

OBSERVATIONS OF PRIMARY SHIP WAVES AT THE MARGINS OF A CONFINED TIDAL RIVER

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ABSTRACT

Primary waves produced by large ships in confined waterways can threaten the sustainability and safety of coastal regions near maritime shipping routes, but the present understanding and predictability of primary wave shallow-water characteristics is hindered by a scarcity of available field observations. This study presents hydrodynamic measurements from 296 primary waves observed in 3.5 to 4.4 m mean water depth throughout four deployments on the channel margins of the Savannah River in Georgia, USA. Ship details and tidally-varying waterway parameters are paired with pressure and fluid velocity data to investigate relationships between ship characteristics, waterway conditions, and primary wave magnitudes. Findings show that although larger and faster ships tend to produce larger primary waves, there are inconsistencies among the magnitudes of waves generated by similar ship passages. Additionally, depression prediction equations perform well for most observations, but a small group of “atypically-large” primary waves with depressions

exceeding 75 cm are consistently underpredicted and require further investigation. Hydrodynamic, waterway, and ship data are made available in Supplemental Materials.

INTRODUCTION

The wake system of large ships traveling in confined waterways like shipping channels includes a low-frequency (about 0.005 - 0.01 Hz) primary wave fixed to the hull and extending to the edges of the waterway. As the primary wave passes over a shoreline location, water recedes for 1 - 2 minutes before returning in a surge that often exceeds the still water level and can range in form from a gradual water level rise to a bore. With wave heights reaching 2 m in severe events (e.g. Parnell et al. 2015; Scarpa et al. 2019; Muscalus and Haas 2022), primary waves can pose risks to shoreline stability, coastal ecosystems and infrastructure, and public safety near maritime shipping routes.

The primary wave stems from a water surface depression that spans from the bow wave to the stern wave and is produced by a pressure-driven return current along the length of the ship (e.g. Schijf 1949; Bundesanstalt für Wasserbau 2016; Schiereck 2017). Although the primary wave generally decays with distance from the ship (e.g. Sorensen 1973; Bhowmik et al. 1981), it is subject to transformation processes on shallow waterway margins (e.g. Rapaglia et al. 2011; Parnell et al. 2015; Rodin et al. 2015).

Primary wave investigations have been driven largely by erosion concerns along waterways, with field studies linking primary waves to increased suspended sediment concentration (Garel et al. 2008; Davis et al. 2009; Rapaglia et al. 2011; Mao et al. 2016; Scarpa et al. 2019; Ulm et al. 2020) and turbidity (Gelinas et al. 2013; Göransson et al. 2014; Larson et al. 2017). Wave characteristics such as energy, energy flux, and forcing have been used to assess contributions of primary waves to erosion in waterways including Galveston Bay in the USA (Figlus and Fuller 2019), the Meuse River in the Netherlands (Duró et al. 2020), the St. Lawrence Waterway in Canada (e.g. Gaskin et al. 2003), the Venice Lagoon in Italy (Zaggia et al. 2017), and Wootton Creek in England (Garel et al. 2008). The importance of primary waves to erosion is site-dependent, often owing to differences in vessel traffic and local hydrodynamics. For instance, near the mouth of the Savannah

River, USA, erosion is driven by wind waves and pilot boat Kelvin wake rather than primary waves (Houser 2010). However, 8 km upriver at a site sheltered from wind waves and infrequently passed by pilot boats, primary waves are the dominant contributor to erosion (Muscalus and Haas 2022).

In addition to erosion, primary wave impacts can include plugging tidal creeks (Ravens and Thomas 2008), damaging groins (Melling et al. 2019; Melling et al. 2021), and slamming tidal gates (Uliczka et al. 2009). Primary waves can also displace and hinder the growth of aquatic plants (Ali et al. 1999), damage marsh vegetation (Silinski et al. 2015), strand fish (Adams et al. 1999; Pearson and Skalski 2011), and flush juvenile fish from shallow habitats (Wolter and Arlinghaus 2003; Wolter et al. 2004). Primary waves are a public safety concern as well, capable of stranding and capsizing small boats and overpowering waders and swimmers (e.g. Jong et al. 2013).

In general, larger and more impactful primary waves are associated with larger and faster ships (e.g. Bain et al. 2022). The size of a ship relative to the waterway in which it travels is parameterized with a blockage ratio,

$$C_B = \frac{Bd}{A_c}, \quad (1)$$

where B (m) is ship beam, d (m) is ship draft, and A_c (m²) is channel cross-sectional area. Hereafter, C_B is expressed as a percentage. Similarly, ship speed is typically parameterized with the depth Froude number,

$$Fr = \frac{S'}{\sqrt{gh_c}}, \quad (2)$$

where S' (m/s) is ship speed relative to local flow, g (m/s²) is gravitational acceleration, and h_c (m) is channel depth. Fr is used to characterize sailing regimes as subcritical ($Fr < 0.8$), transcritical ($0.8 < Fr < 1.0$), critical ($Fr \approx 1.0$), or supercritical ($Fr > 1.0$). In the confined waterways where primary waves are of interest, large ships usually travel in the subcritical regime.

