

# **Current Status of Modelling Trajectories of Lost Shipping Containers in the Oceans**

Brandon J. McNabb, Hauke C. Blanken, Leif-Matthias Herborg, Kayleigh Gillespie, Cathryn Clarke Murray, Michelle Bigg, and Anya Dunham

Ocean Sciences Division  
Pacific Region  
Fisheries and Oceans Canada

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## **Canadian Technical Report of Hydrography and Ocean Sciences**

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## **Abstract**

McNabb, B.J., Blanken, H.C., Herborg, L.-M., Gillespie, K., Murray, C.C., Bigg, M., and Dunham, A. 2025. Current Status of Modelling Trajectories of Lost Shipping Containers in the Oceans. Can. Tech. Rep. Hydrogr. Ocean Sci. 408: vi + 68 p.

Every year, shipping containers lost overboard at sea present ecological, pollution and collision risks to the oceans and mariners. This report addresses the current capabilities for trajectory modelling of these lost containers, with relevant methodologies synthesized from related fields, where applicable, to bridge key gaps. Topics discussed in this review include the key physical forcings and container properties that influence their trajectories at sea; the sources and limitations of various data and model outputs available to force trajectory models; various approaches applicable to modelling surface drift of containers, such as the leeway method, stochastic ensemble techniques, multi-model ensembles, fuzzy numbers, machine learning, and backtracking; and the factors, forces and approaches relevant to developing a novel sinking trajectory model for shipping containers. Potential approaches to addressing the uncertainties associated with trajectory model frameworks and forcing data resolutions are also discussed.

## **Résumé**

McNabb, B.J., Blanken, H.C., Herborg, L.-M., Gillespie, K., Murray, C.C., Bigg, M., and Dunham, A. 2025. Current Status of Modelling Trajectories of Lost Shipping Containers in the Oceans. Can. Tech. Rep. Hydrogr. Ocean Sci. 408: vi + 68 p.

Chaque année, les conteneurs maritimes perdus en mer présentent des risques écologiques, de pollution et de collision pour les océans et les marins. Ce rapport aborde les capacités actuelles de modélisation des trajectoires de ces conteneurs perdus, en intégrant des méthodologies pertinentes issues de domaines connexes, lorsque cela est applicable, afin de combler des lacunes clés. Les sujets abordés dans cette revue incluent les principales forces physiques et les propriétés des conteneurs qui influencent leurs trajectoires en mer; les sources et les limites des diverses données et résultats de modèles disponibles pour alimenter les modèles de trajectoire; les différentes approches applicables à la modélisation de la dérive de surface des conteneurs, telles que la méthode du “leeway”, les techniques d’ensemble stochastiques, les ensembles multi-modèles, les nombres flous, l’apprentissage automatique et le rétrocalcul; ainsi que les facteurs, les forces et les approches pertinents pour le développement d’un modèle de trajectoire de naufrage inédit pour les conteneurs maritimes. Les approches potentielles permettant de traiter les incertitudes associées aux cadres des modèles de trajectoire et aux résolutions des données de forçage sont également discutées.

## 1.0 Introduction

The global demand for marine commercial shipping of goods has continuously increased over the past two decades, with port traffic nearly 274% higher in 2022 compared to 2000 (World Bank Group, 2025). The increasing number of commercial shipping vessels in operation comes with an increasing risk of accidents and cargo loss. The latter primarily occurs through spillage of shipping containers into the oceans, which may be due to several factors, including improperly secured connections between containers, improper stack heights and distribution of container weight (*e.g.* heavier containers stacked atop lighter ones, and uneven distribution of interior contents), overweight containers, weakened container structural integrity, navigational errors resulting in abrupt ship motion, and extreme weather (Frey & De Vogelaere, 2014; Saliba et al., 2022).

Estimates on the total number of containers lost at sea vary greatly. During the early 2000s, many media outlets reported that a maximum of 10,000 containers may be lost at sea per year (reviewed in Frey & De Vogelaere, 2014). Subsequent surveys, however, have produced more conservative estimates of annual loss rates. The World Shipping Council (WSC) estimates an average of 1,566 containers were lost at sea per year between 2008 and 2022, based on self-reporting of member shipping companies (WSC, 2023). A similar survey by the Surfrider Foundation Europe estimates that a total of 16,635 containers have been lost at sea between 1994-2019, with an annual container loss rate of 1,390 between 2013-2016 (Surfrider Foundation Europe, 2019). Unfortunately, recovery rates are estimated to be only 2.6% between 1994 and 2019 (Surfrider Foundation Europe, 2019), although a 33% recovery rate was reported for 2023 (WSC, 2024).

It is important to note that shipping container losses at sea are not evenly distributed throughout time (Fig. 1). Rather, they are marked by catastrophic spill incidents that, on average, represented 64% of total container loss between 2008-2017 (WSC, 2017). For a comprehensive list of spill events from 1917 to 2021 the reader is referred to Saliba et al. (2022). Some notable modern examples of these events include the 2004 storm-driven loss from the *M/V Med Taipei* (Frey & De Vogelaere, 2014; MBNMS, 2011); the 2011 grounding of the *M/V Rena* (Ross et al., 2016; TAIC, 2012); the 2013 sinking of the *MOL Comfort* (WSC, 2023); the 2015 sinking of the *SS El Faro* (NTSB, 2017); the 2020 storm-driven loss from the *ONE Apus* (JTSC, 2024; Wan et al., 2022); and in 2021, the *X-Press Pearl* disaster (Partow et al., 2021; Sewwandi et al., 2022; X. Zhang et al., 2023). Also in 2021, the *M/V Zim Kingston* experienced heavy parametric rolling (up to 36°) induced by 5-6 m wave swells that caused the collapse of container stacks into Canadian waters along the coast of British Columbia (TSB, 2024). The event led to a total of 109 containers being lost at sea (Sutherland et al., 2024; TSB, 2024). In total, between 24 to 4,293 containers were lost at sea during each of the catastrophic incidents listed above.

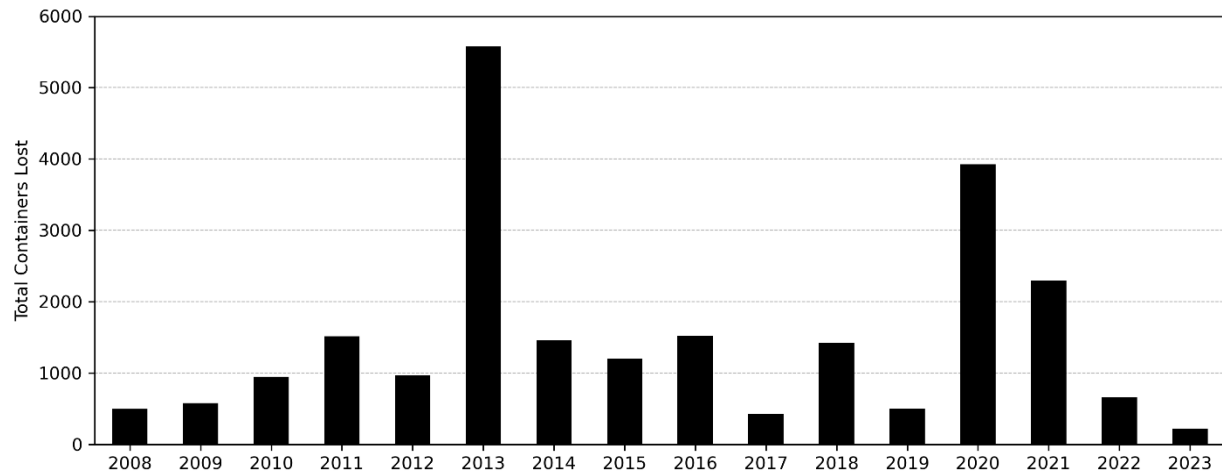


Figure 1. Time-series of estimated annual total container loss at sea from 2008-2023 (WSC, 2024).

Developing models to robustly track the fates of these lost containers is critical, as they may pose serious ecological and toxicological risks to marine life. The contents of shipping containers can vary greatly, ranging from commercial products to hazardous and noxious chemicals (Saliba et al., 2022). Deformation and damage of fallen containers can result in the spillage of these contents into the oceans. During the 2021 *X-Press Pearl* disaster, shipping container loss resulted in significant amounts of spilled nitric acid (25 tons), caustic soda (1,040 tons), methanol (210 tons), epoxy resin (9,700 tonnes) and plastics (1610 tonnes) (Partow et al., 2021), which coincided with an unusual increase in sea turtle mortalities (+744%) (Ekanayake et al., 2023) and mass mortalities of fish (Cumaranatunga et al., 2023). A significant release of microplastic nurdles during this event (Sewwandi et al., 2022) likely contributed to wildlife mortalities through ingestion (Cumaranatunga et al., 2023). While microplastic release from container loss incidents represents an emerging pollution issue (Turner et al., 2021; Wan et al., 2022), larger plastic debris released from containers will also wash up along shorelines following these events (TSB, 2024). Some of these plastic debris will also likely weather and degrade to form a source of microplastics (Sewwandi et al., 2022; Turner et al., 2021). There is evidence that continual release of larger debris from sunken containers remains a problem well after the initial loss incident (TSB, 2024), motivating the development of modelling tools to aid in locating these containers and characterizing the potential spread of associated debris.

The grounding of sunken containers on the seabed can also produce significant initial damage and disturbance to benthic marine fauna communities (Taylor et al., 2014). Over time, these sunken containers may eventually act as artificial reef systems, providing a hard substrate for benthic organisms to colonize (McDermott et al., 2023; Taylor et al., 2014). However, colonization observations are thus far only available from a single container lost during the 2004 *M/V Med Taipei* incident (Frey & De Vogelaere, 2014). In other instances where lost containers

contained toxic chemicals, such as during the 2021 *M/V Zim Kingston* and *X-Press Pearl* incidents (Partow et al., 2021; TSB, 2024), undamaged containers spilled into the ocean may subsequently incur structural damage from seafloor impact, which could release these chemicals into the nearby sediments or create subsurface liquid plumes (Partow et al., 2021). The ecological impacts of such scenarios are largely unknown.

Finally, containers can drift for weeks and become mostly immersed in seawater (Fig. 2), which reduces their visibility to other vessels and increases risks of collisions, particularly during poor weather (Daniel et al., 2002; McDermott et al., 2023). Although collisions are suggested to be rare (Fretter, 2017), they do occur; one confirmed report exists of a fishing vessel sinking from damage sustained due to colliding with a drifting container (Comisión Permanente de Investigación de Accidentes e incidentes Marítimos, 2015), while at least eight yacht collisions with suspected containers have been reported alongside near misses (Fretter, 2017; Kraken Yachts, 2021). There are also concerns that unmapped sunken containers present a collision risk for trawling nets and may endanger fishing vessel crew (pers. comm. BC Deep Sea Trawling Association). Development and implementation of container collision avoidance systems for vessels is ongoing (Molina-Padrón et al., 2024), and accurate modelling of container drift trajectories following loss events can identify risk areas for vessels to avoid.

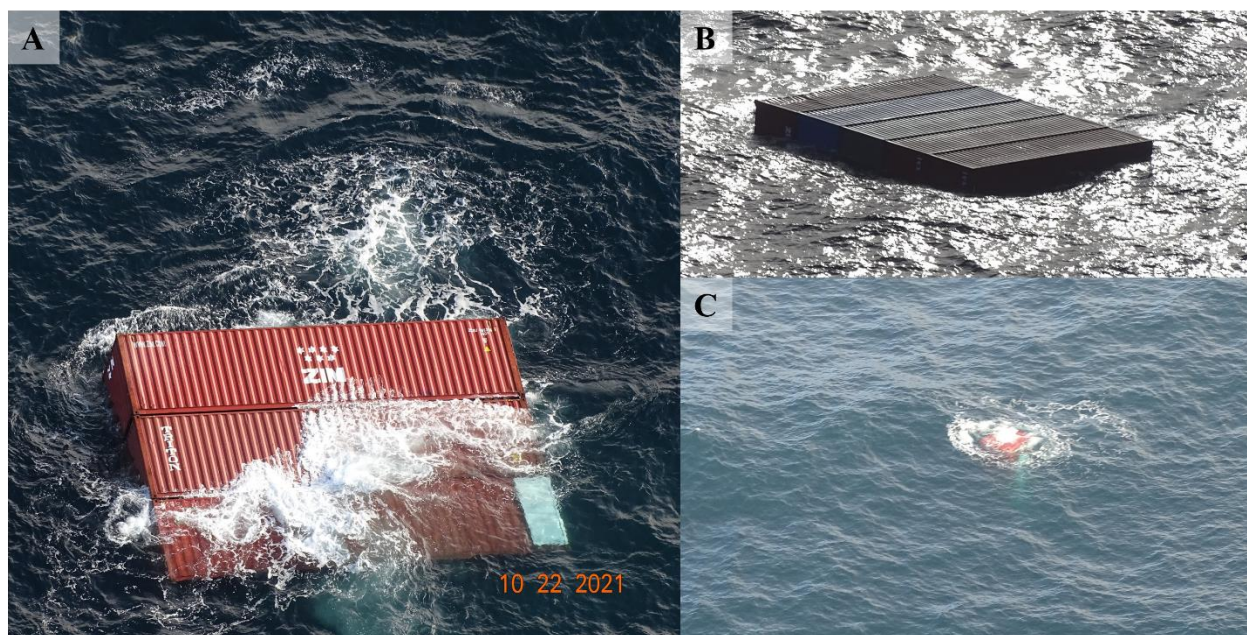


Figure 2. Examples of drifting shipping containers. (A,B) Examples of adrift rafted container stacks. (C) Single adrift container immersed longitudinally (source: U.S. Coast Guard).

Robust modelling systems to track the fates of lost containers are therefore a crucial tool to assist in assessing environmental impacts, mitigating collision risks with other vessels, and

narrowing search fields for recovery and clean-up efforts. Cases of drifting containers have received the most attention, since drift parameterizations and trajectories can be validated by observational experiments and beached containers (Breivik, Allen, et al., 2012; Breivik et al., 2011; Daniel et al., 2002). The fundamental approach to modelling surface drift of lost shipping containers assumes that drift is primarily current and wind-driven, and container drift is thus parameterized as a force balance between drag from the ambient water and air on exposed sections of the container (Breivik et al., 2011; Daniel et al., 2002). This approach often involves discretizing the wind forcing vectors into separate crosswind and downwind components (known as the ‘Leeway’ method) (Allen & Plourde, 1999; Breivik & Allen, 2008). In practice, trajectory models for drifting objects contain significant stochastic components, and various approaches have been developed to address these. For example, empirically-derived coefficients describing downwind and crosswind motion (leeway coefficients) can be ensembled with random sampling approaches (e.g. Monte Carlo) to address uncertainty in container trajectories (Breivik & Allen, 2008). Further work has built on this approach by explicitly parameterizing geometric effects on wind drag forcing (Wang et al., 2014). More recent alternative approaches have addressed this stochastic uncertainty through the use of fuzzy numbers (Blanken et al., 2021, 2023) machine learning (Bhaganagar et al., 2022; Song et al., 2024), or random walk approaches (Beegle-Krause, 2001; Dagestad et al., 2018; De Dominicis, Pinardi, Zodiatis, & Archetti, 2013). Regardless of the trajectory modelling approach, factors such as the container’s immersion level (Daniel et al., 2002), geometry (Allen & Plourde, 1999; Breivik et al., 2011) and physical properties (e.g. density); level of detail resolved by the input hydrodynamic and atmospheric models used (Blanken et al., 2023; Breivik & Allen, 2008); and relevant physical forcings will need to be appropriately accounted for, as each has a strong influence on the modelled drift trajectories.

