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A statistical representation of oil spill fate in the Salish Sea (Part 1)☆

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ABSTRACT

Transport of different oil types as fuel or cargo varies within the Salish Sea and over time. Although many studies have focused on the future health of Salish Sea ecosystems under a warming climate, no study has addressed how market-based dependencies on fossil fuels introduces geographic and temporal variations in ecosystem vulnerabilities. This paper aims to help address this knowledge gap with details of oil transport and oil spill risk in the Salish Sea. Part 1 describes the method that we developed to statistically generate individual oil spill scenarios based on ship traffic data, Washington state oil transfer data, and information on past oil spill events. We examine a set of these 10,000 random spill scenarios, referred to as "Study Spill Set," and we compare this Study Spill Set to other sets of 10,000 spills. The Study Spill Set generated by this Monte Carlo method is the spill set that was used in the model simulations described and presented in a second paper in this special issue, Part 2 (Mueller et al., 2025). While Part 1 focuses on the methods and results from statistically generating 10,000 spill scenarios, Part 2 focuses on the likelihood of oil spill impacts in the Salish Sea based on the fate and transport of these 10,000, statistically-generated spill scenarios. In this paper, we explain the development of our Monte Carlo approach and show that Salish Sea oil spill risks are regionally variable by oil type and spill volume.

1. Introduction

The Salish Sea is an estuarine transport corridor located between Vancouver Island and the mainlands of the United States and Canada (Fig. 1). Despite hosting 8,300 deep draft vessel transits (Van Dorp and Merrick, 2017) and around 45 billion liters of oil transported as cargo each year (Washington State Department of Ecology, 2018), the Salish Sea has yet to experience a major oil spill. Most peer-reviewed studies on oil spill impacts since 1968 have occurred in the aftermath of major spill events that capture public interest (Murphy et al., 2016), with a focus on the circumstances of those spills. Given the lack of a major spill event in this region, a majority of oil spill risk assessment in this region is documented in grey literature rather than peer-reviewed literature.

A review of grey literature research related to oil spill risk assessment in other regions highlights the importance of peer-review in assessments of oil spill impacts (Lubetkin, 2020). An example of misreporting in grey literature is demonstrated by a stochastic modeling study of a potential oil spill just west of our study region that showed no risk of oiling to Washington state shorelines (NOAA Office of Response and Restoration, 2013). Further investigation of this case has confirmed risk to Washington state shorelines during non-winter seasons using the open source GNOME modeling suite (NOAA Office of Response and Restoration, 2025), developed by the National Oceanic and Atmospheric Administration (NOAA) (Mueller et al., in prep.; NOAA Office of Coast Survey, 2025). The oversight in the previous

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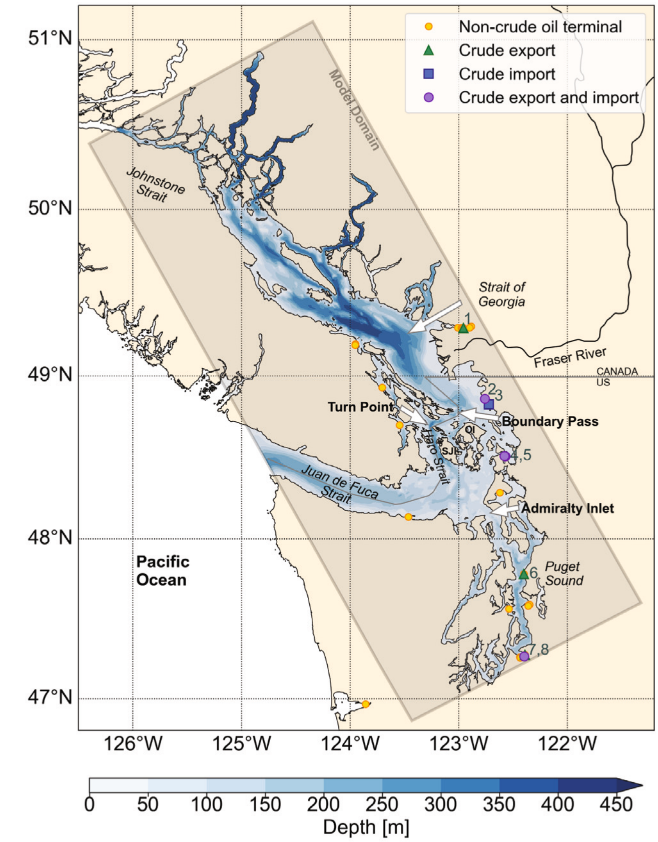

Fig. 1. Location of this study with the boundary for oil spills and oil spill fate shown in darker brown, which is also the limit of the SalishSeaCast model domain. The seafloor depth is shown in blue. The yellow dots mark the locations of Non-crude oil transfer terminals while all other markers show crude oil transfer stations distinguished as: green triangles for crude export only, a blue square for crude import only, and purple circles for locations that import and export crude oil. The crude-oil terminals are listed in Table 1 according to the numbers shown in this graphic. In 2018, Washington crude-oil terminals reported oil transfers of Bakken, "crude oil", and/or Bitumen (Washington State Department of Ecology, 2018). Westridge Marine Terminal, BP Cherry Point Refinery (2) and Marathon Anacortes Refinery (5) receive light to heavy crude from the TransMountain pipeline. Westridge primarily exports heavy crude to California and Asia (Canada Energy Regulator, 2023).

study may have been caused by the use of a model that was not open source (a term used to describe code that is freely available for anyone to use, modify, and distribute) and a lack of details about the model setup. Using numerical models with open source code allows those who interpret and communicate model output to have access to model parameterizations, settings, and setup. This access allows for review and verification of information, which supports a more accurate representation of results. The research we present here, in advance of a major spill, is for the purpose of providing critically-evaluated information that is free and openly accessible, with full access to the methods, in support of informed decisions on how to best prevent harmful impacts from a major spill.

Statistically representing oil spill risk in the Salish Sea requires mapping out local traffic, determining spill risks, and assigning spill characteristics to each simulated incident (inclusive of oil type and volume). In this Part 1 paper, we present a method of developing statistical distributions for spill location, spill times, oil type spilled, and spilled volumes for the purpose of providing a more comprehensive and accurate prediction of oil spill impacts in this region. The resulting impacts from fate and transport modeling of these statistically generated spill scenarios are presented in a second paper within this special issue, Part 2 (Mueller et al., 2025). Part 2 also describes the modeling framework used to evaluate the fate and transport of the spill scenarios resulting from the work presented here, in Part 1.

Previous studies in this region have evaluated the prospect of impacts from numerical model simulations at five different locations in the Salish Sea with fixed volumes of spilled oil (Niu et al., 2017; Page et al., 2019; Zhong et al., 2018; EBA Engineering Consultants, 2013; EBA Tetra Tech, 2013); however, pre-selecting spill locations introduces a human bias in assuming where spill accidents will occur, which does not represent the actual risks of traffic accidents. In addition, these modeling studies have relied on proprietary software with restricted access to the code and details of how statistics are generated. They have also not included statistical variability of impacts across seasons, vessel traffic, spill locations, and oil types. This paper lays the groundwork for a different approach that uses statistics derived from ship track data to determine spill locations and spill volumes in a way that removes human bias and includes both traffic and environmental variability.

A motivation for using statistics to determine spill characteristics is the random the nature of past incidents in this region. Those that have either threatened or resulted in a spill include: (1) a sunken push tug spilling 110,000 liters of diesel because the one person on the bridge fell asleep and the safety navigation alarms were not activated (as near-shore transits that might trigger safety alarms can help reduce fuel costs), Transportation Safety Board of Canada (2016), Downing (2021); (2) an uncoupling of a push tug from its oil tank barge carrying 4,000,000 liters of crude oil due to a mechanical failure of the push-pin coupling that was compromised by wave action (Ship-source oil pollution Fund, 2017); (3) a gas tank left open after bunkering (Pawson, 2018), resulting in a continuous in-transit spill of 30,000 liters; (4) and an in-harbor spill of 2,700 liters that was attributed to a faulty valve and an improperly installed alarm system (Woodward, 2019). None of these incidents occurred at the locations chosen in previous studies. The randomness of spill incidents demonstrates a need to adopt an approach that removes human bias from choices of spill characteristics and relies instead on statistics derived from marine transportation data. Here, we demonstrate a statistical approach that removes human bias for the purpose of providing a more comprehensive evaluation of oil spill risks in this region.

We do not know of another study anywhere that has considered both the stochastic nature of where an oil spill may occur as well other stochastic processes, like spill volume and environmental conditions. For example, Amir-Heidari et al. (2019) varies time and amount of oil spilled but not the location of the spill. Other researchers use statistical models to determine the fate and transport of oil spilled at a single spill location under differing environmental conditions (e.g. Guo (2017)) or use a Monte Carlo method to simulate the diffusion of oil (Gong and Pang, 2019; Dąbrowska and Kołowrocki, 2020). This study is the first of its kind for the Salish Sea (and likely for the world) to capture variability in shipping, environmental conditions, and oil transport.

Salish Sea marine shipping services five oil refineries (Fig. 1 and Table 1 labels 2, 3, 4, 5, 8) and three oil transfer terminals (Fig. 1 and Table 1 labels 1, 6, 7) that support a range of markets and, hence, oil types. Ship traffic, cargo oil, and fuel oil vary over time and space, imposing a dynamic and heterogeneous seascape of oil types and volumes spilled. Planning and preparing for a response to a major spill event requires statistics that encompass these variations, including: types of spilled oil, potential volumes of spilled oil, plausible locations of spilled oil, and timing of spills. Location and timing matters because some regions of the Salish Sea have surface currents that are dominated by tidal fluctuations while other regions have surface currents that are more dependent on wind forcing and/or river discharge. Tides, seasonal cycles, and interannual variability affect Salish Sea circulation differently in different regions, and these regional variations will introduce variations in oil spill fate and transport. In this paper, we describe a statistical method for including regional differences in oil types and volumes to include these regional variations in our statistical representation of spill risks, calculated in Part 2 (Mueller et al., 2025).

Table 1
Crude-oil transfer terminals in 2018, shown in Fig. 1.

Fig. 1 label	Name of marine terminal	transfer direction
1	Westridge Marine Terminal	export
2	BP Cherry Point Refinery	import and export
3	Phillips 66 Ferndale Refinery	import
4	Shell Puget Sound Refinery	import and export
5	Marathon Anacortes Refinery (formerly Tesoro)	import and export
6	Alon Asphalt Company & Refining	export
7	SeaPort Sound Terminal & Refining	export
8	U.S. Oil	import and export

Table 2
AIS identification of "COARSE_TYPE" used to classify the vessel types in this study as well as the AIS ship type that is designated to each "COARSE_TYPE". Monte Carlo ship types with * required tailored modifications, as described in Section 2.1.