Concerns about ship wake impacts have motivated the development of analytical depression prediction equations for computing primary wave depression magnitudes from ship and waterway characteristics. These equations all neglect temporal and alongshore variability, and whereas some evaluate the depression as a function of the cross-shore coordinate, the majority compute only the

maximum depression magnitude. Most depression prediction equations are semi-empirical and use modifications of the Schijf equations (Schijf 1949), which relate ship volume displacement to the strength of the return current and depression, to fit observational or experimental data. Most depression prediction equations have been developed with limited data, oftentimes from a single field site or experiment, resulting in site-specific performance and a variety of published equations. For instance, the Hochstein depression prediction equation (Hochstein 1967) was developed with observations from St. Mary's River in Michigan, USA and accounts for the speed of the ship relative to the critical ship speed ($Fr = 1.0$). A modified version (Hochstein and Adams 1989) includes the effects of waterway ice coverage. The Dand and White (1978) equation uses regression parameters fitted to experimental data from scale models of the Suez Canal, and the Bhowmik et al. (1981) approach uses nonlinear regression parameters in addition to a cross-shore ship-to-shoreline distance parameter to fit field observations from the Illinois River and Mississippi River in the USA. The Maynard (1996) equation incorporates cross-channel decay and waterway asymmetry to fit experimental data from scale model experiments representing the Ohio, Illinois, and Mississippi Rivers. To reduce site-specificity, the Almström and Larson (2020) equation defines non-dimensional parameters of ship and waterway characteristics and assigns each a power coefficient by fitting the full expression to observations. The accuracy of the equation was demonstrated with observations from the Stockholm archipelago in Sweden, but the power coefficients are to be determined on a site-by-site basis. For additional details on semi-empirical depression prediction equations, readers are referred to reviews provided by Almström and Larson (2020) and Dempwolff et al. (2022a).

Since depression prediction equations tend to exhibit site-specific performance and do not resolve temporal or alongshore variability, wake prediction efforts are increasingly turning to numerical modeling. Published field observations of primary waves are scarce, so most models are validated with data from scale model experiments. Computational Fluid Dynamics (CFD) models, which simulate fully 3D hydrodynamics, produce primary wave results consistent with physical scale models (e.g. Bechthold and Kastens 2020; Kochanowski and Kastens 2022) and have

104 been used to assess wake impacts such as bank erosion (Huang et al. 2022) and loading on groins
105 (Dempwolff et al. 2023) and moored ships (Zheng et al. 2023). However, applications for multiple
106 ship passages in domains spanning multiple kilometers, realistic of most shipping channels, are
107 resource-intensive. Depth-averaged 2D shallow water equation (SWE) and Boussinesq-equation
108 (BE) models require fewer computational resources at the expense of accuracy where 3D flows
109 dominate, as may occur near embankments and structures. Since primary wave hydrodynamics are
110 not strongly 3D, SWE and BE models have successfully simulated primary waves measured in scale
111 model experiments (e.g. Dempwolff et al. 2022b; Dempwolff et al. 2023) and field observations
112 (e.g. Almström et al. 2021; Everett et al. 2022; Lam et al. 2022; Chakraborty et al. 2023). Although
113 numerical models are useful for examining ship wake behavior in detail and predicting primary
114 waves for specific events at sites of interest, depression prediction equations still hold practical
115 value for rapidly assessing primary wave predictability within large (hundreds of events) data sets.
116 The equations are also useful for obtaining initial estimates of wake magnitudes at sites where
117 numerical models are unavailable, which can inform siting decisions for future observations.

118 This study examines the hydrodynamics of 296 primary waves at the channel margins of a
119 confined tidal river with respect to ship and channel characteristics. The specific objectives are to

- 120 • evaluate the accuracy of using linear wave theory to estimate primary wave hydrodynamics
121 from wave height,
- 122 • assess relationships between primary wave magnitude and common metrics of ship size and
123 speed,
- 124 • examine the consistency of primary waves produced by similar passages at different times
125 and locations, and
- 126 • evaluate the performance of existing depression prediction equations.

127 MATERIALS AND METHODS

Site Information

Primary wave observations for this study were collected just offshore of Bird/Long Island in the Savannah River, a major tidal river in the southeast United States at the border of South Carolina and Georgia (Figure 1). Bird/Long Island divides the river into the Main Channel, which contains a shipping channel for ships traveling to and from the Port of Savannah, and the smaller, shallower South Channel to the southwest. Tides are semi-diurnal, with a maximum tidal range of about 2.8 m along Bird/Long Island. Peak tidal currents reach 2 m/s in the shipping channel and about 1 m/s on the channel margins.