Most lost containers do not remain drifting in the surface ocean. During the 2021 *M/V Zim Kingston* incident, only 4 of 109 (~3.7%) containers remained afloat long enough to drift ashore (Sutherland et al., 2024), and more broadly, only 0.25% of lost containers reported in 2021 were washed ashore (McDermott et al., 2023). A small fraction of the remaining containers are likely undiscovered onshore or continuing to drift, leaving the vast majority of the remaining lost containers presumed to have sunk to the seafloor. Predicting trajectories and settlement locations of these sunken containers is a significant challenge, and available literature in this area is scarce. The main physical forcings affecting container sinking trajectories will be subsurface currents, and it has been noted that short-term, turbulent currents due to factors such as internal waves (Ouimet & Cortés, 2013) and eddy forcing (Thomson et al., 1990) are likely significant. Experimental work exploring falling containers has shown their impact angle with the surface ocean can induce initial rolling velocity that translates into horizontal migration (Y. Li et al., 2022), which may be exacerbated by subsurface currents. Analogous studies modelling the sinking trajectories of dropped pipes have further supported this (Xiang et al., 2017, 2019). Modelling of containers that are initially surface drifting and subsequently become inundated with water and sink has not been explored to date. In these cases, the porosity and weight of the

containers will likely be key determinant factors in parameterizing their sinking behavior. Additionally, final container seafloor settlement locations may not necessarily align with initial seafloor impact locations; mobilization along the seafloor can be induced by current and wave forcing, and the degree of movement will be dependent on weight of the containers, the current and wave forcing, and sediment characteristics (*e.g.* density and grain size) (Chu et al., 2022). Storm-driven current and wave forcing may also further re-mobilize sunken objects, likely including containers, over time (Papili et al., 2014). Ultimately, trajectory models will need to capture both the drifting and sinking components of lost containers at sea to provide a complete picture of their fates.

This report addresses the current state of models for the fate of lost shipping containers at sea, aiming to 1) summarize key methodologies for modelling trajectories of drifting and sinking containers, and 2) synthesize relevant methodologies from related fields, where applicable, to bridge key gaps in container trajectory modelling. The sections of this report are organized as follows: Section 2.0 reviews the various factors and considerations that generally influence all modelling approaches for the fate of lost shipping containers. Section 3.0 outlines common sources of input data for trajectory models, including observations and hydrodynamic/atmospheric models. Section 4.0 reviews the available methods used to model trajectories of surface drifting containers. Section 5.0 discusses the problem of modelling container sinking trajectories and locating sunken containers along the seafloor. As this is significant gap in current research, this section draws methods from related fields that hold promise to be applicable to modelling shipping containers. Section 6 identifies the key limitations in our current modelling capabilities and opportunities to adapt methodology from related marine problems to modelling the fate of lost shipping containers at sea.

## **2.0 Factors and considerations for predicting trajectories**

### **2.1 Overview**

The following section outlines physical processes and container properties that significantly influence the trajectories of drifting and sinking containers. General sources of uncertainty applicable to all model frameworks are also discussed, along with approaches to handle these uncertainties.

### **2.2 Physical forcing**

### 2.2.1 Primary forcing mechanisms

For surface drifting containers, trajectory models are typically derived from the balance of forces acting upon them. The primary external forces are the wind drag forces ( $F_a$ ) on the air exposed surfaces, and the water drag ( $F_w$ ) on the submerged surfaces (Fig. 3). The height/depth of the container above/below the sea surface ( $Z_a/Z_w$ ; Fig. 3A) determine the relative contributions of the wind and water drag forces to the container's net motion. Vertical forces (*i.e.* buoyancy,  $F_b$ , and gravity,  $F_g$ ) are generally assumed to be balanced for floating objects, but can become imbalanced if water ingress due to structural damage and/or changes in orientation of existing vents leads to sinking (Fig. 3A; see Sections 2.3-2.6, and 5.0).

For motion in a rotating reference frame, Coriolis forcing must be considered (Blanken et al., 2021; Daniel et al., 2002) (Fig. 3). Wave radiation forcing can be assumed negligible for objects shorter than 30 m in length, where the wavelength in typical sea states typically exceeds the objects length by approximately six-fold (Breivik et al., 2011; Breivik & Allen, 2008), and is therefore usually ignored (Blanken et al., 2021; Daniel et al., 2002; Röhrs et al., 2012). Nonetheless, direct wave effects are not completely negligible. As discussed in Section 2.2.3, Stokes drift arising from wave orbital motion (Fig. 3B) may have significant effects on drift trajectories (Bosi et al., 2021; Sutherland et al., 2024). The Coriolis term associated with the container itself is also typically ignored (Daniel et al., 2002). Rotational effects on currents and winds are accounted for in the calculation of air and water drag. However, rotational effects also result in tilting in the orbital motion produced by wave-driven Stokes drift ( $u_s$ ) that produces a separate Coriolis-Stokes force ( $f \times u_s$ ; Fig. 3C, Polton et al., 2005), and research suggests that consideration of this forcing can further improve trajectory models (see Section 2.2.4). Notwithstanding this caveat, surface drifting trajectory models are usually simplified to a force balance between the water and airside drag forces (Blanken et al., 2021; Daniel et al., 2002).

The drag forces on a container are a quadratic function of the velocity differences between the containers drift velocity and the wind and current (Daniel et al., 2002; Röhrs et al., 2012). However, since wind speeds generally far exceed the container drift speed, the wind drag force is usually computed from the wind speeds alone. This introduces some methodological uncertainty at low wind speeds, especially when they coincide with strong currents. Further, since drift speed is generally greater than the current speed but less than the wind speed, drag forcing from the water generally opposes wind drag and slows the container's drift. When wind speed goes to zero, so does the difference between the container's drift velocity and the ocean current velocity, and therefore all drag forces go to zero. The relative strengths of the wind and current drag forces are also proportional to the cross-sectional areas of the air-exposed and submerged portions of the containers, respectively (*i.e.* the immersion ratio; see Section 2.4). Therefore, as discussed in Section 2.2.2, the near-surface vertical shear in wind and current velocity must be adequately resolved to accurately determine drag forces.

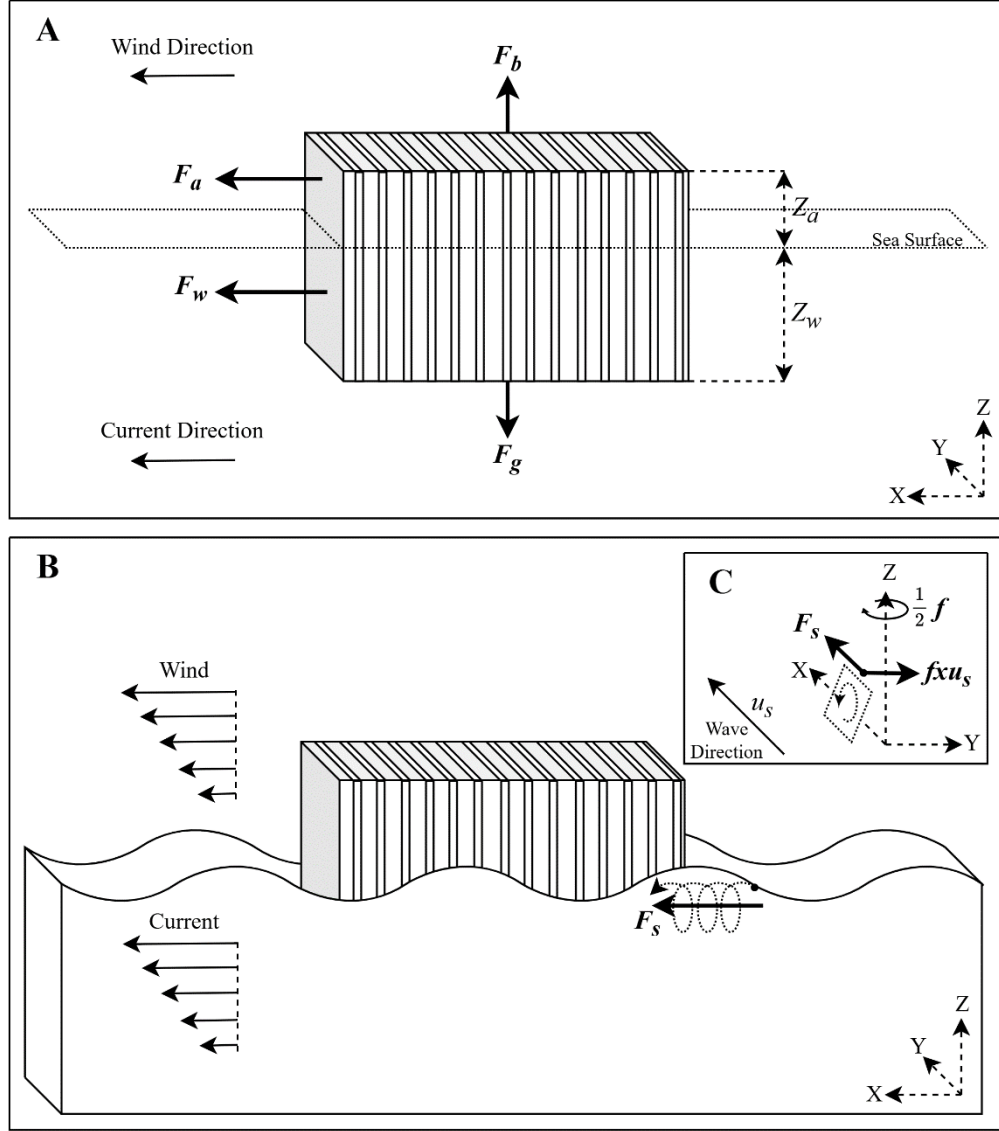


Figure 3. Forcing relevant to the surface drift of lost shipping containers. (A) Free body diagram of forces acting on a floating shipping container, as described in text (adapted from Daniel et al. (2002)). (B) A drifting container in a surface wave field, depicting the wind/current shear profiles, motion due to Stokes drift, and the Coriolis-Stokes forcing (inset panel (C); adapted from Polton et al. (2005)). Note that the cartesian coordinates in (C) are rotated by 90 degrees about the z-axis relative to (A,B).

### 2.2.2 Current and wind shear

Both currents and winds are strongly sheared near the water surface due to boundary layer effects (Fig. 3), and it is necessary to characterize the shear between the measurement height/depth and the level of the container (Blanken et al., 2021; Craig & Banner, 1994; Röhrs,

Halsne, et al., 2023). Shear is an important consideration for containers, as their immersion level is likely to vary with time (see Section 2.4) (Craig & Banner, 1994; Röhrs, Halsne, et al., 2023). Wind shear is an important consideration since winds are generally reported at a reference height of 10m. In order to accurately quantify the wind drag term on a container floating partially above the water surface, the change in wind speed between the 10m reference height and the level of the container must be accounted for (see Section 3.0). One approach for this is to interpolate over known shear relationships for a range of wind speeds and degrees of atmospheric stability (given by the difference between sea surface temperature and air temperature at the wind reference height) (Blanken et al., 2021; S. D. Smith, 1988). For drift tracking studies employing anemometers attached directly to the containers (Daniel et al., 2002), parameterizing wind shear is not necessary. Further, wind drag is no longer applicable once the container becomes fully immersed. In this case, the container can be considered to follow the subsurface currents.

### 2.2.3 Stokes drift

Stokes drift describes the cumulative advection of an object, or parcel of water, that arises from the orbital motion induced by propagating wave crests (Stokes, 1847) (Fig. 3B). Stokes drift is relevant only to surface drifting objects, as it rapidly decays within meters below the surface (Clarke & Van Gorder, 2018; van den Bremer & Breivik, 2018). Since Stokes drift acts in the direction of the wave field, it is generally thought to also act in the direction of wind forcing. Because of this, Stokes drift has generally been ignored in leeway calculations for surface drift trajectories, as it is assumed that Stokes drift primarily acts along the downwind component and is thus implicitly accounted for in empirically derived leeway components (Breivik et al., 2011; Breivik & Allen, 2008).

However, Stokes drift can be explicitly considered in trajectory models (Röhrs et al., 2012; Sutherland et al., 2020, 2024). Moreover, due to the presence of swell, Stokes drift does not necessarily act in the direction of wind forcing as originally assumed, suggesting the effects of Stokes drift may be underestimated (Röhrs et al., 2012; Tamtare et al., 2022). More recent modelling work has confirmed that when Stokes drift is considered directly, it can produce first-order improvements (Blanken et al., 2021; Röhrs et al., 2012) on trajectory predictions, and the effect is particularly pronounced for objects with extended drifting periods before seafloor settlement or beaching (Bosi et al., 2021; Sutherland et al., 2024). In their analysis of drift trajectories of containers released from the *M/V Zim Kingston* incident, Sutherland et al., (2024) report that deviances in predicted trajectories can reach 95 km after 5 days when Stokes drift is not incorporated into leeway calculations. Similar work has described ~34-40% reductions in the mean separation distances between drifter observations and modelled trajectories (Tamtare et al., 2022). Furthermore, other recent studies have demonstrated the importance of Stokes drift in producing more accurate trajectory calculations for debris drift from the missing Malaysian flight

370 (Durgadoo et al., 2021) and dispersed microplastics (Bosi et al., 2021). Thus, Stokes drift is an important forcing term that needs to be explicitly considered when assessing the trajectories of containers drifting at the ocean surface.

#### 2.2.4 Coriolis-Stokes drift

There exists an interaction between the Stokes drift and Coriolis force, where the orbital motion by Stokes drift is tilted due to the planetary vorticity (Polton et al., 2005; Weber et al., 2015). This tilt creates a horizontal velocity component that is correlated to the vertical velocity component, but at an angle diverging from the wave direction, creating a forcing known as the Coriolis-Stokes force (Polton et al., 2005) (Fig. 3C). This divergence angle produced by the Coriolis-Stokes force can be significant (Lewis & Belcher, 2004; Polton et al., 2005), and the Coriolis-Stokes force can be up to 80% of the magnitude of the Coriolis force alone (Röhrs et al., 2012). This forcing may therefore be a significant source of uncertainty for drift trajectory modelling, which has not been addressed to date. For modelling submerged container trajectories, the Coriolis-Stokes force will be of lesser importance, as its effects are constrained to the surface ocean (Blanken et al., 2021; Ekman, 1905; Polton et al., 2005; Röhrs & Christensen, 2015).

### 2.3 Container physical properties

The physical properties of a shipping container and its contents play a key role in determining its drifting and/or sinking trajectories as they largely determine how much of the container is exposed to the air and the water. Typically, shipping containers are either a standardized 20 ft (6.058 x 2.438 x 2.438 m) or 40 ft (12.192 x 2.438 x 2.438 m) size (Daniel et al., 2002), although special variations are in use (AIMU, 2008).

The weight and buoyancy of lost containers will be determined by the contents, which can vary significantly from fairly benign raw goods to hazardous chemicals (Partow et al., 2021; TSB, 2024). During the 2021 *M/V Zim Kingston* incident, containers that were found to have drifted and washed ashore contained lighter, more buoyant cargo (e.g. plastics, refrigerators) (TSB, 2024). Insulated containers with airtight sealing (e.g. refrigerated containers) will also be more likely to remain buoyant and adrift (AIMU, 2008). Conversely, overweight containers are believed to be a contributing factor to container loss events (Frey & De Vogelaere, 2014); during the 2007 *MSC Napoli* grounding event, 20% of the containers onboard were overweight by 3-20 metric tons (AIMU, 2008), and overweight containers have also been identified in the review of the *M/V Zim Kingston* incident (TSB, 2024).

Object geometry, and consequently the level of immersion of a drifting container, is a key variable in drift trajectory modelling as changes in draft and shape directly translate to important changes in drift behavior (Röhrs & Christensen, 2015; Sutherland et al., 2020). Different studies have attempted to either consider the effect of geometry analytically (*cf.* Blanken et al., 2021; Daniel et al., 2002) or through empirical determination of the drift of different types of objects relative to the wind and current (*i.e.* the Leeway method; Allen & Plourde, 1999; Breivik & Allen, 2008).