Monte Carlo ship type	AIS ship type	COARSE_TYPE
Tanker	Tanker	8x
Cargo	Cargo	7x
Fishing	Fishing	30
Cruise*	Passenger	6X
Ferry*	Passenger	6X
Small Passenger*	Passenger	6X
ATB*	Tug	31, 32, 52
Barge*	Tug	31, 32, 52
Other	Pilot Vessel	50
	Port Tender	53
	Pleasure Craft	37
	Sailing Vessel	36
	Sear and Rescue	51
	Law Enforcement	55
	Wing in Ground	2X
	High Speed Craft	4X
	Anti-pollution	54
	Dredger	33
	Dive	34
	Unknown	100
	Military	35
	Other	9X
	Local vessels	56
	Local vessels	57
	Medical transport	58
	Special craft	59
	Reserved	39
	Reserved	39

We do not presume to know when or where accidents might occur and instead capture this regional and temporal variability by modeling a large set of spills at locations identified by a Vessel Time Exposure method (VTE) (Van Dorp and Merrick, 2017) that uses AIS ship track data to determine location, vessel characteristics, and timing of spills. Oil transfer data (Washington State Department of Ecology, 2018) is used to match vessel characteristics with oil types and historical spill data is used to determine the fraction of the ship's oil capacity that is spilled in each, separate scenario. We created a method to generate statistics from this information and to estimate a large set of random oil spills from which to evaluate likelihood impacts by simulating spills using a suite of numerical models. In Part 2 (Mueller et al., 2025) (also published in this special issue), we show the results from one iteration of 10,000 simulated spill scenarios using this method. We refer to this set of 10,000 spills as the Study Spill Set. The purpose of the Study Spill Set was to create a large enough sample size for statistics while also operating within our computational restraints. In this Part 1 paper, we show how the Study Spill Set compares to other iterations of 10,000 spills in order to demonstrate the reproducibility of our Monte Carlo method as well as to provide context for how the Study Spill Set is similar to or different from other sets of 10,000 spills.

2. Methodology

We statistically generate oil spill characteristics using Spire's 2018 Automatic Identification System (AIS) ship track data (Spire Maritime, 2018) to determine the VTE and, thus, the probability of spill incident from vessel tracks to determine spill location, timing, vessel type, and vessel length. Vessel type and length are then used to identify oil type and fuel tank and/or cargo tank capacity using statistics generated from a combination of Washington State Department of Ecology oil transfer data (Washington State Department of Ecology, 2018) and other information sources (described further down in this section). Section 2.1 describes the grouping of vessel types in the AIS data into nine vessel categories. Section 2.2 describes the method for creating maps of the amount of time that vessels spent in each grid cell, which was used to weight probabilities on spill location and month. Although traffic and seasonal variation are determined by the 2018 AIS ship track data, we allow spill time, day, and year to be randomly selected within the time frame of available hydrodynamic model output (1/1/2015–12/31/2018), using 4 years to capture inter-annual circulation changes. The specific latitude and longitude within a given cell was chosen uniformly. The vessel type was then selected according to the VTE weighting within the cell, and a specific vessel track was then chosen. The selected AIS ship track provided information on vessel type and length. Section 2.3 explains the method used to stitch together AIS ship tracks of vessels carrying oil as cargo (referred to as "tank vessel traffic") to identify origins and destinations for a more accurate determination of oil type. These "tank vessel traffic" vessels included a selection of articulated tug barges (ATBs), tank barges, and tankers. As explained in Section 2.4, vessel length was used to attribute spill capacity for all vessels except Handymax tankers and ATBs. Section 2.5 describes the attribution of oil type.

Table 3
ArcMap line density tool parameters.

ArcMap field	Input value
Population field	INVRSPD_KM
Output cell size	1000 (m)
Search radius	707 (m)
Area units	SQUARE_KILOMETERS

2.1. AIS vessel categories

AIS "coarse type" was used to group vessels into the nine categories of tanker, ATB, barge, cargo, cruise, ferry, fishing, small passenger, and other. An overview of AIS coarse types attributed to our nine ship type classifications is shown in Table 2; however, some additional refinements were needed. The cruise, ferry, and small passenger classifications required hand-editing because they all share the same coarse type (6X). Details of the MMSI attributed to each vessel type can be found in the Oil_capacity.xlsx spreadsheet in our data repository (Mueller et al. (2018)). ATB and barge types also required hand-editing because the tugs in these systems–rather than the barges–are tracked by AIS. Using the information contained in the Department of Ecology oil transfer data (Washington State Department of Ecology, 2018), we estimated the dedicated oil-carrying ATB and barge vessels and what proportion of time they are carrying oil (Appendix). Section 2.4 provides more details on how the spill volume is derived from fuel and cargo tank oil capacities as well as our method of accounting for empty cargo vessels.

2.2. AIS Vessel Time Exposure (VTE) by vessel category

Ship transit time density (referred to as "VTE", Van Dorp and Merrick (2017)) was mapped according to the month and the type of vessel using Automated Identification System (AIS) data provided by Spire Maritime. ArcMap's Line Density tool was used to map ship track density in hours per square kilometer. The NEMO-based SalishSeaCast model, used in Part 2 (Mueller et al., 2025) for hydrodynamic forcing, has a horizontal grid spacing of approximately 0.5 km by 0.5 km in the

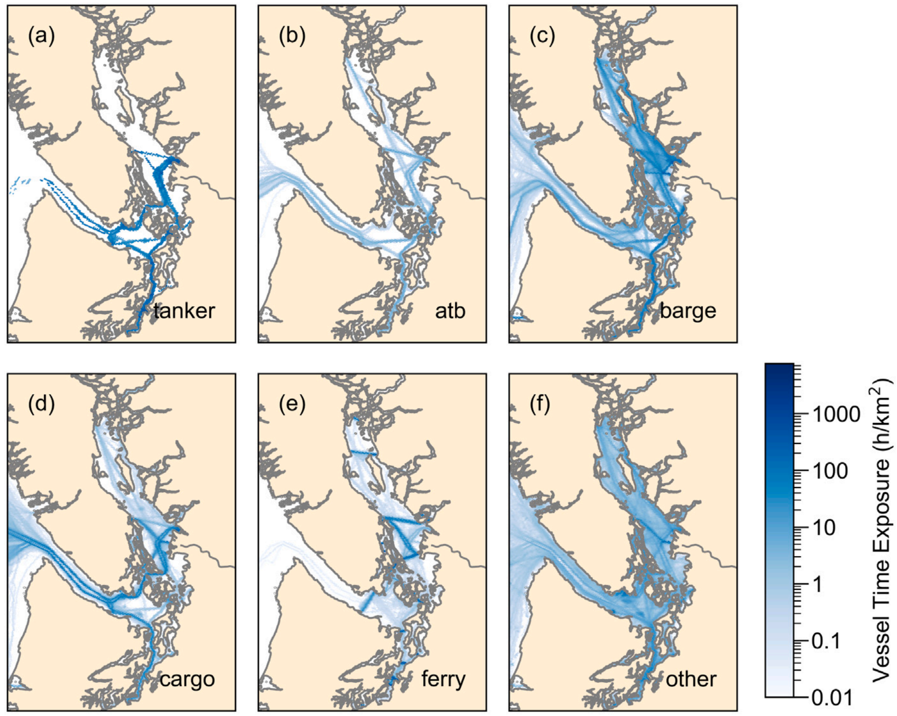

Fig. 2. Total hours for vessel traffic in 2018 (Vessel Time Exposure, h/km^2), shown by vessel classifications used in this study, specifically showing traffic time for: (a) tankers, (b) ATBs, (c) barges, (c) cargo vessels, (d) ferry vessels, and (e) other vessels.

horizontal directions, and we used this grid when generating the rasterized GeoTIFFS of AIS ship tracks. For each grid cell within this grid, the lengths (km) of vessel tracks within a 1 km radius were multiplied by the inverse vessel speed (hr/km), summed, and divided by the search area (km^2). The resulting grid units are hr/km^2 and were exported to GeoTIFF (see Table 3 for the ArcMap tool parameters used for this calculation). Our VTE calculation has two sources of error: (1) Smearing from interpolation, and (2) sampling area mismatch with grid. These errors are in addition to AIS errors, which are discussed in Section 4.1. Smearing from interpolation occurs when grids are projected from lat/lon coordinates. The length of decimal degrees varies with latitude and vessel track density is calculated in a cartographic projection with map units in meters. Vessel track density is also calculated within a radius from the center of the cell (i.e. the density reported in a square grid cell is calculated from a circular area). Because the search radius encompasses the grid cell, some vessel tracks included within the radius might fall outside the cell boundary. Both of these errors are inherent in all grid cells and not of concern in biasing results. The output coordinate system used was WGS_1984.

Fig. 2 shows the resulting 2018 Vessel Time Exposure (VTE) maps. We use these maps of VTE to statistically determine vessel type, vessel length, spill location, and spill month. Given that VTE reflects the length of time a vessel type is in a grid cell, our method assumes that the risk of an incident increases with the amount of time that a vessel is in the water and that all incidents represent a potential oil spill. We do not account for vessel drift away from incidents and the role of vessel drift on spill scenarios (e.g. grounding) and hope that future studies will advance algorithms for spill risk attributions.

2.3. Attributing tank vessel origins and destinations

We created two different shapefile products that are referred to as a comprehensive shapefile and a voyage shapefile. The comprehensive file includes all of the 2018 ship tracks received from Spire Maritime and has features that represent individual ship track segments. A ship track segment is a line connecting two consecutive AIS pings. The comprehensive dataset was used to generate the VTE maps used for the statistics of spill location and timing (Section 2.2). The voyage shapefile contains voyage information for the sub-sample of ship tracks with unique vessel IDs (Maritime Mobile Service Identity, typically referred to as MMSI) that we classified as tank vessels, or vessels that carry oil as cargo. These are tankers, ATBs, and barges.

A voyage refers to a joined series of track segments that make up any given shipping route. We created voyages as polyline features that join ship track segments from those within 100 m of an oil transfer terminal origin to the end destinations (Hilliard, 2019). Ship tracks with the same MMSI were joined if (a) the subsequent ship track is within 4 h of the previous ship track and (b) the vessel speed was less than 80 knots between the two ship tracks. If either of the criteria were not met, then the voyage was ended. The result yielded both voyages that appear complete from origin to destination as well as voyages that appear to represent segments of a complete origin-to-destination voyage. For example, if the criteria were satisfied for all AIS pings during a voyage between Vancouver and Seattle, then the voyage would be represented as a single feature; if, however, somewhere along the route the AIS transmitter turned off for over 4 h or the ship track spuriously jumped to a non-local location then the voyage is represented by two or more features (depending on the number of interruptions). These errors are discussed in more detail in Section 4.1.