The Main Channel is a natural channel with an irregular shoreline and widths ranging from about 600 m to 700 m along Bird/Long Island. The approximately 200 m wide shipping channel within it is maintained through annual dredging and managed by the United States Army Corps of Engineers (USACE). Large ship traffic is comprised of bulk carriers, vehicle carriers, chemical tankers, feeder container ships, Panamax container ships, Post-Panamax container ships, and Neo-Panamax container ships. To reduce tidal constraints on the passages of the largest, deepest-draft ships calling on the port, the seven-year Savannah Harbor Expansion Project deepened the channel from an allowable depth of 12.80 m (42.00 feet) to 14.33 m (47.00 feet). Deepening in the vicinity of Bird/Long Island took place from September of 2021 to January of 2022. Despite this alteration of the maintained shipping channel and scarp retreat at the shoreline (Alexander and Calabria 2019), repeated bathymetric surveys conducted by the authors along Bird/Long Island show little observable change in channel margin bathymetry during the years spanned by the field observations.

Field Measurements

Primary waves were measured at the shipping channel margins in 3.5 to 4.4 m mean water depth, $\bar{h}$ (m), during four separate deployments: Upper-Island 1 (UI-1) in October of 2017, Upper-Island 2 (UI-2) in early February of 2022, Mid-Island (MI) in mid-February of 2022, and Lower-Island (LI) in June of 2022. Additional deployment details are given in Table 1.

UI-1 pressure and velocity data were collected with a 2 MHz Nortek Aquadopp deployed on the bed in a 30-kg gravity frame connected to a marker buoy with an offset anchor weight (Figure 2a).

Due to data storage and battery constraints, the Aquadopp recorded data in burst mode, collecting 1024 measurements at 1 Hz every 20 minutes and leaving 176-second gaps between bursts. UI-2 and MI pressure data were collected continuously at 2 Hz with an RBR*solo*³D pressure transducer deployed on the bed in a PVC housing fixed to an 18-kg, low-profile gravity frame attached directly to a marker buoy (Figure 2b). LI pressure and fluid velocity data were collected continuously at 1 Hz with a Nortek Aquadopp deployed in a low-profile frame similar to those used for the RBR pressure transducers but with an offset anchor weight and marker buoy.

Reported instrument accuracy is ± 0.5 cm/s for the Aquadopp horizontal velocities, ± 5 cm for the built-in Aquadopp pressure sensor, and ± 1 cm for the RBR pressure sensors. The accuracy of pressure data was verified through comparison to measurements (not shown) from nearby standalone pressure transducers with reported accuracy ranges of ± 1 cm to ± 3 cm.

Field Data Processing

Pressure data quality control was performed by discarding isolated, instantaneous pressure deviations greater than the equivalent of 60 cm water depth. The influence of atmospheric pressure variability was removed using meteorological observations at the Fort Pulaski NOAA station (Station ID 8670870) located approximately 5 km from the center of Bird/Long Island. Depth-averaged velocities were obtained directly from wave bursts for the UI-1 data set and by manual depth-averaging from 20 cm above the sensor to 20 cm below the surface for the LI data set.

Using band-pass filtering, the pressure and fluid velocity data were separated by frequency, f (Hz), into high-frequency ($f > 10^{-1}$ Hz), mid-band (600^{-1} Hz $> f > 10^{-1}$ Hz), and tidal ($f < 600^{-1}$ Hz) signals. High-frequency signals are dominated by wind waves and Kelvin wakes and are henceforth neglected. Mid-band water surface fluctuations, η (cm), and mid-band fluid velocity fluctuations, $\vec{v}$ (cm/s), are dominated by low-frequency wake components such as primary waves. The cross-shore component of the $\vec{v}$ vector is defined as positive onshore, and the alongshore component is defined with respect to the direction of ship travel: positive when “with-ship” and negative when “against-ship.” The tidal signals include the tidal current, $\vec{V}$ (m/s), and tidal stage, ξ (m), with respect to mean sea level. The tidally-varying water depth, h (m), is therefore the sum

of $\bar{h}$ and ξ .

Ship Record Collection and Processing

Ship details for each data set were obtained from Automatic Identification System (AIS) data, pings of information that are broadcasted by ships and include Maritime Mobile Service Identity (MMSI) identification numbers, position, length, width, speed, and heading. The data are available from many web-based resources that typically provide processed data at thirty-second to two-minute temporal resolution for each ship. Different AIS resources may provide different sets of pings for a given ship, so to increase temporal resolution, AIS data were combined across multiple sources: Marine Cadastre AccessAIS, ShipTracks.com, FleetMon.com, and USACE.

AIS pings were organized into individual ship records by grouping pings of the same MMSI (same ship). For each group, raw “tracks,” or time series of ship position and speed, were formed from chronological pings and paired with the ship name, length, and width to form the ship record. Drafts were obtained from United States Vessel Entrances (US Customs and Border Protection 2023a) and Clearances (US Customs and Border Protection 2023b) tables, which provide drafts to the nearest 2.54 cm (1.00 inch), and were paired with AIS ship records manually.