Jibing, swamping and capsizing are key variables that can affect drift trajectory predictions based on the Leeway method (Breivik & Allen, 2008). Jibing (taken from sailing terminology) describes a change in direction of an object's drift in the water, which affects the crosswind leeway components (Allen, 2005; Breivik & Allen, 2008). Objects experience jibing primarily in weak or strong winds, rather than intermediate winds (Allen, 2005). For drifting shipping containers, jibing may change the drift orientation of the container from being in longitudinal alignment with the wind direction to longitudinally perpendicular to the winds. This can increase the chances of wave action causing capsizing or rollover of the container, which may lead to the container side with ventilation holes becoming immersed, thereby increasing water intake and immersion levels (Ren et al., 2024) (see Section 2.4). In orientations where the ventilation holes are not submerged, wave splashing can still gradually increase water intake. Over time this may lead to complete swamping and sinking of the container.

Punctures in a container from physical impact can also lead to swamping and sinking. During container loss events, container stacks can become unstable and collapse. This can lead to damage to falling containers from impact with other containers, the ship's equipment, the vessel itself, or with the sea surface (Frey & De Vogelaere, 2014; McDermott et al., 2023; TSB, 2024). The battering effects of waves over time can further exacerbate damage to containers and will dictate how quickly containers sink or remain suspended and drifting at the surface (McDermott et al., 2023). Impact with the seafloor may also result in damage to sinking containers (Fig. 4).

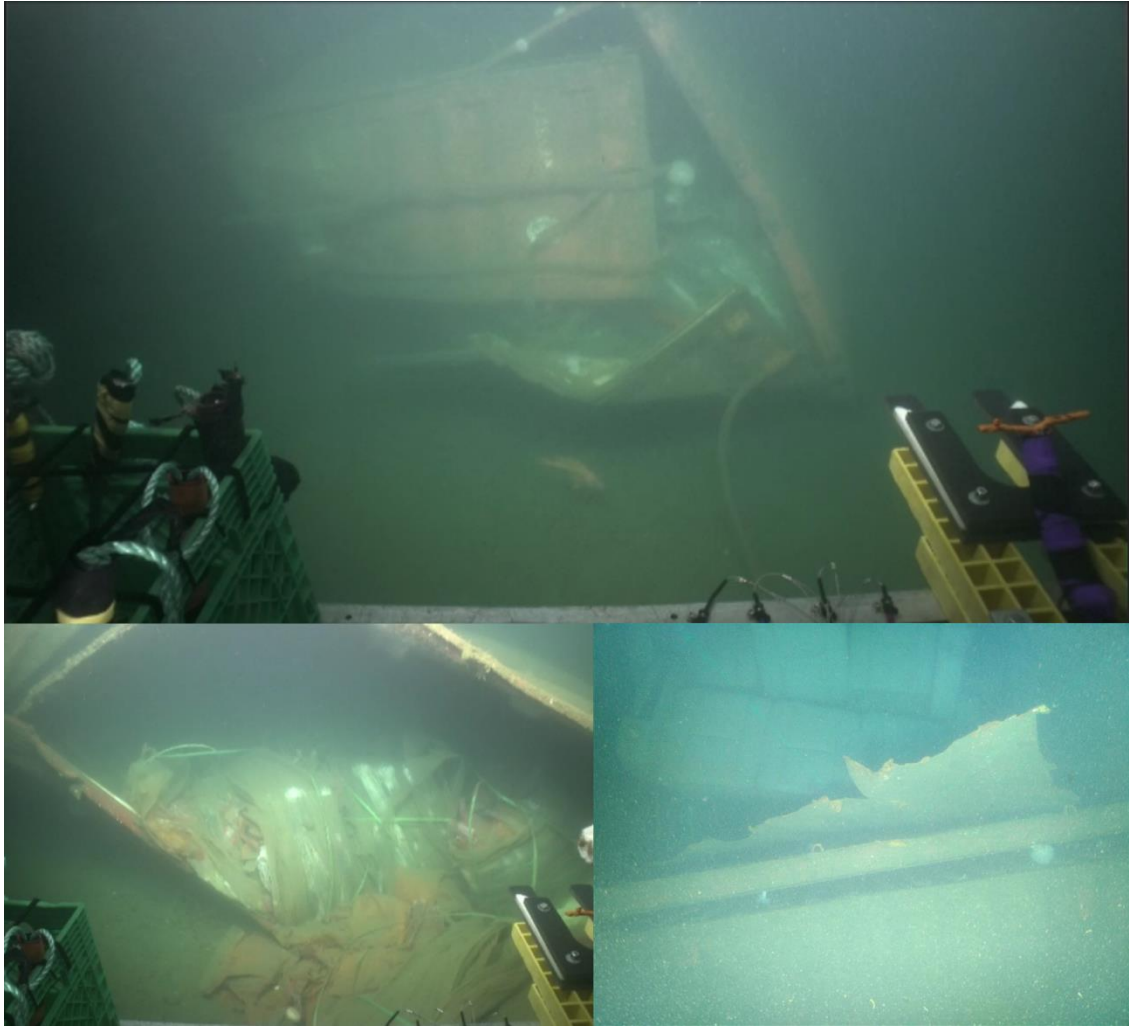


Figure 4. Remotely operated vehicle (ROV) imagery of damaged sunken containers from the 2021 *M/V Zim Kingston* incident (source: DFO).

Undamaged shipping containers are typically uniform in size and shape, and drift in an upright orientation. However, changes in mass distribution may alter the orientation of floating containers. This can result from improperly braced contents shifting inside the containers as they pitch and roll to wave forcing. This mass re-distribution can induce tilt of the container, changing the geometry and surface area of both submerged and air-exposed fractions, which will in turn affect the strength of wind and water drag forcing (Daniel et al., 2002; Ren et al., 2024). It will also have a direct effect on the crosswind components in leeway models (Breivik, Allen, et al., 2012). Likewise, highly compressible shipping materials (*e.g.* Styrofoam or plastics) can allow for mass re-distribution as they are compressed by increasing pressure while sinking. This re-distribution will change the orientation of sinking containers, which will in turn affect the container's orientation relative to subsurface currents and thus its sinking trajectory (Xiang et al., 2017, 2019). In most cases, the weight and mass distribution of containers will be unknown *a*

*priori*, and models to date have not directly incorporated mass distribution effects, although methods parameterizing geometric changes in container orientation will implicitly account for some these effects (Ren et al., 2024).

## 2.4 Immersion level

Early work identified the immersion ratio (*i.e.* the ratio between the submerged and air-exposed container surface areas,  $Z_w/Z_a$ ) as a key factor in parameterizing trajectories of surface drifting containers (Daniel et al., 2002). The immersion ratio is mainly dependent on the weight of both the container and its contents, as well the number of openings in the container. More air-tight container designs (such as refrigerant containers) will have smaller immersion ratios compared to ventilated containers (AIMU, 2008). Container contents will also determine the immersion ratio, as a cargo of less dense materials (*e.g.* Styrofoam, plastics, wood, etc.) is likely to maintain buoyancy while reducing the amount of total water ingress. As mentioned previously, mass re-distribution of container contents will also affect the overall immersion ratios of containers (see Section 2.3).

For drifting containers with reduced immersion, their greater air exposure results in their drift trajectories being strongly dependent on wind drag forcing, whereas more immersed containers primarily respond to water drag forcing (Daniel et al., 2002; Ren et al., 2024). The wind-driven leeway motion of containers is inversely proportional to the immersion ratio (Daniel et al., 2002; Geyer, 1989; O'Donnell et al., 1997) and leeway predictions for drifting shipping containers are sensitive to their immersion levels (Breivik, Allen, et al., 2012). In particular, high immersion levels tend to result in less accurate results from the leeway method due to the wind forcing becoming a less important forcing term (Breivik, Allen, et al., 2012; Daniel et al., 2002). This is because available information on currents is often more sparse and sometimes less accurate.

In cases where the contents of lost containers can be identified from the shipping manifest, it is possible to estimate a container's immersion level based on its gross weight. However, in most cases, immersion level is not known *a priori*. For the purpose of trajectory modelling can be either estimated by aerial surveillance (Sutherland et al., 2024) or trajectories can be calculated across a range of possible immersion levels (Breivik, Allen, et al., 2012; Daniel et al., 2002). Even if the contents are known, structural damage sustained during the container loss event may result in increases in water intake and foundering that will increase immersion levels, but are difficult at best to quantify. Containers that incur significant structural damage during the loss event are likely to rapidly sink to the seafloor near the point of entry into the ocean (Xiang et al., 2017, 2019).

Typically, leeway modelling studies simplify immersion level parameterizations by setting immersion ratios as a fixed percentage for the duration of the simulation (Breivik, Allen, et al., 2012; Daniel et al., 2002). In reality, immersion levels are usually variable. Even undamaged containers are not typically water tight, as they are commonly designed with ventilation holes (AIMU, 2008) that will inevitably allow seawater to seep inside containers at a rate depending on container orientation (see Section 2.3). Recent work has shown that parameterizing variable immersion levels can help improve leeway model predictions (Ren et al., 2024). Depending on the training dataset used, immersion levels may be implicitly parameterized for by machine learning models (Bhaganagar et al., 2022). For other modelling approaches, sensitivity to immersion levels has not been explicitly tested to date.

## 2.5 Sources of uncertainty

Uncertainty in trajectory models for lost containers arises from two primary source categories: information available about the nature of the loss event, and information about the currents, winds, and waves used to force the model. The former category includes the size, type, and weight of the containers, which may or may not be available from the cargo manifest, as well as the time and location of the loss event. Time and location of the loss may be well constrained if the vessel is at anchor or grounded and attentively monitored, however uncertainty can arise when the vessel is transiting or drifting during the loss event. The crew may be fully engaged in the operation of the vessel during these times, and uncertainty about both location and time of container losses (which can occur repeatedly over several hours, such as in the *M/V Med Taipei* incident; Frey & De Vogelaere, 2014) can arise if losses are not noticed and recorded promptly. Forcing fields for trajectory models generally vary in time and space, and therefore any uncertainty in initial time and location directly results in trajectory uncertainty, which can be reduced through stochastic sampling of possible initial times and locations (Breivik & Allen, 2008) (see Section 4.3).

Additional uncertainty is associated with forcing data for the trajectory model. Forcing can be either based on observations of currents, waves, and wind, or hydrodynamic and atmospheric models. Observations are generally collected at a fixed location in space, and the representation uncertainty associated with using this data to make trajectory predictions at another location is significant, even if the other location is nearby. Observational data is also generally collected at time intervals of tens minutes to hours, greater than the time step of a trajectory model (seconds to minutes). Therefore short-term fluctuations, which may have a significant impact on trajectories, will not necessarily be captured by observations. Similarly, state-of-the-art hydrodynamic and atmospheric models with coarser spatial and/or temporal resolution will not adequately resolve local small-scale variability. A more detailed discussion of forcing data sources and uncertainty is provided in section 3.0, but it is clear that the choice of

instrument or model for input data sources is important. Sampling frequency, instrument design, and model resolution can all introduce uncertainty in trajectory models. Cross-calibration between different types of observational instruments and models, when available, is recommended to alleviate some of this uncertainty.

## 2.6 Summary of main points

- Floating container trajectories are described to first-order by the balance of airside and waterside drag forces. Immersion level has an important role in determining the relative contribution of airside and waterside drag (Blanken et al., 2021; Daniel et al., 2002; Röhrs et al., 2012). For sinking containers, trajectories will be determined by subsurface currents on all time scales (Chu et al., 2022; Ouimet & Cortés, 2013; Thomson et al., 1990).
- Stokes drift has typically been assumed negligible (Daniel et al., 2002) or implicit (Breivik, Allen, et al., 2012; Breivik & Allen, 2008) in drift calculations, but has more recently been recognized to play an important forcing role in drift trajectories (Bosi et al., 2021; Sutherland et al., 2024).
- The Coriolis-Stokes may additionally be an important, but understudied, forcing term in surface drifting trajectories.
- Weight, volume, available air space, number of openings, geometry, orientation and immersion levels are key variables that will contribute to tendency of lost shipping containers to either remain adrift or sink.
- Drift and sinking trajectories of shipping containers are subject to significant uncertainty. Sources of uncertainty include the timing and locations of container loss, instrument and model limitations and biases, as well as changes in physical container properties while drifting.
- Information obtained from shipping manifests, cross validation of observations and models, and application of techniques such as stochastic modelling (Breivik & Allen, 2008), are all potential methods to address these uncertainties.

## 3.0 Forcing data and model sources

## 3.1 Overview

Container drift (and sinking) trajectories are dependent on waves, currents and winds. Regardless of the trajectory modelling approach used, data on these is required to initialize, force and evaluate trajectory models. This data can be obtained from either observations or model simulations, and each has their own strengths and caveats. The following section gives a synopsis of some common sources for this data.

## 3.2 Observational data sources

### 3.2.1 Eulerian sources

There exist a variety of *in situ* measurement platforms for current, wind and wave data. In North America, both Environment and Climate Change Canada (ECCC) and the National Oceanic and Atmospheric Administration (NOAA) operate metocean buoy networks via the Canadian Meteorological Service (MSC; <https://www.meds-sdmm.dfo-mpo.gc.ca/>) and National Data Buoy Center (NDBC; <https://www.ndbc.noaa.gov/>), respectively. These buoys host a variety of instruments capable of measuring wind speed and direction, atmospheric pressure, sea surface temperature, wave spectra, and other derived properties. Buoys measuring currents are less common, but do exist.

Ocean observatory systems, such as those operated by Ocean Networks Canada (ONC; <https://www.oceannetworks.ca/>) (Heesemann et al., 2014), provide arrays of instruments such as acoustic doppler current profilers (ADCP), conductivity temperature depth sensors (CTD), and current meters that can measure data for use as forcing in drift modelling (Blanken et al., 2021; Breivik, Allen, et al., 2012; Kohut et al., 2012). Other platforms such as high frequency (HF) radar systems deployed at sea or from land (*i.e.* coastal ocean dynamics applications radar, CODAR) (D. E. Barrick et al., 1977; Halverson et al., 2018) can also be used to provide real-time current observations for drift predictions (Bellomo et al., 2015; Kohut et al., 2012). These data sources can also play important roles in circulation model validation (Halpern et al., 2023), as well as characterizing other physical processes relevant to modelling drift trajectories. For example, comparisons of autonomous underwater vehicle drift with ADCP measurements have been used to characterize the bias associated with Stokes drift (Amador et al., 2017), which in turn, has been incorporated into a more robust formulation of the leeway method for surface container drift (Sutherland et al., 2024).

Observational data sources generally excel in providing high temporal resolution (Röhrs, Sutherland, et al., 2023), but are limited in spatial extent unless instruments are mobilized (*e.g.*

vessel-mounted ADCP) (Sentchev & Yaremchuk, 2016). Resolution trade-offs between frequency and range are also made for stationary deployments of ADCP or HF radar (Röhrs, Sutherland, et al., 2023). However, open-modal analysis and other statistical methods have been applied to extend the range of HF radar data for real-time current measurements in SAR drift modelling applications (D. Barrick et al., 2012; Kohut et al., 2012).