Origin and destination attributes were added to each voyage according to location. If the origin or destination fell within a certain distance from an oil transfer terminal then the voyage was attributed with the given terminal as either the origin or destination (depending on the export or import heading of the vessel). This distance criteria was specific to each marine transfer terminal because some terminals are closely grouped or in close proximity to non-oil marine terminals. We used visual inspection of satellite imagery and clustering of AIS ship tracks to tailor the distance for each location. The search radius of each facility is listed in the archived Oil_Transfer_Facilities.xlsx spreadsheet Mueller et al. (2018). If an endpoint was not located near an oil transfer facility the voyage tracks were given a generic origin/destination value of “Canada”, “US”, or “Pacific”.

The comprehensive dataset was joined with the voyage dataset to add origin/destination attributes to the comprehensive dataset. For each voyage feature, the comprehensive dataset was queried to identify track segments corresponding to the voyage MMSI. Start/end times and the origin/destination attributes were joined to the identified track segments. Voyages less than 1 km were not attributed.

Track segments that lack origin/destination attributes are given a generic oil attribution if the corresponding AIS pings could not be strung together to form voyages longer than 1 km or if the vessel was identified in AIS as “local vessel” or “other” types (coarse type 56/57 for local vessels and 9X for other). Four of the 18 ATBs are classified as these “local vessel” or “other” types (namely: Dublin Sea, Min Zidell, Emery Zidell, and Nancy Peterkin).

2.4. Generating tank vessels spill volume

Tank vessels are not always full of oil cargo. We use different probabilities of full or empty for each of the three tank vessel types in order to leave open the possibility that different vessel types are used in different ways for imports and exports. AIS data was used to identify tank vessels and to query import and export behaviors using Washington State Department of Ecology oil transfer data (Washington State Department of Ecology, 2018). In the category of tanker vessel type, the Handymax size class had the highest count of AIS ship tracks in the Salish Sea in 2018 (Fig. 3a) and is a relatively small tanker, by volume (Fig. 3b). Twenty Handymax tanker MMSI (out of the 140 identified by AIS) account for 58% of the Salish Sea Handymax traffic (Fig. 3c). These tankers participated in 227 oil cargo transfers in 2018 (Washington State Department of Ecology, 2018), 93 of which were transfers in which the deliverer and receiver were swapped in consecutive entries (indicating a two-way transfer of product) and 134 of which had different deliverers and receivers in consecutive entries (indicating a one-way transfer, see Fig. 3c). We did not account for time between consecutive entries when tallying the 93 two-way transfers. Fifty-four of these paired transfers occurred within 24-hours while 21 had a gap of more than a week between transfers. We include all paired transfers in our two-way transfer estimate. We estimate that 93 Handymax voyages were linked to two-way transfers (import and export) and 134 were linked to one-way transfers (either import or export), resulting in a 63% probability of Handymax traffic pings containing cargo. We use a 50% probability of carrying oil as cargo for all other tanker size classes as well as ATBs and tank barges. We consider the 50% of cases selected as not carrying fuel to be fuel oil spill scenarios. For all cases that are determined to be carrying cargo in addition to fuel, we impose a 20% probability of a fuel spill, an 80% probability of a cargo spill and no possibility of both. Volume capacities and oil types are attributed according to the type of spill (fuel versus cargo).

Oil cargo capacities were fixed volumes for all oil tank vessels except ATBs and Handymax tankers. For these vessels, we use probability weights for volume of oil carried as cargo based on the Washington State Department of Ecology oil transfer dataset (Fig. 4(a), Washington State Department of Ecology (2018)). The oil cargo capacity most likely for ATBs is less than the fuel capacity of 18,000 TEU container ships, e.g. Benjamin Franklin, cf. Fig. 4(a) and (b). The percentage of oil capacity that becomes a simulated spill volume is determined by a probability of percent-spilled based on the historical record of oil spills. Historic data from ten oil spills greater than 100,000 liters (see Table 4) were used to create a probability function for percent of oil capacity attributed as spill volume for each spill scenario. The function is shown in Fig. 5 and demonstrates that most of the spills in our study are a small fraction of the attributed spill capacity.

2.5. Oil type attribution according to tank vessel type

Washington State and British Columbia handle oil transfers and oil cargo shipping in different ways. In Washington State, marine terminals are required to record oil transfers greater than ~40 liters, with access to this information through Washington State Department of Ecology’s public records. British Columbia does not require this documentation. In 2018, most marine terminal imports to Washington State were crude oil from tankers and most exports were refined oil to tankers, albeit ATBs and tank barges , combined, exported nearly twice the volume as tankers (Fig. 6). Bunker-C was the persistent oil type most commonly transported as cargo within the Puget Sound and Alaska North Slope crude (ANS) was the most commonly transported persistent oil type as cargo across Washington waters north of the Puget Sound (Fig. 6). Given that the volume of oil types being transported varies by region, transport vessel, and direction of transport (Fig. 6), our attribution method allowed us to better capture these regional variations.

Even with Washington State Department of Ecology data (Washington State Department of Ecology, 2018), we still needed additional information to attribute which type of crude oil would best represent transported cargo in this area. To do so, we considered the data on total transport and remove the volumes transported by rail and/or pipeline. Washington Research Council (2019) delineates net crude imports as 34.4% ANS crude, 23.8% Conventional-sourced Canadian, 10.4% Tar Sands, and 23.3% North Dakota. We assumed that all of the North Dakota crude is transported by rail and/or pipeline and that most of the Canadian-sourced oils are transported by rail and/or pipeline to the Washington refineries in this study. The only reported marine transport of Canadian Oil to the U.S. refineries in this study is 305,104 liters/year of oil sands diluted bitumen (hereafter referred to as Dilbit) transported by 1–3 tug and tank barges per month from Westridge Marine Terminal in Burnaby, B.C., to U.S. Oil refining in Tacoma (Washington State Department of Ecology, 2019). This amount of marine transport would account for only 2% of Dilbit processed by U.S. Oil (Washington State Department of Ecology, 2019); however, we did not find any evidence of Dilbit transfers to U.S. Oil in the 2018 Washington State Department of Ecology data either because (a) these oil transfers were classified as “CRUDE” instead of “BITUMEN OIL (DIL OR SYN)” or (b) shipping trends were different in 2018. In 2018, the Washington State Department of Ecology data shows six export transfers that were classified as “BITUMEN OIL (DIL OR SYN)” from Seaport Sound Terminal and Alon Asphalt Company to tank barges, with a total transfer volume of 11,700,000 liters (Mueller, 2021a,b).

We assume that ANS crude is the majority of the approximately 18.5 billion liters/year of crude oil that was shipped to Washington State marine terminals in 2018. This assumption is consistent with the reporting on page 94 of Washington State Department of Ecology (2019). We use Washington State Department of Ecology (2018) to create oil-type probabilities for all tank vessels with voyages connected to the Washington marine terminals included in this study via origins and destinations (MIDOSS research team (2019)). These probabilities were based on grouping oil types in Washington State Department of Ecology data into 5 different oil groups: ANS, Bunker-C, Diesel, Dilbit, and Other (Table 5). This grouping was necessary because we could only run a limited number of spill simulations and wanted to have a sufficient number of spills in each oil type classification to get a reasonable coverage. We further simplified this grouping by running “Other” spills as Bunker-C because this oil type seemed the most reasonable to represent the major fraction of this group, which was Cat Feed/VGO (Table 5). Most spills in this study are Diesel with Bunker-C following as second with around half of the spill count of Diesel (Table 6). The “Other”’ grouping only accounts for less than 1% of spills (Table 6).

Most crude oil exported from Canada is transported by Aframax tankers from Westridge Marine Terminal to markets outside of the Salish Sea. The Transmountain pipeline servicing Westridge Marine

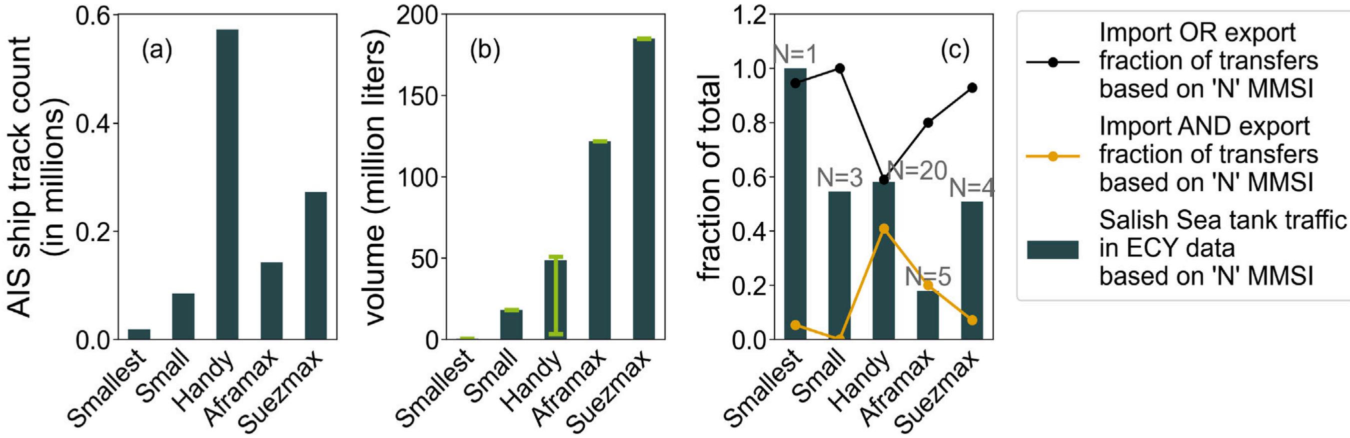

Fig. 3. Oil tanker transport characteristics. (a) 2018 AIS ship track count by tanker vessel size class, (b) cargo volume capacity for each size class with light green bar or range showing the volumes (ML) used in this study, and (c) the fraction of AIS ship tracks accounted for based on the *N* number of MMSI used to identify one-way transfers (black line) and two-way transfers (yellow line) in Washington State Department of Ecology (ECY) oil transfer data.