The raw AIS tracks exhibited noise in the position data and occasional rounding of reported speeds (Figure 3), so position data were processed into smoothly varying time series of speed and position. Processing steps included discarding the second of nearly simultaneous pings, treating high-resolution ($\Delta t < 15$ s) data with a 4-point moving mean, and discarding points for which the corresponding computed speed and/or acceleration were unrealistic, i.e. the computed speed differed from the reported speed by more than 2 m/s or the computed acceleration magnitude exceeded 5 m/s per minute. The remaining position data were interpolated to 1 Hz, low-pass filtered with a 240-second cutoff period, and used to compute absolute ship speed, S (m/s),

$$S = \sqrt{\left(\frac{\Delta x_e}{\Delta t}\right)^2 + \left(\frac{\Delta x_n}{\Delta t}\right)^2} \quad (3)$$

where x_e (m) is the east position coordinate, x_n (m) is the north position coordinate, and t (s) is

time. The example S time series in Figure 3 demonstrates that the processing produces a more smoothly varying and realistic ship speed than the raw position-based speed or AIS-reported speed alone.

To facilitate comparison of primary waves produced under similar conditions among different data sets, passages were grouped by two systems (D and ND), each with three groups (Table 2). Ranges of the dimensional (“D”) parameters S' and ship length, L (m), define Groups D1: small but fast ships such as bulk carriers and tankers, D2: large but slow Post-Panamax and Neo-Panamax container ships, and D3: large and fast Post-Panamax and Neo-Panamax container ships. Ranges of nondimensional (“ND”) parameters C_B and Fr define groups ND1: high- Fr and low-blockage ships, ND2: low- Fr and high-blockage ships, and ND3: high- Fr and high-blockage ships. The D and ND groups of the same number usually describe qualitatively similar events. For instance, many of the fast and small ships in group D1 also belong to the high- Fr and low- C_B group ND1. However, the D and ND groups are not perfectly analogous, and neither system fully encompasses all observations.

Pairing Ship Records to Primary Wave Features

Primary waves for each ship record were identified and characterized from time series of η and $\vec{v}$ using a primary wave detection algorithm, with all results verified manually. The depression, of magnitude $|\eta_d|$ (cm), was identified as the minimum of η within $\pm$ one minute of the ship passage. The surge, η_s (cm), was identified as the maximum of η occurring within the two minutes after the depression. The primary wave period was defined from the last η zero down-crossing before the depression to the first zero down-crossing after the surge such that the primary wave height, H (cm), is

$$H = \eta_s - \eta_d. \quad (4)$$

Peak mid-band fluid velocities in the positive and negative cross-shore and alongshore directions were taken as the extrema of the corresponding $\vec{v}$ time series within the primary wave. The depth-integrated, wave-averaged energy, E (J/m²), was computed by averaging the sum of potential and

kinetic energy over the primary wave period, T (s), so that

$$E = \frac{1}{T} \int_0^T \left(\frac{\rho g \eta^2}{2} + \frac{h}{2} \rho |\vec{v}|^2 \right) dt \quad (5)$$

where $\rho = 1020 \text{ kg/m}^3$ is water density.

The ship information and associated primary wave characteristics were tabulated for all events in each data set in Tables S1 through S4, available in Supplemental Materials.

Channel Characteristics

Tidally-varying channel characteristics were computed for each ship passage. Channel depth profiles near the instruments were obtained by combining survey data from two sources: channel margin bathymetry collected by the authors during each deployment, and maintained shipping channel bathymetry collected monthly by USACE and published in a hydrographic survey database (<https://navigation.usace.army.mil/Survey/Hydro>). Therefore, the channel cross-sections used for each deployment are up-to-date to within about one month.

For each ship passage, the depth profile was adjusted for the tidal stage at the time the ship passed the instrument and used to compute A_c ; channel top width, w_c (m); mean channel depth, h_c (m), equivalent to A_c/w_c ; and mean shipping channel depth, h_{SC} (m), taken as the mean depth over the deepest 200 m in the cross-section. The tidally-adjusted profile and ship track were used to compute the channel top width between the ship and shore, $w_{c,side}$ (m).

Tidal currents in the shipping channel were estimated from Regional Ocean Modeling System (ROMS) simulations of the region including the Savannah River, Wassaw Sound, and Ossabaw Sound using the model domain developed by Defne et al. (2011) and modified with increased grid resolution (30 - 90 m). The tidal forcing was derived from the ADCIRC tidal database (Mukai et al. 2002), and the wind data were obtained from the nearby NOAA Fort Pulaski monitoring station. Each deployment time period was simulated separately, and the tidal currents were verified by comparing time series of depth-averaged currents with the data collected by the Aquadopp. Tidal currents were assigned to each ship record by interpolating the model data in the center of the

shipping channel directly offshore of the sensor to the time of ship passage. As with the mid-band fluid velocity fluctuations, the alongshore tidal current component, V (m/s), is defined as positive in the direction of ship travel. Thus, the relative ship speed, S' (m/s), is

$$S' = S - V. \quad (6)$$

Application of Depression Prediction Equations

The tabulated ship records and channel characteristics were applied to six example depression prediction equations: Schijf (1949), Hochstein (1967), Dand and White (1978), Bhowmik et al. (1981), Maynard (1996), and Almström and Larson (2020). These equations are provided in Appendix II. For all depression prediction equations, S' was used for ship speed to incorporate tidal current effects. In the Schijf (1949) equation, which is based on a simple cross-section with a given depth and area, the depth h_{SC} and area A_c were applied. Mean shipping channel depth, h_{SC} , is used instead of overall mean channel depth, h_c , for this equation because h_c is exceeded by ship draft in many events due to channel margin influence. The performance of each equation was assessed for each data set with the coefficient of determination (R^2) and bias, where bias is the mean difference between the predicted and measured values.