Instrument accuracy can also be an important limitation, complicating cross-validation of measurements between different instrument types. In particular, cross-validation of datasets may be problematic if combining Eulerian and Lagrangian sources, where some processes may not be captured by Eulerian sources (Sperrevik et al., 2017). For example, corrections must be applied to HF radar data for effects from Stokes drift when comparing with Lagrangian drifter measurements (Chavanne, 2018; Dussol et al., 2022; Röhrs et al., 2015). Differences in measurement technologies can also create complications. For example, ADCPs are particularly noisy near the surface due to wave influence (Bruserud & Haver, 2017), and sidelobe reflection contaminates near surface data down to depths of  $\lesssim 14\%$  of distance between ADCP and surface (Lentz et al., 2022). ADCP data quality control is an involved process (Morley et al., 2016), and cases of systematic discrepancies have been reported between instruments such as tandem deployments of current meters and ADCP (Blanken et al., 2021) as well as high frequency radar and Coastal Ocean Dynamics Applications Radar (CODAR) (Halverson et al., 2018). As noted in Section 2.5, cross-calibration among different observational instruments is recommended to identify and correct for different limitations and biases.

Satellite altimetry provides an alternative data source that greatly enhances spatial coverage at the ocean surface. Satellite-derived current estimates use a combination of observed changes in sea surface height and wind stress to estimate geostrophic and Ekman currents (Dohan & Maximenko, 2010). Some examples of available satellite current products include the Centre de Topographie des Océans et de l'Hydrosphère (CTOH) (Sudre & Morrow, 2008), Ocean Satellite Current Analysis Realtime (OSCAR) (Bonjean & Lagerloef, 2002), AVISO Gridded products (Pascual et al., 2006), and Geostrophic and Ekman Current Observatory (GEKCO) (Sudre et al., 2013). These products show strong performance when validated with drifters (Dohan & Maximenko, 2010). Satellite measurements of sea surface wind speeds are provided through a variety of technologies, such as microwave radiometers, scatterometers, synthetic aperture radars, and global navigation satellite system-reflectometry (for further details and available platforms, the reader is directed to the reviews by Bourassa et al. (2019) and Villas Bôas et al. (2019)).

Forcing Lagrangian particle trajectory models with satellite-derived currents can provide comparable or better results than forcing with data assimilative model outputs (Dagestad & Röhrs, 2019; Liu et al., 2014). Adding wind-driven Ekman currents can also increase the accuracy of trajectory predictions derived from satellite altimetry-based coastal current measurements (Liu et al., 2012, 2014). Additionally, the Mercator SURCOUF data product provides a surface field of geostrophic currents and wind stress derived from satellite altimetry

(Larnicol & Guinehut, 2006). Validations against drifter data have demonstrated that, when compared against various Ocean General Circulation Models (OGCMs), SURCOUF demonstrated comparable to superior performance for modelling 7-day open-ocean surface drift trajectories (Scott et al., 2012). However, satellite altimetry data can be problematic in coastal waters, and errors in observations here can propagate to data assimilative models (Birol & Delebecque, 2014; Liu et al., 2014; Vignudelli et al., 2011). This is relevant for container loss events occurring in coastal waters (MBNMS, 2011; Partow et al., 2021; TSB, 2024), and particularly in Canadian waters, where the current suite of operational ocean models mostly lack data assimilation. In these cases, other observational platforms such as buoys or moorings may be more reliable sources of forcing data for modelling container drift trajectories.

### 3.2.2 *Lagrangian sources*

Drifters (also known as drifting buoys) are one of the oldest and most common Lagrangian tools used to measure current velocities. They can additionally be equipped with barometers, hydrophones/anemometers, thermistors, and conductivity sensors to measure atmospheric pressure, wind velocity, temperature, and salinity, respectively (Lumpkin et al., 2017). Drifters have been used to validate oil spill trajectory models (Ivichev et al., 2012; Price et al., 2003) and have an important role in search-and-rescue applications of drift modelling (Breivik et al., 2013). A variety of drifter designs exist; most are constrained to measurements of upper ocean (mixed layer) or surface currents (Hourston et al., 2021; Pawlowicz et al., 2019; Sutherland et al., 2020). However, some studies have employed drifters with deeper drafts (~100-120 m) to study connectivity between surface and deep water forcing (Brügge & Dengg, 1991; Thomson et al., 1990). Further, drogued drifters can provide information on deep current processes such as internal waves (Ouimet & Cortés, 2013). One of the largest drifter datasets available is collected through the Global Drifter Program (<http://www.aoml.noaa.gov/phod/dac/index.php>) (Lumpkin & Pazos, 2007) run by NOAA Atlantic Oceanographic and Meteorological Laboratory (AOML). The data from this program have enabled validation of satellite altimetry-based current products (e.g. CTOH; Sudre & Morrow, 2008) and have aided in the development of drift models applied to determining marine debris accumulation areas (Maximenko et al., 2012). In coastal waters, drifters can quickly become grounded or stuck in intertidal areas, which can result in short deployments (Blanken et al., 2020; Pawlowicz, 2021). Differences in drifter geometry can also have a significant impact on the degree to which wind and wave forcing contributes to drift motion (Lee & Centurioni, 2018; Röhrs & Christensen, 2015). Due to these wind and wave effects, and the resulting vertical shear in ocean currents over the upper meter of the water column, seemingly similar instruments may produce notably different measurements. Good care must be taken to account for these differences during cross-validation with models or other measurements (cf. Callies et al., 2017; Morey et al., 2018). These differences will affect how well measured drift corresponds with currents, and wind and wave effects must be accurately

accounted for when modelling the trajectories of various types of drifters (Dagestad & Röhrs, 2019).

Lagrangian drift tracking techniques can be applied more directly to modelling lost container trajectories by mounting GPS onto either full-scale or miniature drifting containers (Breivik et al., 2011; Daniel et al., 2002). These types of experimental studies may also additionally mount anemometers, ADCPs and current meters (Breivik, Allen, et al., 2012; Breivik et al., 2011; Daniel et al., 2002), providing real-time, Lagrangian measurements of meteorological and oceanographic forcing for containers as they drift. These data are useful for parameterizing empirical drift models (Breivik et al., 2011), but are generally unavailable for characterizing conditions during accidental container release events.

Relevant forcing data for trajectory models can also be obtained from buoyancy-regulating floats and gliders. In particular, the large global suite of Argo profiling floats (Roemmich et al., 2009) primarily serves to obtain temperature and salinity data, has also been adapted to provide some estimates of surface currents (Xie & Zhu, 2008) as they spend 6-24 hours at the surface transmitting data to satellites (Dohan et al., 2010). Deep currents can be estimated from Argo floats based on known buoyancy regulation rates and distance between GPS transmittance positions (J. J. Park et al., 2005), but these measurements must be used with caution. Since GPS transmittance is only conducted while these floats are at the surface, unknown lateral drift during vertical movement of the floats through the water column can produce erroneous measurements (J. J. Park et al., 2005; J. J. Park & Kim, 2013; Wong et al., 2020). Gliders can be an advantageous alternative over buoyancy-regulated floats as their wings allow them to capture both horizontal and vertical structures in the water column (Davis et al., 2008; Rudnick, 2016). Although typically used for measurements of water properties and biological productivity, gliders can also be fitted with ADCPs to measure subsurface turbulence (Rudnick, 2016). Both buoyancy-regulated floats and gliders provide observations of subsurface measurements that are potentially useful for modelling container sinking trajectories. As with most *in situ* data sources, gliders are limited in spatial and temporal extent (Rudnick et al., 2017). For longer glider deployments, biofouling artifacts must also be corrected (Todd et al., 2017).

### 3.3 Model frameworks

#### 3.3.1 *Atmospheric and oceanic general circulation models*

A central limitation of applying *in situ* observational data as forcing in trajectory models is data sparsity, which even when combining satellite and instrumental observational techniques, will still contain significant information gaps across smaller spatial and temporal scales (Isern-Fontanet et al., 2017; Villas Bôas et al., 2019). Furthermore, observational data cannot be used

directly in forecasting applications. However, it is possible to derive forecasts from observations through various extrapolative techniques (*cf.* D. Barrick et al., 2012). Outputs from hydrodynamic and atmospheric models can alleviate this issue by providing predictions through both time and space (horizontally and vertically) in regular intervals. Atmospheric models are commonly used to provide wind velocity fields for application in drift trajectory models. The European Center for Medium-Range Weather Forecasts (ECMWF) suite of model outputs has been used in shipping container drift modelling (Daniel et al., 2002). Other examples of atmospheric models used to obtain wind velocities in drifter studies include the Global Environmental Multiscale (GEM) (Côté, Desmarais, et al., 1998; Côté, Gravel, et al., 1998; Girard et al., 2014; Sutherland et al., 2020) and the MetCoOp ensemble prediction system (MEPS) (Bengtsson et al., 2017; Frogner et al., 2019; Müller et al., 2017; Sutherland et al., 2020).

Ocean General circulation models (OGCMs) present an Eulerian method for calculating current velocity fields that can force drift trajectories. There is a large diversity in circulation models available and used in the literature, with many specialized models being actively developed for specific regions or tuned to better capture certain phenomena. Wave effects (*e.g.* Stokes drift) tend to be modelled separately from OGCMs by wave models such as Wavewatch III (Clementi et al., 2013; Tonani et al., 2015), MASNUM (Han, 2014; Qiao et al., 2016; Sun et al., 2020), and SWAN (Booij et al., 1997). These models may be coupled to OGCMs either sequentially (*i.e.* data flows from OGCM into wave model) or bidirectionally (*i.e.* data is exchanged between OGCM and wave model) to improve representation of wave-current interaction, air-sea fluxes, and upper ocean mixing processes (*cf.* Breivik et al., 2015; Staneva et al., 2021). Recently there have also been advances in fully-coupled modelling of the atmosphere-wave-ocean system (Bernier et al., 2022; L. Wu et al., 2019). Some examples of commonly used OGCMs within the oceanographic and drift modelling communities include: the Princeton Ocean Model (POM) (Mellor, 2004); Hybrid Coordinate Ocean Model (HYCOM) (Chassignet et al., 2007); Nucleus for European Modelling of the Ocean (NEMO) (Madec & NEMO Team, 2015); Massachusetts Institute of Technology general circulation model (MITgcm) (Marshall, Adcroft, et al., 1997; Marshall, Hill, et al., 1997); Regional Oceanic Modeling System (ROMS) (Shchepetkin & McWilliams, 2005); Los Alamos National Laboratory Model for Precision Across Scales Ocean (MPAS-O); and the Semi-implicit Cross-scale Hydroscience Integrated System Model (SCHISM) (Y. J. Zhang et al., 2016).

ROMS, POM and NEMO (Paquin et al., 2024) have documented previous applications to modelling drift in SAR and shipping container contexts (Breivik & Allen, 2008; Sutherland et al., 2024), but this list is not exhaustive and other modelling suites can be used. The choice of OGCM output used to provide forcing for trajectory models will depend largely on whether the chosen model's spatial and temporal resolution is sufficient (see Section 3.3.4). State-of-the-art current models also often show discrepancies when compared with observational data that must be taken into account (Blanken et al., 2021; Paquin et al., 2020).

### 3.3.2 *Data assimilating models*

Data assimilating models, where OGCMs or atmospheric models are combined with *in situ* observations, can provide a means to improve model output accuracy, and therefore the accuracy of trajectory models using these outputs. For example, drift trajectories were significantly improved in coastal areas when HF radar data and CTD measurements were assimilated with ROMS outputs (Sperrevik et al., 2015). Other studies using combinations of OGCMs and ADCPs, CTDs, and satellite-based sea surface height and temperature have all demonstrated comparable improvements (Carrier et al., 2014; Janeković et al., 2013; Powell et al., 2008). Additionally, forecasting applications of these models show significantly reduced overall error when combining observations from multiple datasets (Breivik & Sætra, 2001; Oke et al., 2015). Assimilating observations into atmospheric models can also produce significant improvements in representing sea surface wind speeds, with products such as the cross calibrated multiplatform (CCMP) system providing large improvements filling gaps in satellite coverage due to cloud artifacts (Atlas et al., 2011).

### 3.3.3 *Machine learning sources*

Machine learning models can also be used to derive current and wave data from satellite observations of sea surface height, sea surface temperature, and wind stress (Sinha & Abernathey, 2021). In addition to generating nowcasts, these methods have also been developed to produce forecasts of wave fields (James et al., 2018). Machine learning approaches are advantageous in that they can perform similarly to OGCMs with less computational expense (Gentine et al., 2018), and have been demonstrated to generate more accurate subsurface predictions when trained on sparse observational data (*e.g.* Argo float data) (Chapman & Charantonis, 2017) or low resolution OGCMs (Bolton & Zanna, 2019). However, machine learning methods can be prone to overfitting and poor generalization (Ying, 2019), as well as a loss of stochastic variability (Gentine et al., 2018), which can complicate the broader applicability of these approaches.

### 3.3.4 *Model resolution*

Regardless of the model used, spatial and temporal resolution will play an important role in capturing physical processes relevant to trajectory models (Breivik & Allen, 2008), especially in coastal waters (MBNMS, 2011; Partow et al., 2021; TSB, 2024). Higher spatial resolution

effectively resolving the local Rossby radius is needed to model (sub-)mesoscale eddies (Hallberg, 2013; Maltrud & McClean, 2005; R. D. Smith et al., 2000). Higher resolution models also demonstrate more skillful representation of boundary currents (Kirtman et al., 2012; R. D. Smith et al., 2000). Finer temporal resolution (hourly or higher) can also be important to adequately capture sub-mesoscale processes and other short-lived current phenomena (Elipot & Gille, 2009; Röhrs, Sutherland, et al., 2023), although even high spatial resolution models are unlikely to fully resolve sub-mesoscale eddies (1-2 km scales).

However, higher resolution models come with significant computational costs, which can be a disadvantage in some trajectory modelling contexts such as SAR, where speed is prioritized (Breivik & Allen, 2008). Although these constraints are less of a priority in the context of shipping container trajectory modelling, high resolution models with potentially longer runtime can still affect response times to container release events, which will be of particular importance for locating containers with hazardous contents and coordinating cleanup efforts in a timely manner (Wan et al., 2022). One approach to addressing this may be the use of nesting of high and low resolution spatial domains within regional setups of OCGMs, which can improve biases without incurring large computational costs (Pennelly & Myers, 2020). Efforts are underway to develop and operationalize on-demand capacity for such high resolution nests within regional models (Y. Lin et al., 2022; Trotta et al., 2016, 2021). As mentioned in Section 3.3.3, machine learning models applied to lower resolution OCGMs may provide another potential approach to retain skillful predictions without large computational overhead (Gentine et al., 2018).

### 3.4 Summary of main points

- Trajectory models require forcing by waves, wind, and currents, which can be obtained from observations or numerical models.
- Commonly used Eulerian sources of observational data include weather stations mounted on buoys and ADCPs, CTDs, and current meters mounted on buoys or moored at the seafloor, as well as HF radar and satellite-based instrumentation. Commonly used Lagrangian sources of observational data include drifters, gliders and buoyancy-regulated floats.
- Eulerian data sources generally excel in providing high temporal resolution (Röhrs, Sutherland, et al., 2023), but are limited spatially unless mobilized (Sentchev & Yaremchuk, 2016) or trade-offs in resolution are made (Röhrs, Sutherland, et al., 2023). Lagrangian sources (and satellites) provide improvements in spatial coverage, and Lagrangian sources may capture some processes (*e.g.* Stokes drift) that are not captured by Eulerian sources (Röhrs et al., 2015; Sperrevik et al., 2017).