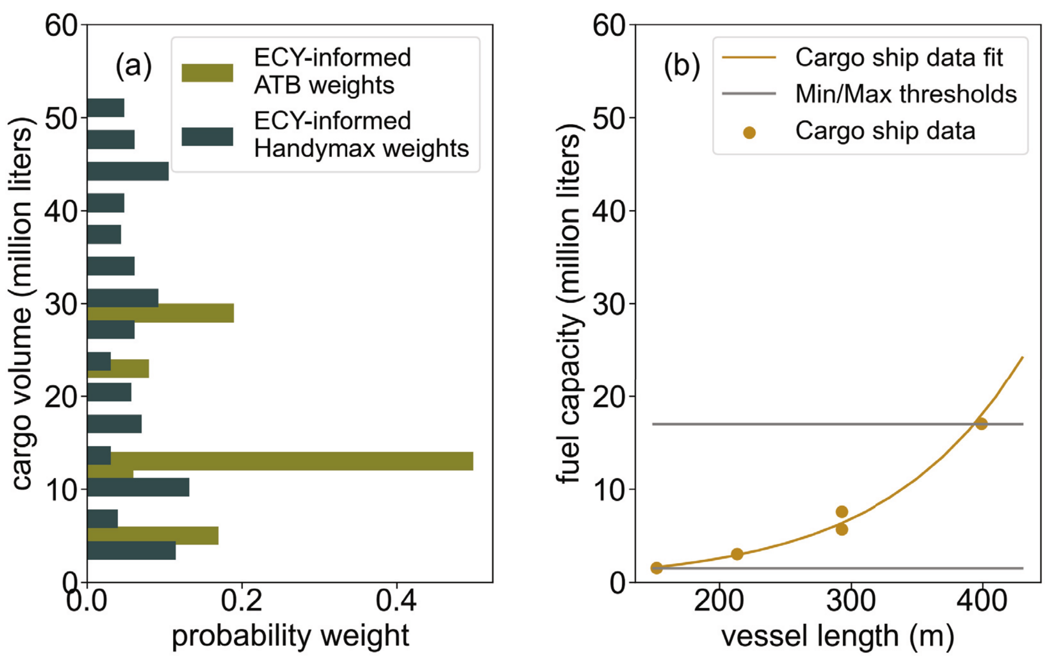

Fig. 4. Oil capacities used ATB and Handymax oil cargo tanks as well as container (cargo) ship fuel tanks. (a) Weights used to determine cargo volumes (ML) for ATBs (light green) and Handymax Tankers (dark green) based on Washington State Department of Ecology (ECY) transfer data (Washington State Department of Ecology, 2018). These are the only two vessel types that had cargo volumes determined by a weighting function. All non-Handymax tanker capacities were fixed by tanker size class and other vessel types had oil capacities set by a length-based function based on line fits to data. (b) Line fit used to determine container ship fuel capacities (ML) based on vessel length (m). Dots represent the data points used to inform line fits. The gray lines show the minimum and maximum allowed capacities.

Table 4
Spills greater than 100,000 liters used to establish probability function for percent of oil capacity attributed as spill volume, as shown in Fig. 5.

Spill event	Oil type	Approx. spill volume (ML)	Oil on board (ML)	Percent spilled
COSCO Busan	Bunker	.203	3.800	5%
MV New Carissa	Bunker-C	.230	1.500	15%
Bouchard No. 120	Bunker-C	.370	15.500	2%
Summer Wind/Miss Susan	RMG 380	.636	3.785	17%
Athos I	Crude	.997	50.000	2%
DM932	Bunker-C	1.020	1.587	64%
MV Selendang Ayu	IFO and Diesel	1.300	1.688	77%
Eagle Otome	Crude oil	1.700	91.714	2%
Westchester	Crude oil	2.100	8.300	25%
DBL 152	Bunker-C and Diesel	7.200	19.000	38%

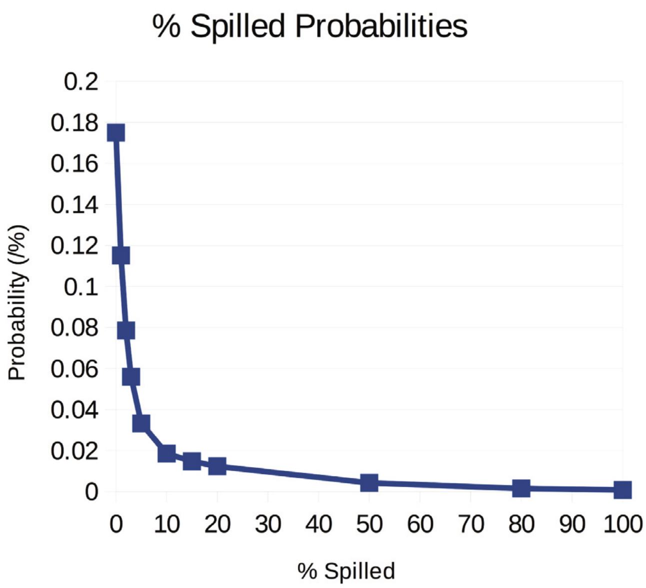

Fig. 5. Probability function for percent of oil capacity spilled in major spill events (greater than 100,000 liters). The spill data used to create this function is shown in Table 4.

Table 5
Oil-type classification used to identify oil types for this study together with the corresponding oil types represented in Washington State Department of Ecology (2018). Cat Feed/VGO is most similar to Bunker-C and is transferred in the largest volume of oil types represented in "Other".

Oil-type classification	Ecology's transfer name (s)
ANS	Crude Bakken
Bunker-C	Bunker Oil/HFO
Diesel	Gasoline, Jet Fuel/Kerosene, Biodiesel, Diesel/Marine Gas Oil Diesel Low Sulphur (ULSD)
Dilbit	Bitumen Oil (DIL OR SYN)
Other	Cat Feed/VGO, Ethanol, Cutter Stock, Naptha, Z-Other, Decant Oil, Edible/Vegetable Oil, Oily Waste, Nonene, Waste Oil, Asphalt/Creoseote Lube Oil/Motor Oil, Hydraulic Oil, Used Oil

Terminal (in addition to Washington marine terminals) is used to transport refined products and crude oils, including Dilbit (Kanjilal, 2019). We assume that tankers leaving Westridge have a 50% chance of being either Dilbit or Conventional Canadian crude. ANS is the most similar to Canadian Conventional crude of the oil types used in our study, so we use ANS as a proxy for Canadian Conventional crude in our Monte Carlo simulation and simplify the attribution of Dilbit as Cold Lake Blend (Environment and Climate Change Canada, 2013). All other terminals are attributed with the Washington cargo probabilities if the voyages have an origin or destination from/to the Washington marine terminals included in this study. If the voyages and destinations are not linked to the Washington marine terminals included in this study then we attribute Diesel as the oil type to/from all non-Westridge

Table 6
Number of spills simulated in each oil-type classification, with the oil-type attribution used in this study represented in parentheses. See Table 5 for lists of oil types represented by each oil-type classification. Spill counts in this table represent spills greater than three liters. Percent of spills shows the percent of spills in each oil-type classification across the 10,000 spills represented in this study. This value is shown next to the value of percent spills when increasing the sample size to 90,000 spills.

Oil type (simulated as)	spill count	percent of total	percent of 90,000 spills
ANS (ANS)	66	0.67	0.58
Bunker-C (Bunker-C)	3378	34.06	33.82
Diesel (Diesel)	6303	63.54	63.82
Gasoline (Diesel)	76	0.77	0.75
Jet Fuel (Diesel)	26	0.26	0.24
Other (Bunker-C)	69	0.70	0.75

terminals in Canada except the two for which we were able to gain more specific information. Suncor Nanaimo (Petro-Canada, 2020b) was attributed with a 25%/75% split between Diesel and Bunker-C, and ESSO Nanaimo Departure Bay (Petro-Canada, 2020a) was attributed with a 50% split between Diesel and Gas, which in this study is represented as 100% likelihood of Diesel.

3. Results

Using the methods described in Section 2, we generated a set of 10,000 spill scenarios (referred to as Study Spill Set) to evaluate oil spill risks in the Salish Sea. Table 6 shows the number of spills by oil grouping for Study Spill Set, the impacts of which are evaluated in Part 2 (Mueller et al., 2025). In addition to creating Study Spill Set, we repeated our Monte Carlo method to generate 9 more sets of 10,000 spills. Here, we compare the Study Spill Set with these other sets of 10,000 spills using heat maps on a 2.5 km x 2.5 km grid. Fig. 7a represents a map of spill counts for Study Spill Set while Fig. 7b and 7c show the average spill count and the standard deviation across 9 iterations of 10,000 spills. This figure demonstrates that the Study Spill Set captures the general pattern of spills across 9 iterations. It also shows that there are limited regions in which the standard deviation of spill count across all iterations is on the order of 10% of the spill count of the iteration used in Part 2 (Mueller et al., 2025).

Across each vessel type, the spill count is also consistent for each of the 9iterations, Fig. 8a shows a level reproducibility of spill count that demonstrates a robust estimate of total spill count by vessel type. In contrast, the total volume spilled by vessel varies across these 9iterations (Fig. 8b), with some vessel types showing a greater spread in total volume by vessel type than others. Vessels with a larger spill capacity (like ATBs, barges, and tankers) have a greater spread because the spill volume is a fraction of the spill capacity, as determined by the probability function in Fig. 5. This spread in volume is also seen in the "Other" category because of an AIS misclassification error with 18,000 TEU vessels (as discussed in Section 4.1). Overall, the number of spills by vessel types is robust while the spill volumes show a greater spread for vessel types.

The spill volume comparison shown in Fig. 9 shows more variation than spill count. Although the pattern of spill volume for 10,000 spills (Fig. 9a) is similar to the average across 9 iterations of 10,000 spills (Fig. 9b), the standard deviation across the 9 iterations (Fig. 9c) is greater than the mean value in some places. Fig. 10 shows spill count and volume by oil type for the Study Spill Set and demonstrates that spill counts are larger within focus vessel tracks (cf. Fig. 2) and that the majority of spill volumes that are well below 10 ML. These are the spill counts and spill volumes represented in Part 2 (Mueller et al., 2025). Fig. 11 shows the standard deviations of spill count and spill volume by oil types across all 9 iterations of 10,000 spills.