RESULTS

Field observations were paired with ship records for 179 passages in UI-1, 47 passages in UI-2, 34 passages in MI, and 36 passages in LI. The ship and channel properties associated with each passage are categorized as primary wave “drivers”, whereas hydrodynamic properties of the primary wave are categorized as “characteristics.” Results are shown first for primary wave signatures and characteristics, second for the ability of linear long wave theory to describe primary wave characteristics, third for observed relationships between primary wave drivers and characteristics, and fourth for the performance of the depression prediction equations.

Variability Between Inbound and Outbound Passages

Ship passage characteristics are similar for inbound and outbound passages. For example, the differences between inbound and outbound ship parameters relative to the combined (inbound and outbound) means range across data sets from 1% to 4% for the distance between the ship and the sensor, 0% to 15% for S' , 0% to 4% for d , and 3% to 13% for ξ (evaluated with respect to the minimum tidal stage for this computation only). In addition, ship length and width are unaffected by ship direction because only one shipping channel serves the port.

Furthermore, the variability of primary wave characteristics between inbound and outbound passages is small with respect to variability among events and data sets. For instance, in UI-1, the mean H of inbound (outbound) ships varied from the mean H of the full data set by 4 (5) cm, which is approximately an order of magnitude smaller than both the standard deviation of all UI-1 H values (39 cm) and the span of mean H values across data sets (30 cm).

The Schijf equations imply that larger and faster ships produce larger primary waves, so correlations between H and L , S' , and direction also can be used to comment on the role of ship direction. Correlations between H and L range across data sets from 0.30 to 0.56, whereas correlations between H and the product LS' are greater, ranging from 0.58 to 0.71. When re-evaluated for ships of the same direction, the correlations between H and LS' range from 0.52 to 0.78. Although ship direction likely does affect primary wave characteristics, these results suggest its effects are weaker than those of L and S' .

Moreover, the depression prediction equations evaluated in this study do not account for ship direction. Therefore, to broaden the data set evaluated, results for ships moving in each direction are combined throughout the remainder of the analysis.

Overview of Primary Wave Characteristics

The primary wave trough presents similarly in all data sets as a depression in η lasting about 100 seconds. This is the most consistent feature in the overlaid time series of primary waves displayed in Figure 4, where a relative time scale, t' (s), aligns events at the time ($t' = 0$ s) of the greatest depression magnitude. Surges, the crest-like $\eta > 0$ primary wave feature following the depression,

are consistently observed in the UI-1 and UI-2 data sets but are less defined in the MI and LI data sets.

The depression and surge both exhibit considerable variability in magnitude within and among data sets. All four data sets include small to moderate depressions ranging from several centimeters to 60 cm, but only the UI-1 data include depressions exceeding 70 cm, which comprise 15% of the UI-1 primary waves. Overall, the UI-1 data set encompasses larger events than the other data sets, as indicated by the greater range of its primary wave signals (compare wave signals among panels in Figure 4, noting the inconsistent vertical axes).

Event-averaged $\vec{v}$ (dashed and dotted lines in Figure 4a,d) show that flows during the depression are offshore and opposite the direction of ship travel. During the transition into the surge, the flow changes direction to onshore, and after the peak of the surge, into alignment with the direction of ship travel. On average, UI-1 exhibits larger $\vec{v}$ magnitudes and faster flow reversals than LI.

The mean and maximum values of primary wave drivers and characteristics, presented by data set in Table 3, suggest that drivers are less variable among data sets than characteristics. For example, mean S' values vary from 5.9 m/s (UI-2) to 6.3 m/s (MI), and mean d values vary from 10.0 m (UI-2 and MI) to 10.2 m (LI). The deepening of the channel directly affects A_c , but the impact on the mean C_B is small; it decreases from 6.1% (UI-1) before deepening to 5.7% (UI-2), 5.3% (MI), and 5.8% (LI) after deepening. The standard deviations of drivers are also similar between data sets, with UI-2 exhibiting slightly more variability than the others. For instance, the standard deviation of d ranges from 1.7 m in both UI-1 and LI to 2.2 m in UI-2.

The primary wave characteristics summarized in Table 3 are more variable both within and among data sets. The standard deviations of all characteristics are at least 50% of the corresponding means. In addition, mean characteristics vary by factors of about two to four between data sets. For example, the mean H varies from 24 cm (LI) to 65 cm (UI-1). Overall, mean primary wave features are smallest in LI, largest in UI-1, and similar between UI-2 and MI.

