at which mariners can visually perceive marine wildlife (Figure 9), which are not detected by radar, high speeds maintained by non-AIS vessels in these conditions may increase strike risk.

4.1 Limitations and biases

The radar system used was land-based, with surveillance restricted to vessels within a line of sight or within the distance the radar can detect. While the radar tracked vessels during the day and night and in foggy conditions, the daylight-only camera was limited in its ability to classify non-AIS vessel types depending on distance, daylight, and other obstructions such as fog and geography. Therefore, our analysis does not include nighttime traffic. However, other research efforts both inside and outside of SF Bay found that there was more AIS traffic during the day than at night (Jensen et al., 2015; Cope et al., 2020). We suspect this same trend holds for most smaller, non-AIS carrying vessels, although fishing vessels may be leaving and returning before and after sunrise/sunset. The vessel classification process was also subjective and susceptible to human error. We addressed this limitation by creating a rubric guide for classifying vessels (Supplementary Table 1), and had only one scorer analyze all tracks within the study period to account for any variability that would be introduced by multiple analysts.

5 Conclusion

While AIS is a valuable and readily available source for vessel traffic data, the results of this study demonstrate that coverage of vessel types varies greatly between AIS and radar detection, with recreational

vessels particularly underrepresented in AIS data. This confirms that only using AIS data in nearshore whale-vessel strike risk assessments can greatly underestimate the quantity and seasonality of vessel traffic, and thus misjudge the overall risk of vessel strike. Vessel strike risk assessments are most effective when they are dynamic and account for temporal and spatial trends of both whale presence and vessel traffic (Blondin et al., 2020). Robust vessel data are crucial to identifying high-risk areas so effective management strategies can be implemented, such as vessel speed reduction zones and the shifting of traffic lanes or separation schemes, to help decrease the risk to whales. We demonstrate the utility of a novel technology package capable of providing comprehensive vessel data in a key urban waterway and transportation corridor that also acts as whale habitat. Our study did not utilize the inherent mobility of the M2, but future efforts could relocate the system in response to shifting habitats or migrations. As our coastal economies continue to grow, and climate change alters distribution for many large whale species, improved vessel monitoring becomes more important in developing informative risk assessments and ultimately mitigating vessel strike risk.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

PR: Data curation, Conceptualization, Methodology, Visualization, Writing – original draft, Investigation, Formal analysis. SK: Conceptualization, Writing – original draft, Formal analysis, Visualization, Data curation, Methodology. RL: Writing – original draft, Formal analysis, Visualization, Methodology, Supervision, Conceptualization, Investigation. JO'H: Writing – review & editing, Conceptualization, Funding acquisition, Methodology. KG: Funding acquisition, Writing – review & editing. WK: Resources, Writing – review & editing, Writing – original

draft. BT: Resources, Writing – review & editing. VZ: Writing – review & editing, Software. EH: Conceptualization, Resources, Writing – review & editing.

The author(s) EH declared that they were an editorial board member of Frontiers, at the time of submission. This had no impact on the peer review process and the final decision.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fmamm.2026.1888831/full#supplementary-material>

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