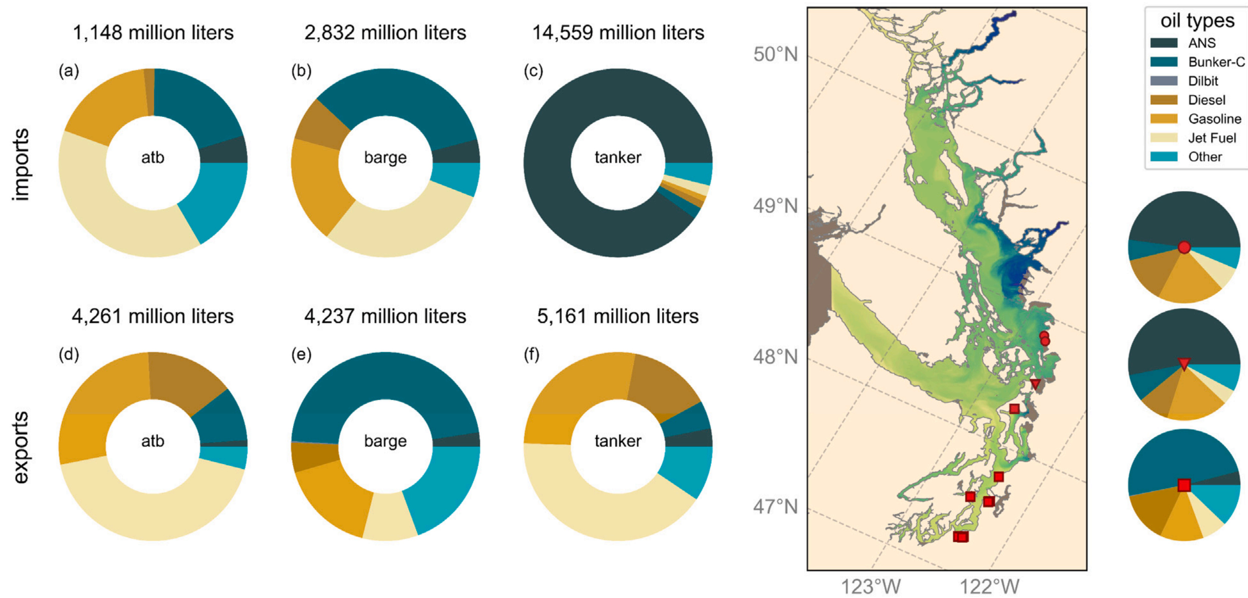

Fig. 6. Fraction of oil cargo volumes imported (upper row) and exported (lower row) by ATBs (a,d), barges (b,e), and tankers (c,f) based on department of Ecology transfer data (Washington State Department of Ecology, 2018), shown in million liters (ML). [right] Map of SalishSeaCast surface salinity (range 0–32.18 [g/kg] on 08/14/2020) and the marine terminals used to show fractions of oil types transferred in regions using Ecology's 2018 transfer data (Washington State Department of Ecology, 2018), [far right pie-charts]: (top pie chart and circles on map) BP Cherry Point Refinery and Phillips 66 Ferndale Refinery; (middle-triangles) Shell Puget Sound Refinery and Marathon Anacortes Refinery; and (lower-squares) Shell Oil LP Seattle Distribution Terminal, Maxum Petroleum - Harbor Island Terminal, Nustar Energy Tacoma, SeaPort Sound Terminal, Phillips 66 Tacoma Terminal, U.S. Oil & Refining, Naval Air Station Whidbey Island (NASWI), NAVSUP Manchester, Alon Asphalt Company (Paramount Petroleum), Kinder Morgan Liquids Terminal - Harbor Island, and TLP Management Services LLC (TMS).

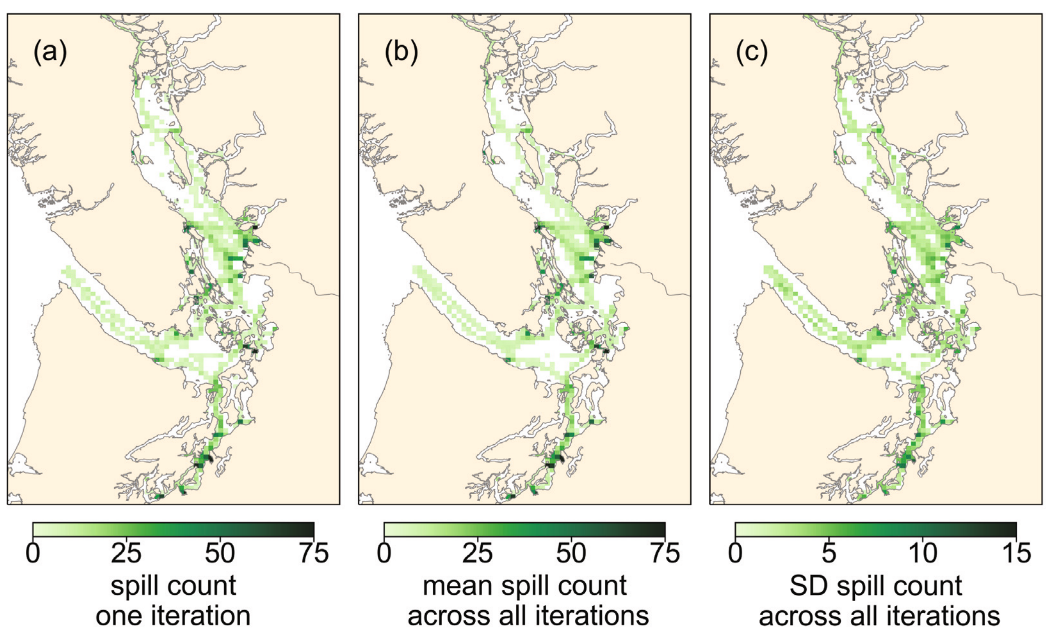

Fig. 7. Spill density maps of (a) spill count for the 10,000 spills evaluated in the companion Part 2 manuscript (Mueller et al., 2025), referred to as the Study Spill Set, (b) average spill density over 9 iterations of 10,000 spills, (c) standard deviation (SD) of spill count across 9iterations of 10,000 spills. Only locations with greater than three spills are shown.

4. Discussion

4.1. AIS

A goal of this study was to determine spill locations, types, and volumes from statistics derived from AIS ship tracks. AIS in this region captures focus vessel oil transport and is well suited for evaluating risks from large oil spills (O'Hara et al., 2023); however, AIS data has errors. Other publications go into more detail on AIS errors, and we refer readers to those publications if more in-depth information is needed (d'Afflisio et al. (2018), Wolsing et al. (2022), Stach et al. (2023)). Here, we explain how errors in this data affects our results. These errors include: mis-identifying vessel types, on-off switching, and kinematic deviation.

An example of mis-identification error in our study is the classification of a 18,000 "20-foot equivalent unit" (TEU) container ship

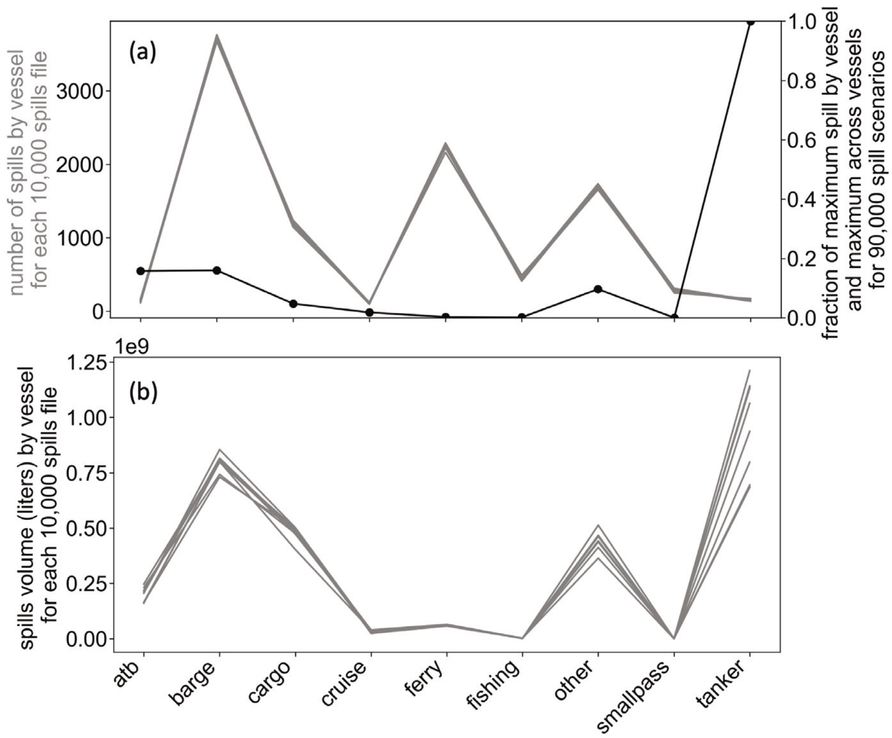

Fig. 8. (a) [left axis, gray lines] Number of spills by vessel types with different lines representing 9 different iterations of 10,000 spills; and [right axis, black line] the fraction of maximum spill volume by vessel type to largest total spill volume across 90,000 spill iterations. (b) Total volume by vessel type for each of the 9 iterations of 10,000 spills.

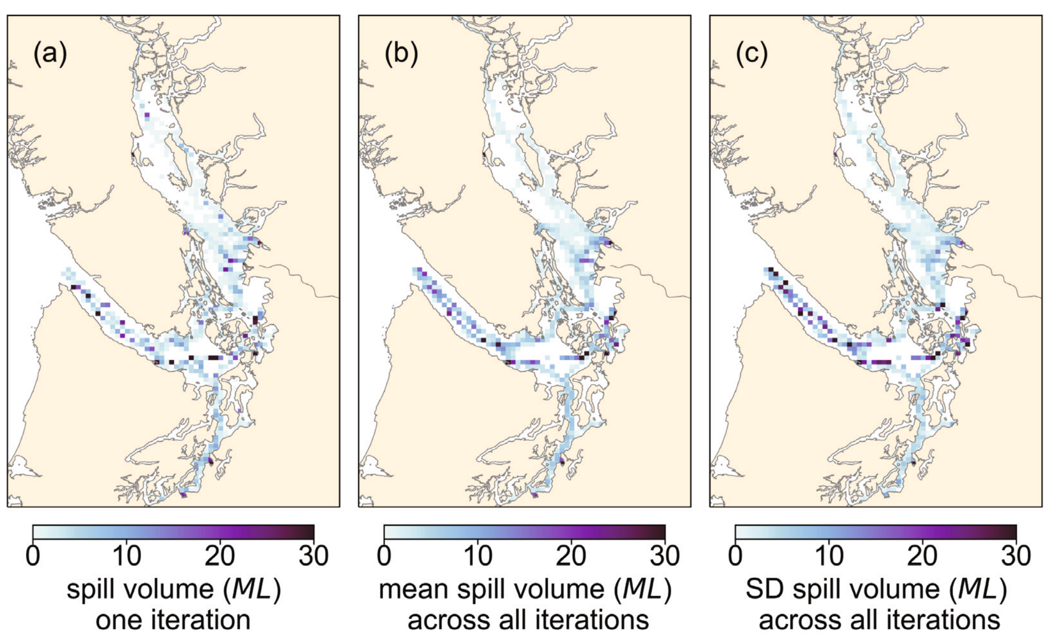

Fig. 9. A companion graphic to Fig. 7 showing 2D histograms of spill volumes (a) for the 10,000 spills used as the Study Spill Set evaluated in the companion Part 2 manuscript (Mueller et al., 2025), (b) averaged over 9 iterations of 10,000 spills, (c) as a standard deviation (SD) of spill volume histograms across 9 iterations of 10,000 spills. Only locations with greater than 3 spills are shown.

as "Other", with a COARSE_TYPE of 9X instead of the Cargo vessel classification of 7X. This AIS error results in our "Other" vessel type classification having larger spills than it would otherwise (as shown in Fig. 8). Liang et al. (2021) estimate that 9% of AIS ship tracks are either missing vessel type classification (6%) or have the vessel type mis-classified as "ship" or "other"(3%). Our method does not include the 6% of vessels that are absent any classification and the 3% error in mis-classifying vessel type, as described above, is relatively benign because the oil spill characteristics are still represented in our study, just with a different ship-type label.