Linear Wave Theory Estimates

Since no fluid velocity data are available for UI-2 and MI, Table 3 provides values of E and peak $|v|$, the maximum fluid velocity magnitude in the primary wave signal, estimated from linear wave theory using H . However, linear wave theory assumes a small wave amplitude, a (m), with respect to h , which may not be a valid assumption for large primary waves in shallow waterway margins where primary wave behaviour can be highly non-linear (e.g. Rapaglia et al. 2011; Parnell et al. 2015; Rodin et al. 2015). Among the four data sets in this study, a/h ranges from 0.001 to 0.519, with a mean of 0.098.

To test the accuracy of linear wave theory under these conditions, the co-located P and $\vec{v}$ measurements in UI-1 and LI are used to compare measured and estimated values of E and $|v|$. The wave number k is estimated with the linear dispersion equation,

$$\frac{2\pi}{T} = \sqrt{gk \tanh(kh)} \quad (7)$$

and ranges from 0.002 to 0.016 m^{-1} throughout the data sets. The kh values are computed using the depth at the instrument and vary from 0.010 to 0.048, firmly below the $\pi/10$ upper limit for long waves. Therefore, the primary waves are treated as linear long waves with celerity (m/s)

$$c = \sqrt{gh}. \quad (8)$$

The estimated amplitude of the linear long wave fluid velocity, $|\hat{v}|$ (cm/s), is then

$$|\hat{v}| = \frac{ca}{h}, \quad (9)$$

where a is assigned the value of $|\eta_d|$ (cm).

The estimated and measured peak $|v|$ agree well (Figure 5a); R^2 is 0.91 for UI-1 and 0.94 for LI. For both data sets, bias is negative but small (-6 cm/s in UI-1 and -2 cm/s in LI), indicating the linear theory slightly underpredicts the measured $|v|$. If a is assigned the value of $H/2$ instead of

$|\eta_d|$ (not shown), R^2 is slightly reduced for both data sets (0.89 for UI-1 and 0.92 for LI), and UI-1 bias is unchanged (-6 cm/s), but the LI velocities are more severely underpredicted with a bias of -56 cm/s. Thus, the assignment $a = |\eta_d|$ is preferred since it produces high R^2 and small bias for both data sets.

The linear wave theory estimate of primary wave energy, $\hat{E}$ (J/m²), was computed with

$$\hat{E} = \frac{1}{8} \rho g H^2, \quad (10)$$

converting H to meters for this application. The results are compared to measured E (see Equation 5) in Figure 5b. The estimated and measured values agree well, with R^2 values of 0.91 and 0.92 for UI-1 and LI, respectively, and little bias.

Overall, the comparisons of measurements with estimates in Figure 5 suggest that peak fluid velocity magnitude and wave energy may be estimated with reasonable accuracy from $|\eta_d|$ using linear wave theory. Hence, the estimates for UI-2 and MI are included in Table 3, as noted above.

Primary Wave Properties vs. Ship Passage Conditions

Primary wave magnitudes are compared to S' and L for both the UI-1 measurements from 2017 (Figure 6a,b) and the combined UI-2, MI, and LI measurements from 2022 (Figure 6c,d). The UI-2, MI, and LI data are combined since they were measured in the same year with the same deepened channel conditions, exhibit similar relationships between primary wave magnitudes and drivers, and collectively comprise a data set closer in size (117 events) to the UI-1 data (179 events) than the individual data sets.

For both the 2017 and 2022 measurements, clustering of large $|\eta_d|$ and large η_s in the upper right quadrant of each Figure 6 panel indicates that larger and faster ships generally produce larger primary waves. However, there are inconsistencies in depression and surge magnitudes at similar size and speed conditions. For instance, there were two UI-1 passages of ships with $L \approx 260$ m and $S' \approx 6.8$ m/s (Figure 6a), and one produced a 134 cm depression (large red marker), whereas the other produced a 44 cm depression (smaller superimposed blue marker). The ship drafts (not

shown) for these two events differed by less than one meter, with values of 10.67 m and 9.75 m in the passages producing the larger and smaller depressions, respectively. It is also observed that S' and L conditions associated with large $|\eta_d|$ are usually associated with large η_s , but there are exceptions to this trend as well. For example, the UI-1 event producing the large $|\eta_d|$ for $L \approx 270$ m and $S' \approx 7.8$ m/s (Figure 6a) does not correspond to a proportionally large η_s (Figure 6b).

The values of $|\eta_d|$ and η_s are shown with respect to C_B and Fr in Figure 7 to incorporate the effects of tidal stage and ship draft into the comparison of drivers and primary wave magnitudes. These non-dimensional parameters cluster primary waves of similar sizes, with the largest $|\eta_d|$ and η_s occurring along a band at the upper right sector of each data scatter. However, similar combinations of Fr and C_B can also produce substantially different primary wave magnitudes. For example, the η_s magnitudes of the combined 2022 data (Figure 7d) are particularly inconsistent around $C_B \approx 7\%$ and $Fr \approx 0.5$.