- Each instrument has its own limitations and biases. Some examples discussed include: wave-associated noise in ADCP measurements at the ocean’s surface (Bruserud & Haver, 2017); different drifter designs capture different wind and wave forcing (Lee & Centurioni, 2018; Röhrs & Christensen, 2015); subsurface current measurements from floats can be erroneous due to lateral drift during vertical movement (J. J. Park et al., 2005; J. J. Park & Kim, 2013; Wong et al., 2020); satellite altimetry data can be problematic in coastal waters (Birol & Delebecque, 2014; Liu et al., 2014; Vignudelli et al., 2011); and long glider deployments are subject to biofouling artifacts (Todd et al., 2017). Where applicable, intercomparison between methodologies is recommended to quantify uncertainties (Blanken et al., 2021).
- Atmospheric circulation models and OGCMs, as well as observational data assimilative models and machine learning-based data sources, provide gridded velocity fields at regular intervals, which can alleviate issues around data sparsity in observations. They are, however, subject to model uncertainty due to numerical limitations.
- Higher resolution models can better capture boundary currents (Kirtman et al., 2012; R. D. Smith et al., 2000) and (sub-)mesoscale phenomena (Maltrud & McClean, 2005; R. D. Smith et al., 2000), but at the cost of higher computational demand. Nesting different resolutions spatially in OGCMs (Pennelly & Myers, 2020) or using machine learning to extract information from coarse model outputs (Gentine et al., 2018) are potential methods to circumvent this issue.

## 4.0 Modelling trajectories of surface drifting containers

### 4.1 Overview

Modelling the drift of objects at sea is an area of active research, and is an important consideration in the fields of search-and-rescue (SAR) (Breivik et al., 2013), oil spill tracking (reviewed in Keramea et al., 2021; Spaulding, 2017), microplastic dispersal (reviewed in H. Zhang, 2017), plankton drift (*e.g.* Feng et al., 2011; Hrycik et al., 2013; Vikebø et al., 2011), and response to container loss incidents (*e.g.* Breivik, Allen, et al., 2012; Daniel et al., 2002; Sutherland et al., 2024). For lost shipping containers, surface drift is largely controlled by the drag forces due to current, wind, and waves, so early trajectory models were linear vector additions derived from a simple force-balance, parameterized by the immersion level of the containers (Daniel et al., 2002) (see Section **Error! Reference source not found.**). Subsequent work has adapted the leeway method (described in Section 4.2) to incorporate the immersion ratio for characterizing container drift (Breivik, Allen, et al., 2012; Sutherland et al., 2024). To date,

these two techniques remain the primary models for tracking the surface drift of lost shipping containers. More recent work has expanded upon these studies to improve accuracy by incorporating Stokes drift (Sutherland et al., 2024) and geometric effects (Ren et al., 2024).

These approaches have been expanded up in a number of ways for modelling surface drift trajectories of objects. Many of these innovations have yet to be applied to container drift, but hold promise to better address the uncertainties associated with the variety of factors that influence an object’s drift (see Section 2.0) and the uncertainties associated with forcing data used (see section 3.0). The following section provides further details on the leeway method, and provides an overview of various recent innovations for surface drift prediction which could be applicable to modelling container drift.

## 4.2 The leeway method

Leeway of a drifting object is defined as follows, proposed by Allen & Plourde (1999):

“Leeway is the motion of the object induced by wind (10 m reference height) and waves relative to the ambient current (between 0.3 and 1.0-m depth).”

The leeway drift model has been developed as an operational model for search-and-rescue (Breivik & Allen, 2008), and has since been extended to consider the container’s immersion level (Breivik, Allen, et al., 2012; Daniel et al., 2002; Sutherland et al., 2024). The leeway method is one of the most popular techniques for modelling surface drift trajectories in various applications (Breivik & Allen, 2008; Y. Chen et al., 2022; J. Gao et al., 2018; Ren et al., 2024; Shchekinova et al., 2016; Sutherland et al., 2020, 2024; Tu et al., 2021, 2022; J. Wu et al., 2023). The method is often used as a baseline for comparing the performance of other modelling approaches (Blanken et al., 2021; Breivik et al., 2025; Tu et al., 2021, 2022) and has provided the foundation for further work (Bhaganagar et al., 2022; Ni et al., 2010; Ren et al., 2024; Wang et al., 2014).

The leeway model is based on a set of empirically determined coefficients describing the drift speed and direction relative to the downwind direction (*i.e.* the leeway speed and divergence angle); (Breivik et al., 2011). In practice, the leeway coefficients of a specific object are generally derived by a linear regression, with least squares best fit, of the downwind and crosswind drift components against the wind speed (Breivik & Allen, 2008) (Fig. 5). Assessment by the downwind and crosswind components is more robust than the leeway divergence angle (Fig. 5) at low wind speeds (Allen, 2005; Breivik et al., 2011; Breivik & Allen, 2008). The crosswind component is separated into left and right components, and the sign changes between these components due to jibing (see Section 2.3) can be assessed by use of progressive vector diagrams (Breivik et al., 2011). Monte Carlo can then be used to sample the distribution of uncertainty in the coefficients (see Section 4.3) to account for uncertainty in the overall drift trajectories (Breivik & Allen, 2008). Other work has addressed uncertainty in the currents by a

separate drift coefficient describing the response to currents, in addition to the leeway coefficient describing the response to winds, to improve drift trajectories (Tu et al., 2022; J. Zhang et al., 2017).

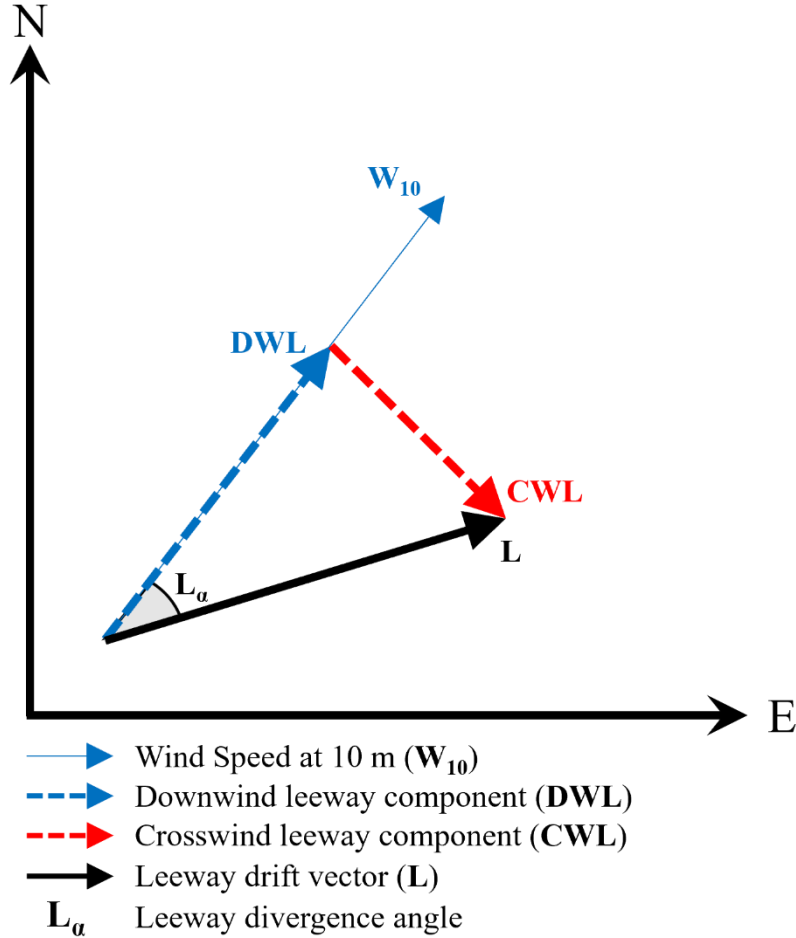


Figure 5. Vector diagram illustrating the relationship between the leeway components (downwind,  $DWL$ ; crosswind,  $CWL$ ); the resultant leeway drift vector ( $L$ ); the leeway divergence angle ( $L_a$ ); and the wind speed at 10 m above sea level. Figure adapted from Allen & Plourde (1999).

As the leeway characteristics will change depending on an object's physical characteristics (*e.g.* geometry, weight, immersion ratio, tendency to jibe or swamp, etc.; see Section 2.3 and 2.4), the regression coefficients have to be determined from empirical measurements for different object types. To date, leeway coefficients have been determined for a total of 63 types of objects (Allen & Plourde, 1999). The leeway coefficients for objects can be determined from either indirect or direct observations. The indirect observational method describes an early method of measuring leeway as the difference in an objects drift from the ambient currents, which were either measured some distance away from the drifting object (*i.e.* using nearby current meters or

drifters) or by qualitative methods (*i.e.* visual inspection of the drift of dye patches, nets or floating debris) (Breivik et al., 2011). The direct method, which is more commonly used now due to technological advancements, involves co-located measurements of currents, wind speeds and drift measured using anemometers, current meters and GPS trackers attached directly to the drifting objects (Breivik et al., 2011). The leeway coefficients of surface drifting shipping containers at different immersion ratios have been determined using the direct method (Breivik, Allen, et al., 2012). Sutherland et al. (2024) noted that coefficients derived using the direct method do not include contributions from Stokes drift, and that Stokes drift should be considered separately in the drift model.

The leeway method is subject to various sources of uncertainty. In applications to container drift, it is most sensitive to the immersion level and the airside drag coefficient, and resulting uncertainties in the crosswind component significantly expand the range of probable trajectories (Breivik, Allen, et al., 2012). Breivik, Allen, et al. (2012) identified two additional sources of uncertainty when applying the leeway methodology to full size shipping containers. First, the typical draft of a heavily immersed shipping container (~80%) is 2 m, much deeper than the 50 cm depth recommended for measuring leeway (Breivik et al., 2011), and immersion level (and draft) will likely vary over time as the drifting container takes on water (see Section 2.3). Variable immersion levels have since been incorporated into the leeway model (Ren et al., 2024) (see section 4.8.1). Secondly, wave effects (*i.e.* excitation and dampening) are potentially significant for the drift of large containers, but have thus far been ignored (Breivik & Allen, 2008). Breivik, Allen, et al. (2012) argue that direction of wave-driven drift should align with the wind-driven drift, resulting in the leeway coefficients obtained from the direct method implicitly including wave effects (see also (Breivik et al., 2011; Breivik & Allen, 2008)). However, as discussed in Section 2.2.3, more recent work has shown wave-induced Stokes drift can have significant effects, particularly as drift time increases (Bosi et al., 2021; Sutherland et al., 2024). For instance, Sutherland et al. (2024) show that cumulative trajectory errors due to neglecting Stokes drift reach 95 km difference after 5 days.

The regression analysis for determining leeway is sensitive to the sample size of the observations, and range of wind speeds over which they occur. Breivik et al. (2011) recommend that: 1) the regression be symmetrical (*i.e.* left and right crosswind components set equal) for shorter drift studies (*i.e.* samples size,  $n$ , is less than 100), and 2) the regression be additionally constrained (*i.e.* the intercept forced to 0) when a limited range of wind speeds are observed. Non-symmetrical, unconstrained regression is permitted for longer datasets ( $n > 100$ ), where the effects of jibing on separated left and right crosswind components can be assessed by progressive vector diagrams (Allen, 2005). Jibing effects may even be fully characterized in the case of longer datasets ( $n > 500$ ) (Breivik et al., 2011).

Additionally, general circulation models have their own uncertainties in wind, waves and currents used to force the leeway model (see Section 3.3). For trajectory models forced with these model outputs, this introduces additional uncertainties in leeway-derived trajectories,

especially since leeway coefficients are pre-determined from least-squares analysis on a limited, and potentially not fully representative, set of direct *in situ* observations. This source of error may be mitigated by the use of stochastic ensembles (Section 4.3), and more flexible approaches such as fuzzy numbers, machine learning and multi-model ensembles (described below) provide alternatives approaches.

### 4.3 Stochastic ensemble techniques

At small scales, turbulent fluctuations in winds and currents influence the trajectories of drifting objects, and can be addressed by incorporating a stochastic component in the trajectory model. Monte Carlo models represent one approach to this, referring to the addition of random perturbations derived from a probability density function describing the turbulent energy to a trajectory model to generate a spatial probability density function of trajectories. This approach is commonly used in the leeway method to perturb the coefficients, which can improve prediction of search areas in SAR applications (Breivik & Allen, 2008; Y. Chen et al., 2022; J. Gao et al., 2018; Tu et al., 2021, 2022). Monte Carlo routines have also been incorporated into other trajectory modelling routines using auto-regressive moving averages (ARMA) to assess drift uncertainty (Mínguez et al., 2012).

Applying random “kicks” to a particle’s displacement through Markov models to address stochastic uncertainties in forcing fields is known as “random walk” or “random flight” models (Berloff & McWilliams, 2002; Griffa, 1996). Random walk represents the simplest form of these, treating the “kicks” as independent events. This approach has been incorporated into oil spill trajectory models such as GNOME (Beegle-Krause, 2001) and MEDSLIK-II (De Dominicis, Pinardi, Zodiatis, & Archetti, 2013; De Dominicis, Pinardi, Zodiatis, & Lardner, 2013). Random walk has also been utilized in conjunction with the leeway method to account for stochastic uncertainty in current and wind fields (Breivik & Allen, 2008; Nesterov, 2018).

Random flight is the successor model to random walk, and accounts for autocorrelation in the underlying velocity field (Griffa, 1996; Zhu et al., 2023). Random flight may produce smaller search fields compared to random walk, but does not guarantee improvements in predictive performance (M. Spaulding et al., 2006). Nonetheless, comparisons of random flight and random walk models for oil spill prediction have demonstrated that random flight provided 20-40% higher probabilities of success compared than random walk over 120 hour trajectories (Zhu et al., 2021). Random flight has also been demonstrated to yield better performance when compared to random walk approaches for comparisons between CODAR-based particle trajectory models and drifter experiments over 24 hours (Ullman et al., 2006).

In general, Breivik & Allen (2008) argue that stochastic uncertainty in wind and currents captured by random flight is much smaller than the uncertainty in an object’s leeway, and

random flight thus provides little performance gains in the context of leeway trajectory modelling. Similar conclusions that random flight provided no further performance gains were reached by M. Spaulding et al. (2006) when both random walk and random flight models were investigated for predictions of drifter trajectories. Therefore, in the context of modelling the trajectories of shipping containers, random walk models are likely sufficient compared to more complex Markovian models, such as random flight.

#### 4.4 Multi-model ensembles

An alternative, or complement, to stochastic ensembles of trajectories derived from a single circulation model is to address the uncertainty in modelled current and wind fields through collation of outputs from multiple circulation models into an ensemble, from which drift trajectories can then be computed. This multi-model approach is differentiated between combining models of the same type (termed “super-ensembles”) or combining models of different types (*e.g.* OGCMs and atmospheric models; termed “hyper-ensembles”) (Rixen & Ferreira-Coelho, 2007; Vandenbulcke et al., 2009). The rationale behind the multi-model ensemble approach is that the collective inter-model uncertainties can be reduced through optimized combinations of different models within the ensemble, leading to more robust predictions. Evidence for this is provided by Scott et al. (2012), who demonstrate that the multi-model ensemble performance in reconstructing drifter trajectories exceeded any singular OGCM. Multi-model ensembles have successfully been applied to predicting changes in temperature profiles (Rixen et al., 2009), wave forecasting (Lenartz et al., 2010), and modelling surface drift trajectories (Rixen et al., 2008; Rixen & Ferreira-Coelho, 2007; Scott et al., 2012; Vandenbulcke et al., 2009).

In multi-model ensembles, drift trajectory modelling becomes an optimization problem to find a combination of models within the ensemble that produce the most robust results. Each model is weighted, and minimization routines can be applied to find the model combination that best reconstructs known drifter trajectories (Rixen et al., 2008, 2009; Vandenbulcke et al., 2009). Although not technically a minimization method, the most straightforward method is to simply average the outputs across the ensembles. However, this method does not account for individual model biases, and unsurprisingly, tends to result in large uncertainties and error (Rixen et al., 2009; Vandenbulcke et al., 2009). Bias minimization is otherwise done through various different dynamic statistical techniques (Rixen et al., 2009; Vandenbulcke et al., 2009), such as a bias-removed ensemble mean (Rixen et al., 2009; Zhi et al., 2012); least-squares weighted linear regression (Krishnamurti et al., 1999); applying a Kalman filter (Melsom et al., 2012) either in the original formulation (Kalman, 1960) or the more advanced augmented complex Kalman filter (Goh & Mandic, 2007; Vandenbulcke et al., 2009); and utilizing a particle importance resampling filter, which is a sequential Monte Carlo approach that does not assume a Gaussian

distribution (Van Leeuwen, 2003). These techniques can be further combined with principle component analysis (PCA) as a pre-processing step to remove collinearities between the models and reduce the input variance, which can also reduce the number of weights needing to be evaluated (Vandenbulcke et al., 2009).