The 2018 AIS data used in this study (Spire Maritime, 2018) has two main causes for missing vessel tracks: (1) Signal gaps that appeared to

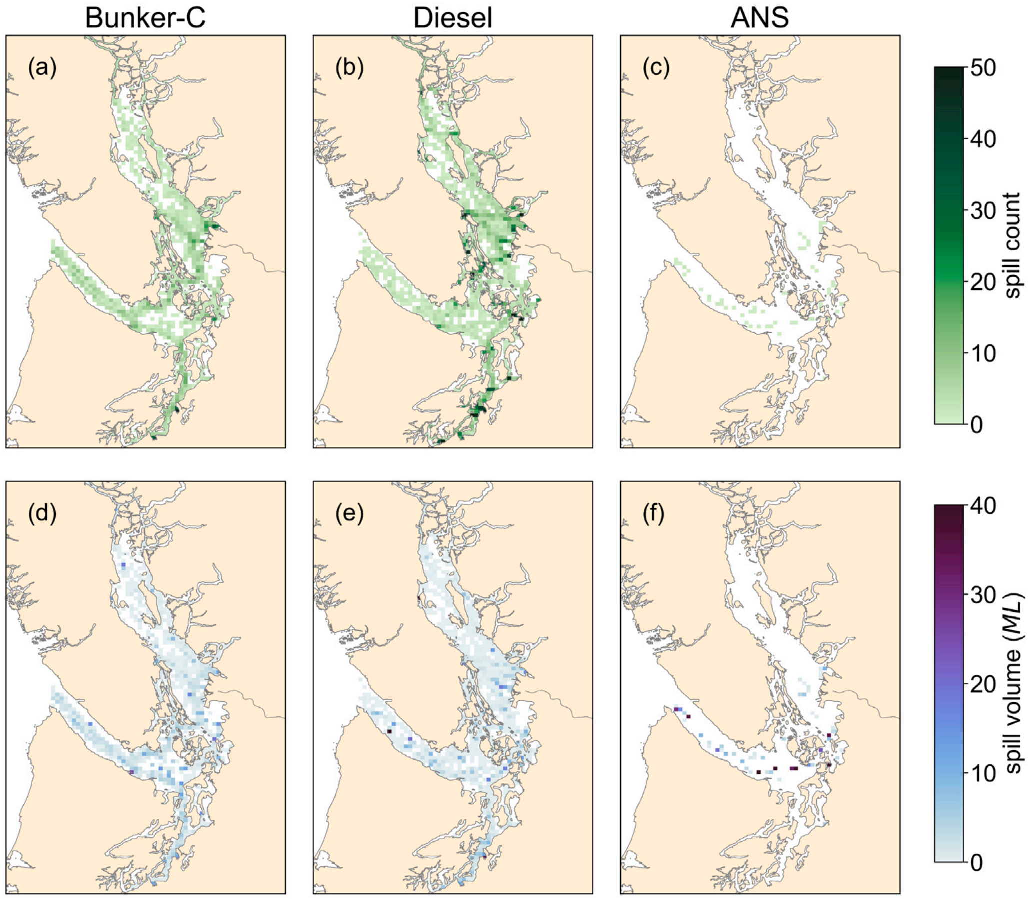

Fig. 10. 2D histograms of (a-c) spill count and (d-f) spill volume (ML) for the three oil classifications evaluated in the Study Spill Set, which are: (a,c) Bunker-C, (b,e) Diesel, and (c,f) ANS.

show AIS being turned off and then back on again; and (2) A "kinematic deviation" caused by the AIS signal intermittently jumping to a non-local location. These two data irregularities show up in the 2018 record as two or more separate ship tracks that are interrupted by a space of no data in between, and transit gaps in space and time that can look like a series of shorter ship track segments (see Fig. 12). The error from missing vessel tracks due to on-off switching or kinematic deviation is a more insidious problem than misidentifying vessel types. Regions in which data gaps are more common (e.g., Haro and Rosario Straits) will be biased toward under-representing actual spill likelihood with our spill algorithm. O'Hara et al. (2023) show that 84%–97% of tanker, tug, and cargo traffic is represented by AIS around Boundary Pass, which gives us confidence that this bias is a small one. Both signal gaps and kinematic deviations affect our method of oil attribution because voyages that terminated in US or Canada waters were attributed using our generic oil attribution rather than the attribution tailored to a specific origin or destination. See Supplementary Document S1 for more details on the number of ship tracks affected by this AIS error.

As demonstrated in this study, AIS has the potential to be useful tool for evaluating oil spill risks; however, AIS data errors compromised the efficacy of this tool. Harm reduction that relies on AIS could benefit from more consistency in vessel tracking and identifications in the AIS record, which include addressing the technical problem and motivations for introducing gaps and discontinuities between vessel tracks. We strongly encourage new approaches that will reduce or eliminate these AIS inconsistencies and errors such that this resource is a more reliable asset that can be used in future harm reduction.

4.2. Spill location and magnitude

Oil spills can result from a variety of incidents that include: collisions, allisions, and groundings as well as losses of propulsion, steering, or electrical power (Washington State Department of Ecology, 2019). Globally, about 30% of tanker oil spills are caused by allision/collision, and 32% are caused by grounding (ITOPF, 2023). Within the Salish Sea, Washington State Department of Ecology estimates that ~27% of oil spills by tug escort traffic (inclusive of tankers, ATBs, and tank barges) are caused by collisions, second only to the "other" category (as reported by Suchar et al. (2024) on results from the traffic risk study reported in Washington State Department of Ecology (2023b)). Our study most closely represents in-transit and stationary spills not caused by a loss of propulsion (e.g. grounding of a larger vessel). These include collisions and allisions. We do not capture grounding accidents from tankers and other larger vessels. However, smaller vessels with AIS that traffic in areas where larger vessels might ground contribute to spill risks in these regions such that our results do include near shore spills from smaller vessels. We provide the first comprehensive evaluation of oil spill risks across the Salish Sea from marine traffic, using statistics from traffic data.

Moving away from human biases that are created by past incidents and toward a traffic-informed approach is important because the locations of previous spills do not determine the locations of future spills. In addition, evaluating spill risk by focusing on one particular region, e.g. Turn Point, neglects the complex pathways and distances of spill fate that winds, waves, and hydrodynamics can cause. The information presented here on potential spill magnitude and location of larger spills is important because small doses over longer time will

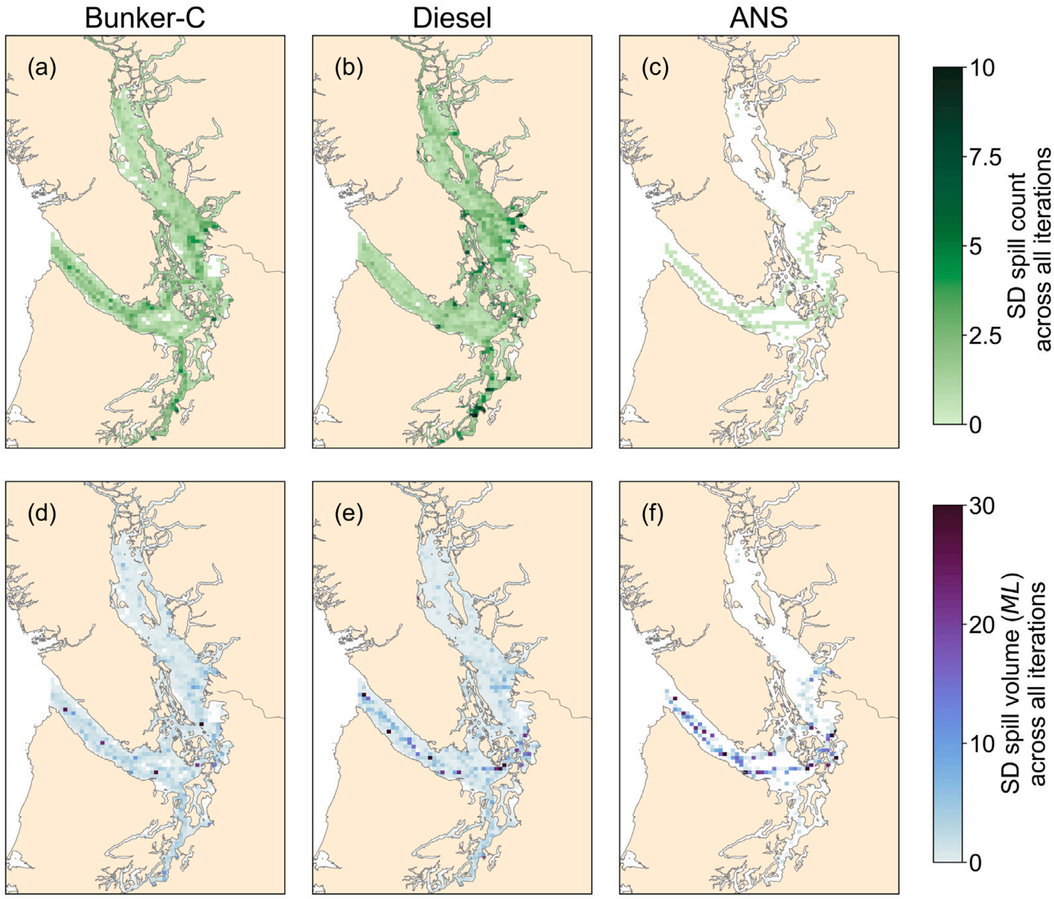

Fig. 11. Standard deviation of 2D histograms across all iterations of 10,000 spills for (a-c) spill count and (d-f) spill volume (ML) for the three oil classifications evaluated in this study: (a,c) Bunker-C, (b,e) Diesel, and (c,f) ANS.

have a different ecosystem impact than a large dosage and higher exposure over a shorter time, especially among endangered populations. Currently, background sources from land runoff and marinas are the greatest sources of oil in the marine environment (Serra-Sogas et al., 2014; Berry et al., 2018; O'Hara et al., 2023). The spill locations and magnitudes presented here are representative of risks from larger oil spills that would amplify the dosage and exposure well beyond background sources.