To examine primary wave magnitudes between the 2017 (UI-1) and combined 2022 (UI-2, MI, and LI) data sets while partly controlling for drivers, primary wave characteristics were examined for groups of similar passage conditions, defined in Table 2 and illustrated with boxes in Figures 6 and 7. Histograms and means of $|\eta_d|$, η_s , and H are shown by ship group in Figure 8 and demonstrate the variability of primary wave magnitude between ship groups and data sets. Comparing among ship groups (i.e., among the rows in Figure 8), histograms generally shift toward higher values from group D1 to D2 to D3, and from group ND1 to ND2 to ND3. This indicates that primary wave size increases with increasing L , S' , C_B , and Fr , consistent with the trends in Figures 6 and 7. Exceptionally large primary waves with H exceeding 150 cm are produced mostly by groups D3 (large L , large S') and ND3 (large C_B , large Fr), with the exception of one group D2 event and two events produced by ungrouned mid-length ships.

Within individual panels of Figure 8, leftwards histogram shifts from 2017 (black) to 2022 (light grey) reflect reductions in primary wave magnitude within ship groups. For the D groups, primary wave features in 2022 are about half as large as the corresponding 2017 features. For example, the mean H for group D3 (circular markers in Figure 8c, left), the fast Post-Panamax and

Neo-Panamax container ships that produce the largest observed events, decreases from 99 cm in 2017 to 58 cm in 2022 despite increases in the mean d and mean C_B of the group (see Table 2). Primary wave magnitudes decrease from 2017 to 2022 more mildly in the ND groups; the 2022 mean H values for the large- C_B groups ND2 and ND3 are 71% and 60%, respectively, of the 2017 values.

Leftwards shifts in the histograms of both $|\eta_d|$ (center column of Figure 8) and η_s (right column of Figure 8) from 2017 to 2022 indicate that decreases in H are caused by combined decreases in the depression and surge magnitudes. The shifts in the mean $|\eta_d|$ and the mean η_s are similar for most groups, meaning both features contribute similarly to the reduction in the mean H .

The spread of the histograms in Figure 8 suggests that primary wave magnitudes cannot be precisely explained by L and S' , or C_B and Fr . Therefore, combinations of drivers and channel characteristics were compared to $|\eta_d|$ to search for a single nondimensional parameter capable of predicting $|\eta_d|$ through a linear relationship. For the observations in this study, the parameter (α) producing the strongest correlation with $|\eta_d|$ is

$$\alpha = \left(\frac{L}{h_c} Fr \right)^2, \quad (11)$$

suggesting that $|\eta_d|$ is proportional to $(S')^2$ and L^2 and is inversely proportional to h_c^3 . The values of $|\eta_d|$ are shown against α for the UI-1 data and combined 2022 UI-2, MI, and LI data in Figure 9. Scatter varies considerably between the two data sets, with an R^2 value of 0.65 for UI-1 and 0.82 for the combined 2022 data, and it is exacerbated for larger values of $|\eta_d|$. The slopes of the least square regression lines (LSRL) differ between the two data sets: 0.61 for UI-1 and 0.51 for UI-2, MI, and LI combined. While α provides some insight into the factors most pertinent to primary wave magnitude, such as the importance of h_c , the persistence of scatter and variability in the slope of the fit suggest more complex dependencies between primary wave drivers and characteristics than are represented with a linear relationship.

Performance of Depression Prediction Equations

Depression prediction equations incorporate more complex relationships between primary wave magnitudes and drivers and were applied to each data set individually to account for channel geometry differences. Figure 10 compares depression predictions, $|\hat{\eta}_d|$, to measurements for the semi-empirical equations of Schijf (1949), Hochstein (1967), Dand and White (1978), Bhowmik et al. (1981), and Maynard (1996), as well as the empirical-fit equation of Almström and Larson (2020). To facilitate comparison among data sets, depression magnitudes are normalized (indicated with the prime symbol) by the maximum $|\eta_d|$ measured in each data set. Agreement between predicted and measured values is generally strong for most equations and models, with R^2 ranging from 0.61 to 0.91, and bias ranging from -23 cm to 13 cm. However, the Bhowmik et al. (1981) and Maynard (1996) equations tend to underpredict $|\eta_d|$ for most data sets, and all semi-empirical equations consistently underpredict $|\eta_d|' > 0.54$ ($|\eta_d| > 75$ cm) in UI-1 (Figure 10, left column). Since tidal variations are accounted for in the application of each equation, it is of note that these underpredicted UI-1 events occurred primarily at low tide (blue markers in Figure 10, left column).

The empirical-fit of the Almström and Larson equation effectively predicts $|\hat{\eta}_d|$ with the equation

$$|\hat{\eta}_d| = C_1 \left(\frac{S'}{\sqrt{g h_c}} \right)^{C_2} \left(\frac{B}{w_{c,side}} \right)^{C_3} \left(\frac{B}{w_c} \right)^{C_4} \left(\frac{d}{h_c} \right)^{C_5} \left(\frac{L}{d} \right)^{C_6} \quad (12)$$

where $C_{1,2,...,6}$ are fitted coefficients (values provided in Table 4) taken as the median values from 10,000 fits, each using a randomly selected 50% of the data set as the training set. The specificity of the coefficients to each data set is demonstrated by variability in the center, spread, and skewness of the coefficient distributions shown in Figure 11. It is also indicated by an increase in bias if the UI-1 coefficient values are applied to other data sets; in this alternate application (not shown), the bias is 9 cm for UI-2, 10 cm for MI, and 14 cm for LI.