Other work has applied more advanced non-linear methods to solve the minimization problem in hyper-ensembles, namely genetic algorithms (GA) and neural networks (see Section 4.6) (Rixen & Ferreira-Coelho, 2007). GA are an innovated form of Monte Carlo approaches that are conceptually modelled after evolutionary biology and natural selection (Gallagher et al., 1991). GA mimics evolutionary mechanisms by randomly applying “mutations” (*i.e.* changing a parameter in a possible solution) or “cross-over” (*i.e.* interchanging parameters between possible solutions) into a set of possible solutions (*e.g.* weights) at each iteration. After each iteration, the pool of possible solutions are evaluated and only the “fittest” (*i.e.* those providing the lowest regressive error) are selected and retained into the next iteration, with the process repeated until a final solution is converged upon. GA, however, are not an ideal approach, and can be 10-100 fold more computationally expensive compared to the least-squares method while providing only similar, or sometimes worse, forecasting accuracy (Rixen & Ferreira-Coelho, 2007). Similarly, for neural networks there is evidence that the added complexity does not provide significant accuracy gains in multi-model ensembles when compared to simpler linear techniques (Rixen & Ferreira-Coelho, 2007; Vandenbulcke et al., 2009; Zhi et al., 2012).

## 4.5 Fuzzy numbers

Fuzzy numbers are a method that defines a set of possible ranges of values at varying degrees of belief to describe the uncertainty within a dataset (Zadeh, 1965, 1978). Fuzzy numbers have been applied to various geophysical problems, including assessing variability in ocean temperature and salinity (Y.-P. Huang et al., 2007), defining water masses (Fengqi et al., 1988), predicting dissolved oxygen (Khan et al., 2013), characterizing uncertainty in satellite-derived chlorophyll-a concentrations (Moore et al., 2009), and for assessing rainfall-induced landslide risks (H.-J. Park et al., 2017). More recently, fuzzy numbers have been used to assess the contributions of different causes to initial container falls from ships (Öztürk, 2024), and in the prediction of surface drift trajectories (Blanken et al., 2021).

The basic approach of fuzzy numbers is to define a membership function, which is a set of ranges a value might take associated with membership levels (or *degrees of belief*) in each member of the set. Membership ranges from zero, for the largest range of values believed to be possible (also called the *support*), to one, for the (usually singular) value believed to be certainly possible. The span of intermediate ranges decreases monotonically with increasing membership (Blanken et al., 2021). This membership function is subject to a “consistency principle” which dictates that the possibility, or membership, of each value within the support, must equal or

exceed its probability (Zadeh, 1965). Membership functions, therefore, do not reflect the probability of occurrence of a particular value, but only the possibility that value might occur (Blanken et al., 2021; Zadeh, 1965). For surface drift modelling, drift trajectories have been derived by ‘fuzzifying’ current, wave, and wind forcing to account for the uncertainty associated with them and applying the commonly used linear trajectory model based on the balance of airside and waterside drag forces (Blanken et al., 2021; Daniel et al., 2002).

In comparison to the leeway method, the strength of the trajectory model based on fuzzy numbers is flexibility, as this approach does not rely on prescribed empirically determined coefficients (Blanken et al., 2021). Performance of this method has been demonstrated to be comparable to the Leeway method (Blanken et al., 2021; Breivik & Allen, 2008). However, some physical forcings remain uncaptured within the underlying force-balance trajectory model, as Blanken et al., (2021) note that some errors observed in their case study in the Northeast Pacific may be the result of a lagged wind response, or the absence of Coriolis-Stokes forcing. Subsequent work have extended this fuzzy number framework to uncertainty in spatially variable forcing velocity fields, which hold promise to better account for uncertainty in the inputs to trajectory models (Blanken et al., 2023).

## 4.6 Machine learning

In recent years, machine learning has been adapted to drift trajectory modelling (*e.g.* Bhaganagar et al., 2022; Jenkins et al., 2023; Lin et al., 2024; Song et al., 2024). There is a diverse array of statistical techniques that are considered machine learning, and Shadmani et al. (2023) review many of these algorithms in the context of wave energy forecasting. Artificial neural networks (ANN), which are designed to mimic the neural pathways in human brains, have gained popularity in recent years as a powerful machine learning technique. The simplest ANN framework, termed a multilayer perceptron, consists of an input layer, a hidden layer of interconnected neurons, and an output layer (Gardner & Dorling, 1998). The neurons consist of an activation function, which predicts the output from a combination of the input data, and a matrix of weights, which represent the strength of connectivity between the different connected neurons. In practice, “deep learning” approaches that utilize more complex ANNs with multiple interconnected hidden layers (termed deep neural networks; DNN) have shown strong improvements in predictive performance (LeCun et al., 2015; Mathew et al., 2021). Convolutional neural networks (CNN) are an example of a DNN, which adds convolutional layer(s) to identify patterns from 3D datasets, making them well suited to computer vision problems (LeCun et al., 2015). Recurrent neural networks (RNN) are another popular DNN framework that excel in sequence operations, and can be useful in parameterizing time-series information (Che et al., 2018; Connor et al., 1994). Whereas information in an ANN framework can only pass from input to output (termed “feedforward” architectures; Gardner & Dorling,

1998), RNN differ by incorporating a recurrent unit, which provides a feedback loop in the form of a “hidden state” layer which stores the current iteration’s output and feeds it back as input into the next training iteration (Che et al., 2018; LeCun et al., 2015). A popular RNN architecture is the long short-term memory (LSTM) design, which addresses weight shrinkage over time from the successive multiplicative operations on the hidden state during the backpropagation training process (an issue referred to as “vanishing gradients”; Hochreiter & Schmidhuber, 1997; Noh, 2021).

CNN have been applied to SAR applications by using real-time ship-board camera imagery and LiDAR data to determine the leeway coefficients, trajectory and drift velocity for persons in water (Bhaganagar et al., 2022). This approach requires a real-time camera feed of the drifting object, which is generally unavailable for lost shipping containers at sea. However, CNN frameworks can also be applied to current and wind velocity fields generated from models or satellite altimetry. For example, Jenkins et al. (2023) demonstrate the use of CNN in a probabilistic Lagrangian framework, where the CNN is trained on a probability density map of the drifting object locations (randomly sampled from particle advection model simulations) and velocity output fields from the NEMO OGCM to generate drift trajectories. This framework could be potentially be adapted to modelling shipping container drift, although in its current state the model design is limited to one day forecasts using daily mean model outputs (Jenkins et al., 2023).

LSTM RNNs have also recently been applied to drift prediction. An LSTM framework trained on drift trajectories obtained from the Global Drifter Program and satellite altimetry data was compared against TrackMPD, a 3D model for marine plastic debris drift (Jalón-Rojas et al., 2019; H. Lin et al., 2024). The LSTM predictions were found to have an overall higher average skill scores during the initial 60 hours of drift, but were less accurate compared to TrackMPD over longer drift trajectories (H. Lin et al., 2024). More sophisticated frameworks have a coupled LSTM-DNN forecasting framework that first encodes the velocity fields into an LSTM to forecast changes in current and wind velocities, which is then subsequently fed into a DNN to predict drift trajectories (X. Li et al., 2022). This approach was found to significantly improve accuracy in drift prediction when compared to an drift model built from an LSTM alone (X. Li et al., 2022). Other studies have coupled LSTM models with clustering algorithms (Zhao & Shi, 2019) and CNN-based frameworks (D. Gao et al., 2021) to improve LSTM drift prediction for vessels.

The central limitation for LSTM in drift trajectory forecasting applications is that time-series information tends to be lost in LSTM for datasets with longer durations, leading to greater forecasting errors with time (Song et al., 2024). Transformer models are a more recently developed neural network framework that have been designed to improve upon this limitation by developing an attention mechanism, which permits parallelized training of sequential information, therefore potentially improving retention of times-series information (Abbasimehr & Paki, 2022; Vaswani et al., 2017). An alternative drift modelling approach, then, is to leverage

the strengths of multiple neural network frameworks, including transformers, within a single framework. For example, Song et al. (2024) developed a hybrid CNN/RNN/transformer model for drifting buoys that combines a CNN architecture with gating (LSTM) and attention (transformer) mechanisms to retain time-series information over longer drift trajectories (Song et al., 2024). This approach can reconstruct the drift trajectories over periods up to 72 hours for buoys with differing drogue set-ups. Similar work combining CNN and transformers has shown promising results for short-term vessel drift predictions (P. Huang et al., 2022). Transformers can also be powerful tools when utilized independently; other work has demonstrated transformer frameworks with more sophisticated attention mechanisms can reduce mean square error and mean absolute error in trajectories for buoys and autonomous underwater vehicles (AUV) over 5-hour drift trajectories by up to ~28 - 90% compared to other variations of CNN, LSTM, RNN and transformer frameworks (C. Zhang et al., 2024).

Other machine learning techniques are also beginning to be adapted to surface drift prediction. Gaussian process regression (GPR) has been demonstrated to reconstruct drifter trajectories with an accuracy exceeding 90%, although its performance degrades significantly in slow flowing current conditions (Xia et al., 2025). More complicated GPR frameworks have incorporated pre-processing steps of clustering environmental factors and applying PCA to reduce input data complexity (M. Zhang et al., 2023). This approach has demonstrated ~86 – 92% reductions in error of different drift characteristics when compared to other GPR permutations and RNN (M. Zhang et al., 2023). Gradient boosting, an ensemble technique for decision tree algorithms, has also shown recent promise in surface drift modelling of icebergs (Yulmetov, 2021).

The relative sparsity of container drift observations presents a challenge when applying machine learning to directly predict container drift trajectories. As with empirical, regression-based approaches (*e.g.* the leeway method), any errors in the underlying training data will be propagated through to the machine learning model, and may limit its ability to generalize to other datasets. Additionally, studies applying machine learning to shipping container drift would need to be cautious in the training dataset used. As described above, in the absence of a large database of container drifting trajectories, machine learning models could be trained on known drifter trajectories, and then applied to model shipping container drift. The obvious drawback of this approach is that drifters have varying geometries that affect the physical forcing that dictate their drift (Röhrs & Christensen, 2015), which will translate to erroneous trajectories if drifter-trained machine learning models are applied to shipping container drift without accounting for differences in geometry. A sufficiently large training dataset of known trajectories would also be necessary to avoid issues with overfitting (Ying, 2019).

Alternatively, neural networks have been applied as sophisticated optimizers to solve non-linear relationships within other model frameworks, such as hyper-ensembles (Rixen & Ferreira-Coelho, 2007) (see Section 4.4). However, this approach need not be restricted to only multi-model ensemble frameworks; deep learning approaches could be applied in hybrid model

frameworks, where the DNN provides complimentary technique to parameterize uncertainty in underlying velocity fields. In this case, the approach would be to train a DNN framework on the stochastic components of drift tracking, so that it captures the fraction of variance in trajectory models that is unexplained by deterministic approaches. Thus, the machine learning models can act as a separate “parameterization” for unknown physical forcing, much like how fuzzy numbers frameworks can be applied (Blanken et al., 2023). This technique has been applied to constrain errors in ROMS-based surface current predictions relative to HF radar (Shen et al., 2022). Drift trajectories have also been improved by use of a hybrid framework combining a deterministic, reduced-order particle trajectory model with an LSTM RNN, which achieved improvements in skill scores by 67% relative to the reduced-order model alone (Aksamit et al., 2020).

## 4.7 Backtracking

In most instances, trajectory modelling involves estimating the final position of an object by making predictions forward in time from a known origin. Backtracking reverses this process and can be applied to model surface drift trajectories in reverse when the point of origin is unknown, or subject to uncertainty relative to an objects current position (Breivik et al., 2025). Backtracking approaches have been commonly applied to debris tracking from airplane crashes, such as from the Air France Flight 447 (C. Chen et al., 2012; Drévilion et al., 2013; Stone et al., 2024) and the Malaysian Flight 370 (Durgadoo et al., 2021; Stone et al., 2024) incidents. Backtracking has also been applied to surface drifting buoy trajectories using HF radar data (Abascal et al., 2012) and super-ensemble approaches (Janeiro et al., 2017).

In most cases, backtracking is of limited use in modelling surface drifting lost containers, as the time and location of container release from vessels is typically well-documented during catastrophic events (*e.g.* NTSB, 2017; Partow et al., 2021; TSB, 2024). However, there are cases where there is uncertainty in the coordinates or timing of container release, such container loss during a vessel’s transit, or if container loss occurs continually as a vessel drifts. In the case of the latter, backtracking may be useful for constraining uncertainty of the release point by using known container locations (*e.g.* beached containers), which in turn, can then be used to inform forward trajectory modelling approaches to locate other lost containers. In cases of container loss from multiple incidents in the same vicinity, backtracking of sunken containers (see Section 5.2) may also be of interest for parameterizing and validating sinking trajectory models, or identifying the responsible parties for clean-up operations in cases where this isn’t possible by other means, such as through identifying markings on located containers.

The simplest backtracking approach is referred to as naïve backtracking, which involves applying forward trajectory models with the velocity fields simply reversed in time (Breivik, Bekkvik, et al., 2012; Breivik et al., 2025). The alternative is to apply Monte Carlo approaches to

generate possible back-trajectories from one or more observed positions of the object, known as Bayesian backtracking (Breivik et al., 2025). However, backtracking approaches are only appropriate when objects have had continuous trajectories (*i.e.* no partial strandings); have not been subject to changes in orientation (*e.g.* swamping, jibing or rollovers); and current flows have had negligible divergence, otherwise significant error is incurred (Breivik, Bekkvik, et al., 2012; Breivik et al., 2025). Backtracking also tends to produce increasing error for longer trajectories (Breivik et al., 2025), and applications of both forward and backtracking to the surface drift of Malaysian Airlines Flight 370 debris have demonstrated significant differences in their probability distributions (Durgadoo et al., 2021). Thus, caution must be exercised.

## 4.8 Other drift modelling considerations

### 4.8.1 Geometric parameterizations

Geometry has an important role on the fates of lost shipping containers (see Sections 2.3 and 2.4), and modelling geometric effects on drift remains a challenge. Although the leeway method uses coefficients parameterizing the motion of different classes of objects with inherently different geometries (Allen & Plourde, 1999; Breivik et al., 2011), this does not implicitly account for dynamic effects associated with geometry throughout an object’s drift, such as variable immersion ratios and tilting as an object becomes inundated. The uncertainties in these geometric properties are typically handled implicitly by the stochastic techniques described in Section 4.3, such as Monte Carlo routines (Breivik & Allen, 2008; Nesterov, 2018).

Other work has more explicitly addressed this problem by modeling drift trajectories through least-squares optimization of a matrix of weight coefficient vectors (Wang et al., 2014). In this approach, the model weights are applied to physical forcing (*e.g.* current and wind vectors) and geometric variables (*i.e.* object dimensions, leeway divergence angles and immersion ratios), and stochastic motion is represented through probability density functions (Wang et al., 2014). More recent work has addressed the uncertainty in immersion ratios by parameterizing an explicit variable immersion ratio scheme coupled to the trajectory model described in Daniel et al., 2002, with stochastic uncertainties accounted for by probability density functions (Ren et al., 2024). Here, Ren et al. (2024) focus on structurally-intact containers (as damaged containers are assumed to immediately sink within the initial drop site) and define four cases of container orientation in their model, with each case characterized in relation to the position and submersion of the container’s ventilation holes. In certain cases, using fixed immersion ratios still outperformed the variable immersion scheme, but in general their approach provided improved accuracy in container surface drift trajectories, with an average reduction in mean bias of 22% across the different cases (Ren et al., 2024).