We use a probabilistic approach to calculating spill volume based on a vessel's carrying capacity and a likelihood of percent spilled from historical data between 1999 and 2014 (see Section 2.4) . It is important to consider that oil spill volumes between 2010–2019 were 92% less than those between 1978–1987 and 56% less than those between 1998–2007 (National Academies of Sciences, Engineering, and Medicine, 2022). In other words, our spill volumes reflect probabilities from a period in which spill volumes are higher than today. Even so, our spill volume estimates are reasonable. The worst case scenario used in the Trans Mountain Expansion application was 16,500,000 million liters. Other studies use scenarios that range from 3,785,412 to as much as 39,746,824 liters (Page et al., 2019). Based on 90,000 spills generated using our spill generation algorithm, our method produces 5.21% of spill volumes between 950,000 liters and 132,489,000 liters, 80.18% of spills between 450 liters and 946,000 liters, 14.61% of spills less than 450 liters (Mueller, 2019b). A very small fraction of our spills (0.0033%) are greater than Washington State Department of Ecology's "most likely" scenario (Mueller, 2019b). Our method moves away from a fixed volume spill evaluation and toward a probabilistic approach, using the best available data, with resulting spill volume scenarios that are reasonable.

This regional variability across nine different 10,000 spill iterations overlays a body of water that is distinguished by regions of unique circulation. The tide-dominated circulation in Haro Strait is different than the Fraser River and wind-driven circulation in the Strait of Georgia, and we ought to expect that wind-forcing will have different influences on oil spill outcomes depending on time of year and location of spill. Evaluating these regional characteristics and how they might affect spill trajectory will require a more in-depth and separate study but is included in the Monte Carlo results as we sample across all seasons and across multiple years.

Another source of error is that our method for generating spill volumes does not take into consideration the type of incident or hull. The requirement for double hulled tank vessels was phased in starting 1992. Since 2015, all tank vessels that are 5,000 DWT have been required to be double hulled (National Academies of Sciences, Engineering, and Medicine, 2022). Similarly, the International Maritime Organization has mandated that large cargo ships built after 2007 have double hulls for fuel tanks (MARPOL Annex I Reg. 12 A) and 50% of the world's cargo ships were built after 2007 (National Academies of Sciences, Engineering, and Medicine, 2022). The Benjamin Franklin is a cargo ship with a double-hull bunker tank that services the Salish Sea and was included in this study. Double hulls reduce the likelihood of bunker spills by 60% (National Academies of Sciences, Engineering, and Medicine, 2022) and reduce the size of tank vessel cargo spills by 20%–62% (Yip et al., 2011). Some incidents–like those caused by engine fires, bunkering or cargo transfer errors, mechanical defects, or operational mishaps–are more difficult to influence through regulations. In addition, oil spills from between-vessel transfers (referred to as "lightering") tend to be smaller. 90% of lightering spills are less

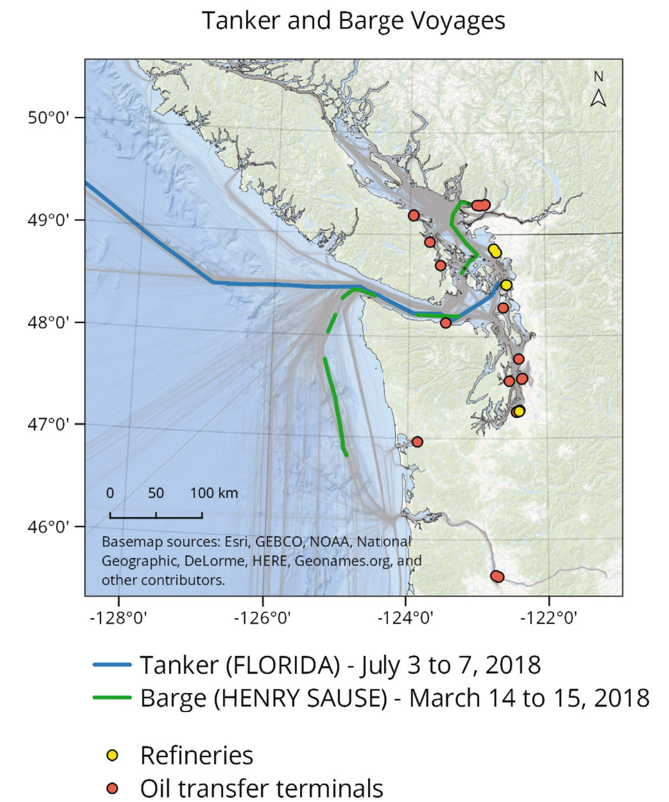

Fig. 12. An example of AIS ship traffic data that is complete (blue line) and AIS ship traffic data that is interrupted by sections where the AIS signal is dropped (green line). If the signal is picked up within 4 hours of being dropped, the ship track may extend through land (as shown for the barge, around Turn Point). We do not correct for these on/off patterns in our VTE maps. The VTE maps shown in Fig. 2 will under-represent traffic risks if there are regions where off-switching is habituated. We are not aware of habituated off-switching in certain regions.

than 160 liters while 62% of tank vessel spills overall are less than 160 liters (National Academies of Sciences, Engineering, and Medicine, 2022). In our study, we do not differentiate spill volume probability by spill scenario because we do not define spill scenario.

4.3. Oil types

Two major regulatory changes have affected oil transport over the past decade. The first was in 2015, when a forty-year ban on crude oil export from U.S. marine terminals was lifted. Over eight years, crude oil exports from U.S. marine terminals rose around 200 billion liters per year, from around 26 billion liters in 2015 to 239 billion liters in 2023 (US Energy Information Administration, 2023c). This trend is largely driven by crude oil export in the Gulf of Mexico (US Energy Information Administration, 2023a). At the time of this study, in 2018, U.S. crude export was around 118 billion liters per year. Within the Salish Sea, total crude oil export from Washington terminals in 2018 was around 0.7 billion liters per year, varying between 0.1–0.7 billion liters per year from 2015 to 2022 (Washington State Department of Ecology, 2018).

The second regulatory change was global and affected both U.S. and Canadian shipping. Starting 2020, the International Maritime Organization (IMO) reduced the amount of sulfur allowed in ship fuels from 3.5% to 0.5% in international waters and from 1% to 0.1% in Sulfur Emission Control Areas (see, e.g., Clear Seas (2020)). This regulation is often referred to as IMO2020. The main purpose of this regulation was to reduce sulfur emission such that ships may use an exhaust gas cleaning systems (also known as scrubbers) to achieve this goal rather than switching to a lower sulfur fuel alternative. The advantage of scrubbers is that they allow ships to continue to use cheaper bunker fuels. A disadvantage of scrubbers is that they produce a highly acidic and polluted byproduct that is disposed of in seawater, with consequences to the marine environment (Lunde Hermansson et al., 2024). For ships that do not use scrubbers, the lower sulfur bunker fuel alternatives include: Liquid Natural Gas (LNG), Marine Gas Oil (MGO), Very Low-Sulfur Fuel Oils (VLSFOs, 0.5% sulfur), and Ultra Low Sulfur Fuel Oils (ULSFO, 0.1% sulfur), Biofuels, Hydrogen, Methanol, and Ammonia. All of these fuel types carry different risks for response and environmental impacts. We discuss LNG, MGO, and VLSFOs in a bit more detail because these are the predominant fuel types used today.

LNG is a methane product that is cooled into a liquid state. If spilled, LNG will quickly evaporate and/or ignite, reducing the marine oiling impacts of traditional fuels but adding risks like methane to the atmosphere, which has 28 times the greenhouse gas heating potential as carbon dioxide. Increased methane emissions due to LNG fuel includes methane slip during combustion at a rate of 3.7–25.5 g/kWh (Aakko-Saksa et al., 2023). The use of LNG fuel grew 30% between 2012 and 2018 with a corresponding increase in methane emissions from international shipping of 150% over this same time period (Faber et al. (2020) in Comer et al. (2024)). Comer et al. (2024) asserts that IMO has underestimated methane slip in LNG combustion engines and highlights the uncertainty of this estimate given this underestimation. Methane emissions from this fuel will likely continue to increase in the coming years due to an increase in the number of LNG vessels, with LNG marine fuels currently predicted to increase 300% between 2019 and 2030 (Comer and Sathiamoorthy, 2022).

Unlike LNG, MGO is liquid at ocean temperatures and similar to diesel. It is in the category of distillate fuels, which are higher in the aromatic or volatile compounds. These fuels are less persistent than crude oils but have a higher fraction of components that dissolve in seawater, which leads to a higher toxicity. Aromatics are important in fuels, however, because they help to stabalize fuel mixtures by keeping the chemical components in solution.

VLSFOs are made from the heavier fractions of fuels that are left when the lighter fractions have been removed by distillation, and they have a lower fraction of aromatic compounds. As a result, a challenge with this fuel type is stability. Making this fuel product is a chemical balancing act that can be upset when bunker oils are mixed, with a potential outcome of asphaltenes precipitating out of solution. In general, VLSFOs have a significantly higher wax content than pre-2020 heavy fuel oils and a higher pour point, which can add additional challenges to cleanup and recovery. In addition, there is a wide variety of densities and viscosities under the label of VLSFO, which complicates response operations. At the time of this study, VLSFO was not a commonly used fuel and was not included in Washington State Department of Ecology's oil transfer database. IMO 2020 has made this fuel more prominent in marine shipping and it has since been added.

Bunker oil types are changing in response to regulations like IMO 2020; however, all fractions of oil are potential sources of income and are, hence, transported. Crude oil has all four fractions (saturates, aromatics, resins, and asphaltenes) and some of these fractions (like asphaltenes) are more persistent, with longer term impacts; whereas refined oils have higher concentrations of aromatics, which pose more of an immediate threat of toxicity and death upon exposure. A part of mitigating risks from spills is understanding where and how these products are transported.

In total, the Salish Sea waterfront includes 5 Washington oil refineries, 17 Washington marine transfer terminals (separate from refineries), and 10 Canadian marine transfer terminals (Fig. 1 and Table 1). According to Washington Research Council (2019), the five Washington State refineries along the Salish Sea coastline (listed here with their 2017 oil refining capacities) are: BP Cherry Point (37,524 liters/day, [2] in Fig. 1 and Table 1), Shell Oil (23,691 liters/day, [4] in Fig. 1 and Table 1), Marathon Petroleum (19,875 liters/day, [5] in Fig.

1 and Table 1), Phillips 66 (17,570 liters/day, [3] in Fig. 1 and Table 1), and U.S. Oil (6678 liters/day, [8] in Fig. 1 and Table 1). According to Washington Research Council (2019), the combined total crude oil and feedstock received by all five of these refineries in 2017 was 96,608 liters/day of which 44.8% was transported by marine shipping, amounting to 43,000 liters/day or 15,797,200 liters/year. For comparison, Washington State Department of Ecology (2019) estimates that 18,548,509 liters/year of crude oil are transported to these refineries by tank vessels. According to the data we received from Washington State Department of Ecology (2018), the twenty-two Washington marine terminals included in this study (all of which are land-based) transferred 38 billion liters of oil, 99% of which was crude oil. Washington marine terminals not included in this study are floating fuel docs or land-based terminals outside the Salish Sea (e.g. along the Columbia River and Lake Washington). These marine terminals that were not included in our study account for 3.2 billion liters of oil transferred with only 25% of these transfers being crude oil transfers.

U.S. consumption is the primary driver of Washington State oil refining with 53% of oil refined in Washington consumed in Washington and 81% of this Washington oil consumption being used by the transportation sector (c.f. 69% for all U.S. petroleum consumption (US Energy Information Administration, 2023b)). Within the transportation sector, 46% is used for "motor gasoline" (Washington Research Council, 2019). 40% of refined product goes to domestic out-of-state and 7% goes to foreign markets (Washington Research Council, 2019). U.S. consumption is also a primary driver of Canada's oil-cargo transport across the Salish Sea via the TransMountain Pipeline supply through Westridge Marine Terminal. Currently, 90% of tar sands' Dilbit exports to U.S. refineries (Oil Sands Magazine, 2023).

BP and Marathon marine terminals (Table 1) receive crude from Canada's TransMountain pipeline (the same pipeline that services Westridge marine terminal) while other Washington marine terminals receive North Dakota crude by rail and pipeline (see, e.g., Oil Spill Task Force (2022)). Exports of Bitumen from Washington State marine terminals is documented as being a negligible amount compared to total exports (Washington State Department of Ecology, 2018); however, it is possible that Bitumen transfers may have been recorded as "CRUDE" instead of "BITUMEN OIL (DIL OR SYN)" (pers. comm. Washington State Department of Ecology Spills Program, November 9, 2023). Washington State Department of Ecology put in place a new requirement (effective July 7, 2023) to record the origin, gravity (API or specific), sulfur content, and viscosity for all crude oil transfers, which may help reduce the inconsistency in the reported data (Washington State Department of Ecology, 2023a). This information on oil transfers is critical for understanding the geospatial landscape of oil transport by oil type, which in turn helps inform response needs. We encourage other countries and states to adopt this practice in support of preparation and planning.

4.4. *The future of oil in the Salish Sea*

The spatial variation in oil type impacts is a natural consequence of the geographic variations in oil transfers at marine terminals (partially shown in Fig. 6) as well as the different traffic patterns of vessels with different oil capacities (Fig. 2, Fig. 8). Oil transfers and traffic patterns vary with changes in regulations and terminal expansions. Here, we discuss how regulatory changes will affect the transport of persistent oils across the Salish Sea.

Prior to the marine terminal expansion in 2024, Canada's Westridge Marine Terminal exported 60 Aframax tankers (~7.2 billion liters) of Canada Conventional crude and Dilbit each year (Kanjilal, 2019). The projected volume export after the expansion was to increase export to 408 Aframax tankers a year, or ~49 billion liters per year. To our knowledge, Parkland Refinery (the only Canadian refinery in our study domain) does not import crude by marine transport (pers. comm. Bikramjit Kanjlal, June 18, 2020). We estimate that Washington refining accounts for 72% of crude oil transported across the Salish Sea in 2018 and that Canada's export of crude oil accounted for 28%. Assuming that Washington refining has remained similar, crude oil transport across the Salish Sea is shifting toward 27% Washington transport and 73% Canada export (albeit presumably to U.S. markets). This traffic shift accounts for an increase in Westridge Marine Terminal export of around 41.8 billion liters per year (Trans Mountain Corporation, 2023), corresponding to a ~7-fold increase in Aframax tankers servicing this terminal (Kanjilal, 2019).

Terminal expansions will also change the landscape of risk. These expansions are being planned for a variety of reasons in response to supply and demand across different industries. As we have explained in this paper, different fuel and cargo types carry different risks as does an increase in vessel traffic, which could also increase the amount of polluted byproduct from scrubbing. Fuels like LNG, Hydrogen, Ammonia, and Methanol are being developed as alternatives to oil and may reduce marine impacts due to oil but carry different risks to human health and to global warming. Using Washington State Department of Ecology's requirement to document product transfers together with AIS ship track data is an example of how monitoring the transport of these products can be used to help facilitate effective preparation and planning throughout ongoing changes.

5. Conclusion

A goal of this study was to support informed decision-making in advance of a major spill by evaluating the risks from a major oil spill in the Salish Sea, with a particular interest in the possible impacts from a major crude oil spill. Crude oil spills have unique response and recovery challenges in addition to causing more persistent impacts (Zhong et al., 2022; NOAA Office of Response and Restoration, 2023). A couple of challenges around crude oil spills include the sinking of weathered crude to unrecoverable depths and the emulsification of crude into recovery volumes that can be up to 4 times the spill volume. The unique challenges of responding to a crude or large oil spill motivate comprehensive planning to help mitigate potential impacts. Our results highlight potential risks from 2018 marine oil transport with crude oil modeled as Alaska North Slope crude (ANS) and other persistent and non-persistent oils represented as Bunker-C and Diesel, respectively. We show that AIS ship track data can be combined with oil transfer data to more precisely identify oil transport and regional risks from spills of different oil types in the Salish Sea.

Based on 2018 traffic data, crude oil spills are most likely in the traffic corridors between Juan de Fuca Strait and the 5 Washington refineries. This area is also the region of greatest variability in potential spill volume for crude oils. Bunker-C and Diesel oil types are transported more broadly across all regions within the Salish Sea. For these oil types, the number of spills increases where focus vessels (e.g. ferries) are more prevalent. Across all oil types, regional differences in oil spill risk and uncertainty overlay regional heterogeneity of ecosystem dynamics, ranging from migratory pathways of upper trophic levels (like whales) to larvae incubation beds for lower trophic levels (like smelt). This combination of heterogeneity in oil spill risks and heterogeneity in ecosystem risks adds complexity to the challenge of accurately assessing oil spill impacts in the Salish Sea.

Here, we provide a comprehensive view of the statistical spills used in Part 2 (Mueller et al., 2025) and highlight the areas in which spill count and spill volumes are most variable between different iterations of 10,000 spills using the method described here. Our method is consistent in replicating number of spills (Fig. 8a), but varies in volume of spills (most greatly with large cargo or fuel vessels, Fig. 8b) due to the statistical nature of our method. Our study highlights the importance of coupling AIS ship track data with oil transfer data in the evaluation of oil spill risks in the Salish Sea. More research is needed to quantify how the regional impacts by oil type may vary by season and shipping or regulatory changes. Seasonal changes in the likelihood of oil type, location, and volume spilled may have important consequences to ecosystem dynamics that are not captured here.

CRediT authorship contribution statement

Rachael D. Mueller: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Susan E. Allen:** Writing – review & editing, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Stephanie Chang:** Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Haibo Niu:** Supervision, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Douglas J. Latornell:** Supervision, Software, Methodology, Conceptualization. **Shihan Li:** Methodology, Conceptualization. **Ryah Bagshaw:** Methodology, Investigation, Data curation, Conceptualization. **Ashutosh Bhudia:** Software, Methodology, Conceptualization. **Vicky Do:** Software, Methodology, Conceptualization. **Krista Forysinski:** Software, Methodology, Investigation, Conceptualization. **Ben Moore-Maley:** Visualization, Software, Methodology, Funding acquisition. **Cameron Power:** Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

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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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This work took place on the territories of the xʷmə θkʷə y̓ə m (Musqueam or "place of the mə θ kʷy̓ flower") First Nation and the federally recognized Lhaq'temish (Lummi or "People of the Sea") and Nooksack ("always bracken fern roots") Nations. These tribes have stewarded these lands since time immemorial and have rights to the governance of these lands and waterways that the authors of this paper are beginning to learn more about. We developed our understanding of how we can advance science together with reconciliation for indigenous communities during this project and have tailored the presentation of our results to better meet community preferences and needs.

The information in this paper reflects the views of the authors, and does not necessarily reflect the official positions or policies of NOAA or the Department of Commerce.

Appendix A. Barge and ATB types

In 2018, Spire Maritime recorded 50 unique tug MMSI. We assumed that all ATB oil tank barges are "married"–meaning that the AIS-tracked tug is only used to transport cargo for a particular oil barge–and we curated a list of 18 MMSI that we attributed as "married" ATBs that exclusively transport oil cargo. Fourteen ATB-tug MMSI were identified by the Washington State Department of Ecology oil transfer dataset (Washington State Department of Ecology, 2018) and 4 additional ATB MMSI were determined by online searches. Details of ATB attribution are in the data files archived at Mueller et al. (2018). The remaining 32 tug MMSI not included in our ATB category are assumed to transport either oil or non-oil cargo barges and comprise our "barge" traffic. The risk of a barge oil spill being a fuel spill versus an oil cargo spill was estimated by the ratio between the number of AIS pings associated with the 18 ATB MMSI and the number of oil cargo transfers with "ATB" or "ITB" in the "Receiver" or "Deliverer" name. The median ATB track distance is 6,321 km compared to 2,179 km for all other tug traffic. We scaled the ATB ping-to-transfer ratio by the track length ratio to estimate ~430 oil tank barge AIS vessel pings for every oil cargo transfer. The number of AIS pings associated with oil cargo was estimated as the product of the ping-to-transfer ratio and the total number of transfers, with the likelihood of a tug being attributed as a barge transporting oil cargo determined by the ratio of this product to the total number of AIS ship tracks (Mueller, 2019a).

Appendix B. Open research section

Data is archived with Canada's Federated Research Data Repository at https://doi.org/10.20383/103.01353. Our code is open access and available on GitHub (MIDOSS research team, 2018). Python 3.6 - 3.12 was used to pre- and post-process model output. Figures were made with Matplotlib version 3.8.2 (Hunter, 2007), available under the Matplotlib license at https://matplotlib.org/. The Miniconda coding environment can be replicated using https://github.com/MIDOSS/MuellerEtAl_MIDOSS_paper/blob/main/environment.yaml. Maps were created with Cartopy 0.22.0 (Met Office, 2010). Code for this project is licensed under either Apache 2.0 (https://en.wikipedia.org/wiki/Apache_License.in) or GNU licenses(https://www.gnu.org/licenses/old-licenses/gpl-2.0.en.html#SEC1), as specified on the repositories.

Appendix C. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.marpolbul.2025.118452.

Data availability

Access to our research code is available on GitHub at https://github.com/MIDOSS/MuellerEtAl_MIDOSS_paper (MIDOSS research team, 2018) and data is archived with Canada's Federated Research Data Repository at https://doi.org/10.20383/103.01353 (Mueller et al., 2018).

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