Other approaches also hold promise to address geometric uncertainties in container drift. Idealized wind-drag coefficients have been used to characterize the wind-driven motion of drifters, but fuzzy numbers could instead be applied to ensemble wind drag coefficients and capture uncertainty associated with geometric effects (Blanken et al., 2021). With sufficient data, machine-learning frameworks may also implicitly learn geometrically-dictated movements, such as jibing, from training on drifter trajectory observations and forcing data, and therefore account for some of this uncertainty. As noted in Section 4.6, machine learning algorithms could also be trained as optimizers to account for the uncertainties (including those associated with geometric effects) in other trajectory models applied to container drift tracking.

#### 4.8.2 *Trajectories from high-frequency radar*

HF radar is now being used for short-term drift trajectory modelling (Breivik et al., 2013; Révelard et al., 2021; M. Spaulding et al., 2006; Zhu et al., 2023). Similarly to the leeway method, a linear autoregressive trajectory model has been developed for HF radar (Frolov et al., 2012). This approach incorporates several pre-processing steps, including applying empirical orthogonal functions to reduce input complexity, utilizing augmented vectors to capture temporal changes, and cost functions to reduce overfitting of the regressed matrices. This approach is most accurate over a few hours, with increasing error introduced for trajectory forecasts up to 48 hours (Frolov et al., 2012).

Open-modal analysis has also been used to extend HF data and fill gaps (D. Barrick et al., 2012). This analysis technique decomposes the vector fields into rotational, divergent and boundary modes, which are then fitted with a multilinear model with coefficients determined by least-squares (D. Barrick et al., 2012). The approach can provide accurate 12-hour drift forecasts. Similar work has combined open-boundary modal analysis with empirical orthogonal analysis to reconstruct drifter trajectories (Solabarrieta et al., 2016).

In general, the trajectories produced from these approaches are constrained to the coastal range of the HF radar, and typically only provide short-term (12-48 hours) predictions (Breivik et al., 2013), which limits their usefulness to tracking the surface drift of lost containers. Nonetheless, used in conjunction with other approaches these techniques could be useful to compensate for forcing errors introduced by coastal biases in satellite altimetry data and data assimilative models (Birol & Delebecque, 2014; Liu et al., 2014; Vignudelli et al., 2011).

### 4.9 Summary of main points

- The leeway model is an empirical approach that models an object’s drift by deriving coefficients from regression against the downwind and crosswind components of the object’s drift (Breivik et al., 2011; Breivik & Allen, 2008). Field experimental studies have applied leeway model to tracking surface drift of shipping containers at different immersion ratios (Breivik, Allen, et al., 2012; Sutherland et al., 2024).
- To date, the trajectory models based on the balance of drag forces parameterized by the immersion level of containers (Daniel et al., 2002) and the leeway method (Breivik, Allen, et al., 2012; Breivik et al., 2011; Sutherland et al., 2024) remain the primary approaches to modelling the surface drift trajectories of lost shipping containers. However, there are a variety of modelling techniques that have been developed in recent years with potential for application to surface container drift.
- Stochastic ensemble techniques including Monte Carlo routines and Markov models (*e.g.* random walk, random flight) can be used to account for uncertainty in drift models such as the leeway method (Breivik & Allen, 2008; Y. Chen et al., 2022; J. Gao et al., 2018; Tu et al., 2021, 2022) and in underlying forcing data (*e.g.* Breivik & Allen, 2008; Nesterov, 2018).
- Multi-model ensembles collate outputs from models of the same type (“super-ensembles”) or different types (“hyper-ensembles”) into a single ensemble to compute drift trajectories (Rixen & Ferreira-Coelho, 2007; Vandenbulcke et al., 2009). Reductions in error and uncertainty can be achieved in this approach through a variety of minimization routines, to produce an optimal combinations of models within the ensemble.
- Fuzzy numbers define sets of possible values to describe the uncertainty within a dataset at varying degrees of belief (Zadeh, 1965, 1978). They have been adapted to propagate input uncertainty through drift trajectory models with comparable performance to the leeway method, without relying on prescribed empirically-determined coefficients (Blanken et al., 2021). Improvements in performance may be gained from applying fuzzy numbers to assess the uncertainties in spatially-variable underlying velocity fields (Blanken et al., 2023).
- In recent years, machine learning has been adapted to drift trajectory modelling (*e.g.* Bhaganagar et al., 2022; Jenkins et al., 2023; Lin et al., 2024; Song et al., 2024). These studies have utilized various model frameworks incorporating different types of neural networks (*e.g.* CNN, RNN, LSTM, transformers) and other algorithms (GPR, gradient-boosted decision trees). The relative sparsity of container drift observations presents a challenge to applying machine learning to directly predict container drifting trajectories. An alternative approach is to apply these algorithms as sophisticated optimizers within hybrid drift model frameworks, where the chosen machine learning algorithm can be

trained to parameterize the fraction of variance in trajectory models that is otherwise unexplained.

- Backtracking is a technique that can be applied to model surface drift trajectories when the point of origin is unknown, or subject to uncertainty relative to an object's current position (Breivik et al., 2025). This technique can be more error prone, particularly for longer drifting durations, when there are discontinuous or divergent state changes observed in either the underlying velocity fields or the object's drift characteristics (Breivik, Bekkvik, et al., 2012; Breivik et al., 2025). This is because the initial timing of occurrence and/or duration of a state change event (*e.g.* swamping or capsizing, or the duration of a partial stranding) is less certain when working in reverse, leading to deviances in drift trajectories (Breivik et al., 2025).
- Other work has addressed the dynamic changes in geometric effects on drift trajectories. One modelling approach applies least-squares optimization of a matrix of weight coefficient vectors to account for variable leeway divergence angles and immersion ratios (Wang et al., 2014). Another approach has parameterized an explicit variable immersion ratio scheme in a traditional trajectory model (Daniel et al., 2002), where stochastic uncertainties are accounted for by probability density functions (Ren et al., 2024).
- HF radar is now being used for short-term drift trajectory modelling (Breivik et al., 2013; Révelard et al., 2021; M. Spaulding et al., 2006; Zhu et al., 2023), through various statistical techniques to develop surface drift trajectory models. Examples are linear autoregressive models, empirical orthogonal functions, augmented vectors, and open-modal analysis (D. Barrick et al., 2012; Frolov et al., 2012; Solabarrieta et al., 2016). These approaches could be applied to container drift modelling, but are constrained to the coastal range of the HF radar, and typically only provide accurate predictions in the short-term (12-48 hours) (Breivik et al., 2013).

## 5.0 Modelling trajectories of sinking containers

### 5.1 Overview

There is an abundance of literature on surface drift trajectory modelling, but few studies have investigated trajectories of sinking objects (Xiang et al., 2023). For lost shipping containers at sea, no predictive models for their sinking trajectories and settling positions have been developed to date. However, there is a foundation in the literature for developing such models. Recent experimental observations have begun to provide insights into the sinking behavior of shipping containers (Awotahegn, 2015; Y. Li et al., 2022), and other work has studied the trajectories of

other dropped objects into the ocean (*e.g.* pipes from oil rigs, or rockets off launch platforms on floating barges) (Xiang et al., 2017, 2019; X. Yu et al., 2020). In addition, many of the factors affecting container surface drift (Section 2.0) and associated models (Section 4.0) may also be applicable to sinking trajectories of lost containers.

As with modelling surface drift trajectories, the trajectories of sinking containers will be subject to both deterministic and stochastic components (Xiang et al., 2023). A key component to assessing the fates of these containers will be accurately capturing both the sinking trajectories, and the behavior of these containers once settled on the seafloor, as they may be displaced through various migration processes (Chu et al., 2022; Papili et al., 2014). Such displacement may have broader implications for benthic communities (McDermott et al., 2023). The following section synthesizes relevant observations from the literature, and outlines relevant parameters and potential approaches to modelling the deterministic and stochastic components of container sinking. The issue of potential mobility and re-settlement of containers on the seafloor is also discussed.

## 5.2 Potential modelling approaches

### 5.2.1 Deterministic components

The force balance for sinking objects along the vertical axis can be generally defined as a balance between the buoyancy, gravity, and form drag forces (Walker et al., 2020), represented here as:

$$\sum F = m_c a_z = F_{drag} + F_{buoy} - F_g \quad (1)$$

Here  $m_c$  is the mass of the container and cargo, and  $a_z$  is the acceleration in the vertical direction. The sum of these forces is zero when the object reaches terminal velocity (Walker et al., 2020). The upward form drag force,  $F_{drag}$ , can be defined as:

$$F_{drag} = \frac{1}{2} C_d \rho_w A v^2 \quad (2)$$

Where  $C_d$  is the drag coefficient,  $\rho_w$  is the density of seawater,  $A$  is the cross-sectional surface area relative to the vertical, and  $v$  is the vertical velocity of the container. The buoyancy force,  $F_{buoy}$ , can be defined as:

$$F_{buoy} = \rho_w V g \quad (3)$$

Where  $V$  is the volume of seawater displaced by the container, which decreases with time as the container takes on water, and  $g$  is the acceleration due to gravity. The force of gravity on the container,  $F_g$ , is:

$$F_g = m_c g \quad (4)$$

The force-balance for sinking containers is represented by the free-body diagram in Fig. 6.

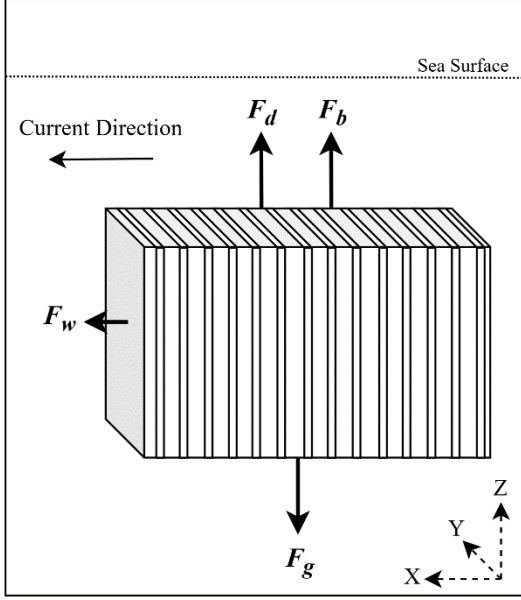


Figure 6. Physical forcing affecting the sinking trajectories of lost shipping containers at sea. Sinking is controlled mainly by the gravitational force exerted on the container ( $F_g$ ), which is opposed by the form drag ( $F_d$ ) and the buoyancy ( $F_b$ ) forces.

An unresolved question at present is if displacement from the release point is dictated solely by surface drift (*i.e.* the container sinks rapidly once it takes on enough water for  $F_{buoy}$  to reduce below a certain threshold) or if subsurface forcing can produce significant displacement after a container as submerged. Subsurface forcing will be due to currents, including those induced by eddies and tidally-driven internal waves through advection (Ouimet & Cortés, 2013; Thomson et al., 1990) (Fig. 6). The degree of displacement observed from these processes will depend on their strength and the time over which these processes can act on the container (*i.e.* dictated by the container's sinking rate and the water column depth).

The impact angle of containers on the sea surface can induce roll during sinking, leading to additional displacement relative to the surface entry point (Y. Li et al., 2022). Observational evidence of this has been restricted to laboratory tests on downscaled model containers (Y. Li et al., 2022), and its not clear whether the displacement produced from this process is significant in the field. Studies that have investigated rolling and other dynamic motions (*i.e.* pitch and yaw) of dropped objects have deterministically modelled these subsurface rotational effects (Xiang et al., 2017, 2019; X. Yu et al., 2020). This could be applied to parameterize horizontal motion for sinking shipping containers, however a simpler approach may be to parameterize these motions through stochastic techniques (X. Yu et al., 2020), as discussed below.

### 5.2.2 Stochastic components

Several factors affecting the sinking behavior of lost shipping containers are subject to high degrees of uncertainty and cannot be modelled reliably using deterministic methods. One key factor is the residence time of drifting containers at the surface of the ocean, before they sink. For damaged containers it is expected that the containers will rapidly inundate with water and sink near the site of the loss event. However, the contents of the container may have an effect here as tightly sealed cargo can slow water ingress. For undamaged containers, the volume fraction of air space and the rate of water ingress will play a large role in how quickly a container sinks, and hence the horizontal displacement from the loss site due to surface drift (Fig. 7). Mass re-distribution and the compressibility of the cargo are also factors that may affect the force balance on the container, and thus affect its sinking rate and trajectory. These factors are dynamic and will result in uncertainty about the containers sinking trajectory, requiring stochastic modelling techniques. The possible fates of lost and sinking containers are illustrated in Figure 7:

1. Released containers may enter the water damaged or intact, as either single containers or rafted stacks (see Fig. 2).
2. Damaged containers are presumed to rapidly inundate with water and sink near the point of entry into the water.
3. Rafted container stacks may become damaged from stresses due to wave action over time, perhaps exacerbated by mass re-distribution of cargo. The latter process may also produce damage in single afloat containers.
4. Intact containers are most likely to initially remain afloat and begin drifting. Here, the geometry and orientation of containers is an important factor, as the orientation and depth of the ventilation holes will dictate the immersion level and the rate of water ingress. For other possible container orientations not depicted here, see Ren et al. (2024).
5. Uncertain factors such as water ingress rates, mass re-distribution, and the volume fraction of air space will create uncertainty in the time required to initiate sinking.
6. Once fully submerged, containers are likely to rapidly sink. The sinking rate and water depth will determine the relative importance of subsurface horizontal advection.
7. The orientation of containers impacting on the seafloor may result in rolling or sliding of the containers along the seafloor, depending on seabed slope and sediment type. Migration (*i.e.* post-sinking re-mobilization) of containers along the seafloor is possible, but will depend on factors such as the strength of currents, seafloor slope, sediment types, container weight, and degree of damage/deformation of the container.

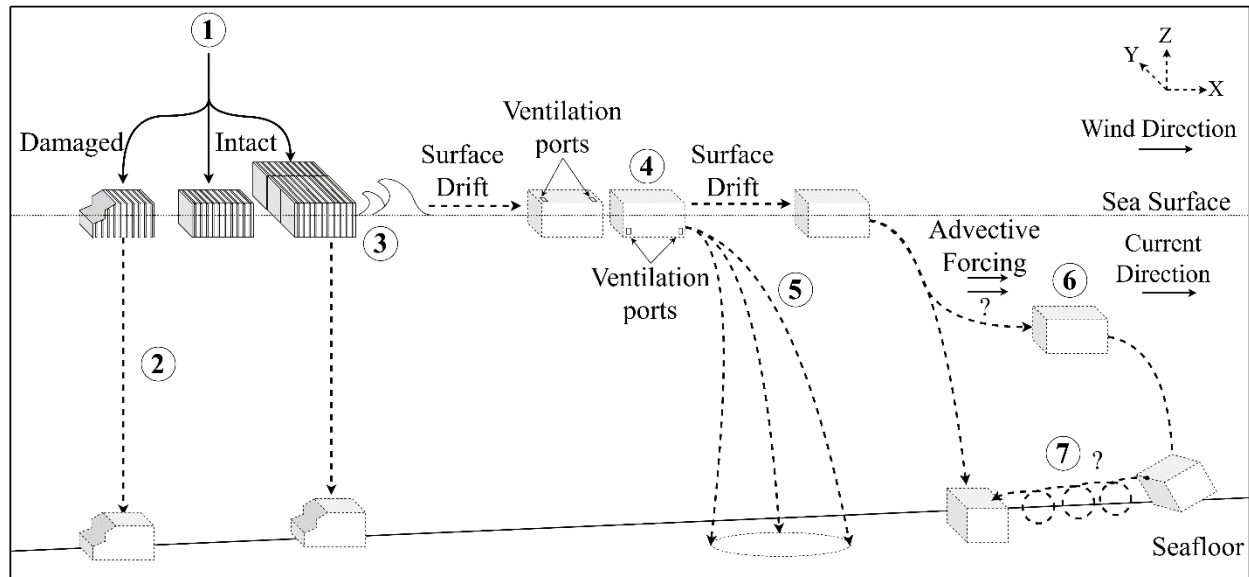


Figure 7. Flow chart for possible fates of sinking shipping containers.

Some of the stochastic methods applied to modelling surface drifting trajectories (see Section 4.0) can be repurposed to capture stochastic components of sinking behavior. For example, LSTM frameworks have been applied to model the sinking and subsurface drift of AUVs (Y. Yu et al., 2022). Monte Carlo routines present another potential approach, and have been used to model the landing points of dropped rockets (X. Yu et al., 2020). They could also be used to account for migration due to rolling induced by the entry angle (Y. Li et al., 2022; Majed & Cooper, 2013). Random walk or random flight routines might be used to address uncertainties in subsurface currents (Ullman et al., 2006; Zhu et al., 2021), which could also be handled by fuzzy numbers (Blanken et al., 2021, 2023). Backtracking techniques may also be useful for validating or tuning algorithms developed for sinking trajectories based on known container settlement locations along the seafloor (see Section 5.2). However, as with surface drifting trajectories, this technique must be used with caution. Backtracking trajectory estimates may be erroneous for containers that experienced nonlinear events, such as a sudden shift of cargo leading to rapid, one-time water ingress, as the timing of these events is difficult to capture in reverse (Breivik, Bekkvik, et al., 2012; Breivik et al., 2025).

### 5.3 Settlement and potential mobility on the seafloor

The final component of the trajectory of sunken shipping containers is their settlement position. In most cases, this will be the position of initial impact with the seafloor. But displacement is possible, and will depend on the substrate type, the slope of the seafloor, the strength of bottom currents, the weight of the container and its cargo, and the degree of damage the container has sustained. For example, the angular momentum induced by the impact angle of containers at the sea surface (Y. Li et al., 2022) may translate into rolling momentum along the seafloor following grounding (Fig. 8A,B), provided the substrate is hard enough to not sufficiently dampen the impact energy and impact damage is not excessive.

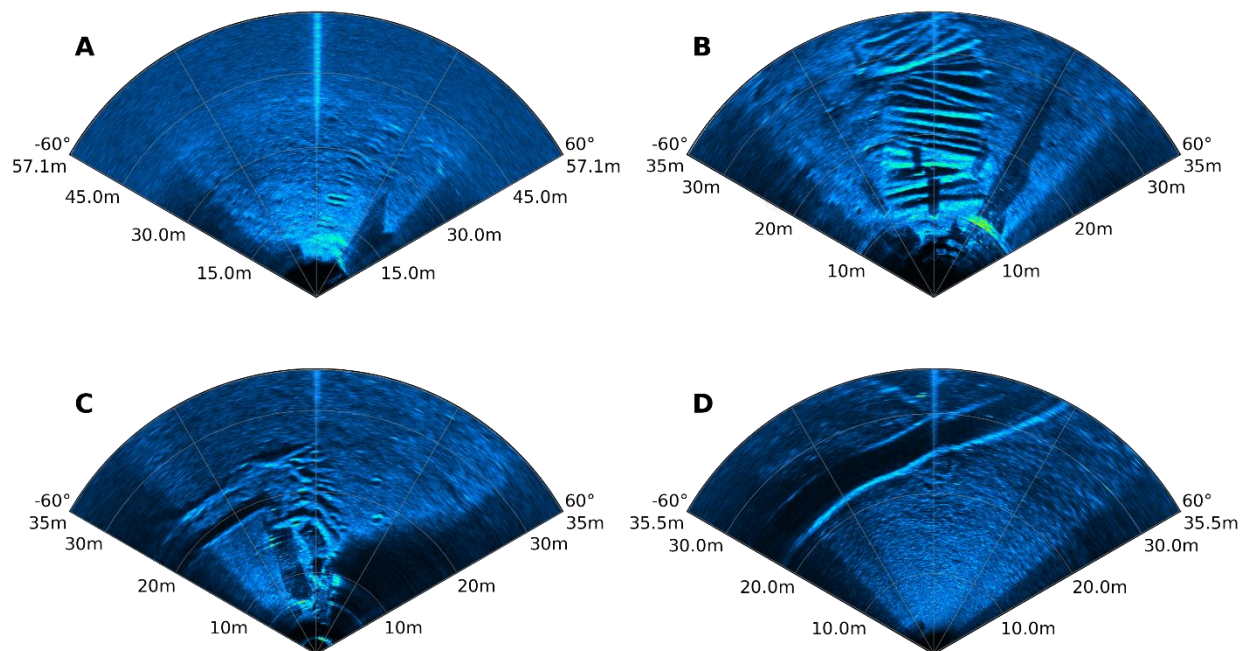


Figure 8. Sonar imagery taken overhead of identified container debris fields, illustrating modes of container scour during impact and settlement. (A) Coupled scour marks ~3 m wide covering a 24.7 m extent, which likely resulted from the container tumbling end-over-end. (B) Scours covering 23.3 m extent from a 40-ft container rolling about its long edge. (C) Scours (average 3.5 m width) from a sliding container, with broken side paneling from the container visible. (D) Sliding scours continued from the same container in (C). Total extent of this scour covered at least 95 m. Source: DFO.

The vast majority of sunken containers remain unlocated, however recent survey work at the *M/V Zim Kingston* container loss site shows some evidence of mobility of containers along the seafloor, either during or after grounding. Imaging sonar data from this survey confirms that sinking containers can demonstrate rolling, sliding and tumbling behavior, covering up to nearly

100 m distance following seafloor impact (Fig. 8). The observed scours are likely to primarily result from the transfer of momentum following initial impact. While re-mobilization of sunken containers after grounding is possible, it is likely rare. Studies on mobilization of sunken objects have focused mainly on cylindrical munitions, which can have variable lateral movement (termed ‘migration’; Menzel et al., 2025), ranging from limited or no migration (Chu et al., 2021, 2022; Menzel et al., 2025) to migrating distances exceeding 100 m (Traykovski & Austin, 2017). However, migration typically diminishes with increasing weight (Chu et al., 2021, 2022), and containers can be on the order of 60-fold heavier than the heaviest munitions studied (Chu et al., 2021, 2022; Traykovski & Austin, 2017), suggesting re-mobilization is unlikely. Indeed, long-term study of the single identified sunken container from the 2004 *M/V Med Taipei* incident has shown it has been stable enough to provide a thriving artificial reef system over at least seven years (McDermott et al., 2023; Taylor et al., 2014).

Migration of sunken containers is thus likely restricted to cases where conditions are such that little force is required to initialize movement. Possible examples include grounded containers with reduced weight (*i.e.* lighter cargo, or spilled cargo from container damage during grounding), containers resting on steeper sloped areas of the seabed, or sediment types with lower friction. In cases where drag forces are high due to strong tidal currents or storm-driven currents and waves (Dalyander et al., 2013; Papili et al., 2014) likelihood of potential container migration increases, and other anthropogenic activities such as trawling may disperse containers and their associated debris fields. Thus, migration may contribute to some limited uncertainty in the final settlement locations of lost shipping containers.

## 5.4 Summary of main points

- The balance of vertical forces on sinking objects (such as shipping containers) is generally defined as a balance of buoyancy, gravity, and form drag (Walker et al., 2020).
- It is an open question at present if subsurface horizontal advection is significant after a container is fully submerged.
- The impact angle of containers on the sea surface can induce roll during sinking, with the angular velocity produced leading to lateral displacement relative to the surface entry point (Y. Li et al., 2022).
- Onset and rate of sinking is affected by the volume fraction of air space, the rate of water ingress, mass re-distribution, and the compressibility of the cargo.
- The parameters governing sinking are dynamic and result in uncertainty that must be addressed stochastically. As with surface drift, methods such as Monte Carlo routines (Majed & Cooper, 2013; X. Yu et al., 2020), random walk or random flight models

(Ullman et al., 2006; Zhu et al., 2021), or fuzzy numbers (Blanken et al., 2021, 2023) can be used here.

- Re-mobilization (migration) of sunken containers along the seafloor is possible, but likely occurs infrequently and over limited distances. If lateral movement does occur, it will be restricted to containers with lighter cargo situated such that environmental factors (*e.g.* steeper sloped areas of the seabed, or sediment types with lower friction) reduce the forces needed to initialize movement.

## 6.0 Gap Analysis

In their report following the 2021 *M/V Zim Kingston* incident, the Standing Committee on Fisheries and Oceans for the House of Commons of Canada recommended that DFO implement a “marine debris monitoring and management plan” (McDonald et al., 2022). This recommendation was largely motivated by the gaps in our current capabilities to locate sunken containers and assess their environmental impact, including the degradation of debris into microplastics (Turner et al., 2021; Wan et al., 2022) and coastal pollution, as debris presumed to originate from this incident continues to wash ashore (TSB, 2024). An important tool in locating containers and assessing these effects will be the development of an operational trajectory model for lost shipping containers with three spatial dimensions (surface drift and sinking), to better predict both the search areas and ship-time costs associated with monitoring and recovery efforts. It was also noted that during the initial response to 2021 *M/V Zim Kingston* incident, the U.S. Coast Guard conducted the initial drift modelling of the lost containers, leading the Standing Committee to further recommend that the Canadian Coast Guard’s capabilities for drift modelling be reviewed by the Government of Canada (McDonald et al., 2022). This report addresses these recommendations by reviewing both the current and potential approaches to modelling the drifting and sinking trajectories of lost shipping containers at sea.

Drift modelling of containers has primarily been done through deterministic consideration of the immersion ratio and associated force balance (Daniel et al., 2002) or the adapted leeway method (Breivik, Allen, et al., 2012; Sutherland et al., 2024). However, other potentially promising approaches have now been developed for modelling trajectories of shipping containers, such as multi-model ensembles, fuzzy numbers, machine learning, and back-tracking, as discussed in Section 4.0. Determining the optimal techniques for real-time operational trajectory modelling will require evaluating the performance trade-offs between the more computationally expensive, higher fidelity approaches and the more flexible frameworks with greater uncertainty.

A primary example of these cost-benefit analyses is the choice of resolution of OGCMs and atmospheric models providing input fields for trajectory modelling. Increasing model resolution

in forcing fields can yield improved trajectory predictions, but this is not guaranteed (Dagestad & Röhrs, 2019) and comes with the drawback of significant computational costs. Computational expense can be mitigated by nesting smaller high domains within regional tunings of OCGMs. This has been shown to reduce computational costs and biases in velocity fields used to force trajectory models (Pennelly & Myers, 2020). Development of relocatable, on-demand high resolution nests within regional models in an operational capacity is ongoing (Y. Lin et al., 2022; Trotta et al., 2016, 2021). Some machine learning approaches can also provide similar performance to OGCMs with less computational overhead (Gentine et al., 2018), by training them to account for uncertainties in sparse observational data (Chapman & Charantonis, 2017) or low resolution OGCMs (Bolton & Zanna, 2019). Data assimilative models (Breivik & Sætra, 2001; Oke et al., 2015) and multi-model ensembles (Scott et al., 2012) are additional advances in ocean modelling that have yet to be fully leveraged in the context of trajectory modelling for lost shipping containers.

The accuracy of trajectory predictions can be improved by explicitly considering as many relevant forces as possible, including deterministic values where possible and appropriate, and capturing uncertainty in the forcings through stochastic methods (Breivik & Allen, 2008; Nesterov, 2018). For example, explicitly including Stokes drift in the leeway method provided significant reductions in trajectory uncertainties, which compound over longer drift durations (Sutherland et al., 2024). This becomes an important consideration for lost shipping containers which can remain afloat drifting for days to weeks (Frey & De Vogelaere, 2014). Incorporating explicit consideration of Stokes drift, as well as the associated Coriolis-Stokes force (Polton et al., 2005; Weber et al., 2015), into trajectory estimates could yield accuracy gains regardless of the modeling framework used. Similarly, the documented improvements in container trajectory predictions through parameterizing variable immersion ratios (Ren et al., 2024) could be adapted to other frameworks. There are further opportunities to build and improve parameterizations for sinking of containers by considering factors such as mass re-distribution and water ingress rates.

Further improvements in trajectory predictions may be achieved by leveraging machine learning for a variety of use cases, from improving forcing data (Bolton & Zanna, 2019; Chapman & Charantonis, 2017) to modeling drift trajectories directly (*e.g.* P. Huang et al., 2022; Jalón-Rojas et al., 2019; Lin et al., 2024; Song et al., 2024). They can also be used as sophisticated “optimizers” to further remove uncertainty in other model frameworks. For example, a DNN framework could be trained on the outputs of other trajectory models, with known container beaching or seafloor settlement locations used as the ground truths. This would allow the DNN to study the variances in both sinking and drifting trajectories relative to other oceanographic variables, effectively allowing the DNN to serve as a separate parameterization for some of these uncertainties. This technique has been successfully used in some trajectory modelling studies (Aksamit et al., 2020; Shen et al., 2022), but has not been widely adopted to date.

The sinking behavior of lost shipping containers remains the largest knowledge gap, as no model frameworks currently exist in the literature. The key variables that will need to be addressed in developing a sinking trajectory model are: 1) The rate of water ingress, which is linked to container geometry and mass distribution and other factors such as mass re-distribution, degree of container damage, and compressibility of cargo, will dictate the duration of the drifting and sinking phases of the trajectory; 2) the sinking rate, which will be dependent on water ingress rates and cargo buoyancy; and 3) whether subsurface advection is significant in altering sinking trajectories, which depends on the water depth, sinking rate, and strength of subsurface currents. Some of these factors may be considered deterministically, but due to their uncertain nature some stochasticity is unavoidable. Many of the methods applied to drift modelling can be adapted to address stochastic processes, such as Monte Carlo routines (Majed & Cooper, 2013; X. Yu et al., 2020), random walk or random flight models (Ullman et al., 2006; Zhu et al., 2021), or fuzzy numbers (Blanken et al., 2021, 2023). Back-tracking trajectories (Breivik, Bekkvik, et al., 2012; Breivik et al., 2025) may also prove useful in tuning parameterizations and providing validation of sinking trajectory models.

Observations of the final positions and condition of shipping containers lost during documented events are highly valuable in developing sinking trajectory models. Laboratory experiments with model containers can also provide some insights into sinking dynamics (Y. Li et al., 2022), with the caveat that calm water experiments will be unable to capture the *in situ* effects of subsurface forcing. Simulations of sinking containers and their cargo using high-fidelity computational fluid dynamics (CFD) techniques, such as smoothed particle hydrodynamics (SPH), may also yield further insight.

Finally, the Standing Committee on Fisheries and Oceans recommended investigating the feasibility of fitting shipping containers with tracking devices to aid in locating them once lost (McDonald et al., 2022). If this recommendation were implemented by the industry, it could aid in response efforts after a loss event as well as trajectory model development. Data from these trackers could provide validation of drift durations and container drifting speeds, as well as settlement locations of containers along the seafloor, pending successful retrieval of the tracking devices. As one outcome of the *M/V Zim Kingston* incident, DFO has been developing a rapidly deployable tracker that attaches to drifting containers and marks their sinking location via satellite tracking. In the past, experimental studies rigging containers with GPS and meteorological sensors have proved fruitful in refining leeway model parameters (Breivik, Allen, et al., 2012; Sutherland et al., 2024), and building sizeable observational datasets would enable robust parameterization of models for container drift and sinking, including training and use of machine learning frameworks.

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