DISCUSSION

Relating Primary Wave Drivers and Magnitudes

Observations from all four data sets indicate that larger and faster ships tend to produce larger primary waves, which is consistent with the known effects of flow constriction and return current strength on producing primary waves via conservation principles. These principles are embedded in the semi-empirical depression prediction equations, most of which perform well for small to moderate depressions. However, compared to the Schijf (1949), Hochstein (1967), and Dand and White (1978) approaches, the Bhowmik et al. (1981) and Maynard (1996) equations tend to underpredict primary wave depressions. These two equations apply cross-channel decay to the depression, so the underprediction of events measured at the margins of the channel could be explained by a dominance of shoaling over decay.

It is observed throughout the measurements that primary wave magnitudes can be inconsistent for similar conditions (Figures 6, 7, and 8). This complexity is also evident in the effort to scale $|\eta_d|$ linearly with a non-dimensional parameter α ; the relationship exhibits increasing scatter for events of increasing $|\eta_d|$ (Figure 9). Additionally, the semi-empirical depression prediction equations consistently underpredict primary waves magnitudes for $|\eta_d| > 75$ cm (Figure 10). Together, these findings point to a complex relationship between primary wave drivers and magnitudes that requires further investigation, particularly for larger primary waves.

A likely contributor to the unexplained primary wave variability is the prior trajectory of the ship, or the properties of the ship track (including speed, heading, position and orientation within the channel) before the ship reaches the instrument site. This study evaluated ship and channel characteristics when and where the ship most closely passed the sensor, but conditions prior to this instant may influence the wave measured. Primary waves are subject to shallow water transformation processes that are complicated by natural irregular bathymetry (Rapaglia et al. 2011; Parnell et al. 2015), and simply unshoaling UI-1 waves does not satisfactorily improve agreement between depression prediction equations and measurements. It is unknown how rapidly changes in bathymetry and ship trajectory properties influence the presentation of the wave near the shoreline. These spatial and temporal lags in channel margin wave response are likely complicated by tidal

currents, so initial investigations into this topic should be conducted with numerical or physical scale modeling rather than field observations in a natural tidal channel.

The empirical Almström and Larson (2020) depression prediction equation was most effective at predicting large events and is not prone to bias since it is fitted to partial data sets. However, it is essential that its coefficients be evaluated precisely for a given site of interest, as recommended by Almström and Larson (2020). This was confirmed here by the introduction of positive bias when applying UI-1 coefficients to the UI-2, MI, and LI predictions, as well as by the variability of the coefficient distributions among data sets.

Detailed analysis of channel deepening impacts on primary waves requires further investigation. However, the C_B values computed here show that the increase in the channel cross-section due to channel deepening was offset by an increase in the ship sizes. For example, the mean C_B (Table 2) for the D3 and ND3 ship groups associated with large primary waves increased slightly from 2017 to 2022. This is expected because the deepening project intended to improve access to the port for larger ships. Therefore, although observed primary wave magnitudes are smaller in the data sets measured after the deepening project, the effects of the project on wave magnitudes cannot be concluded from this study.

Atypically-large Primary Waves

About 10% of the UI-1 events are unusually large with respect to the corresponding driver conditions. These “atypically-large” primary waves are underpredicted by each of the semi-empirical depression prediction equations applied in this study and consist of UI-1 events with $|\eta_d| > 75$ cm.

Because depression prediction equations originate from physical principles and generally perform well for events with $|\eta_d| < 75$ cm, the consistent underprediction of UI-1 atypically-large primary waves suggests there are unaccounted-for processes affecting these depressions. This is also suggested by the positive bias observed in the Almström and Larson (2020) depression prediction results for other data sets when UI-1 events are used for assigning the coefficients. The bias implies that the conditions giving rise to large events in UI-1 produced smaller events in other

data sets despite accounting for variation in ship dimensions and channel geometry through the non-dimensional parameters. Its persistence in even UI-2 implies that bathymetric irregularities and ship tracks (i.e. trends in positions, headings, and speeds), which are largely the same between UI-1 and UI-2, are not the sole cause of the atypically-large primary waves.

Depression prediction model errors are not well-correlated with ship acceleration, distance from shore, or direction. However, atypically-large primary waves, and primary wave variability in general, could be affected by the prior trajectory of the ship, hull shape, orientation, and/or trim, which were not quantified in this study. Since atypically-large primary waves were associated with low tidal stages, they could also be affected by hydrodynamic processes that are more prominent in shallower water, such as reflection, shoaling, and refraction, as well as interactions between the primary wave and other ship wake components.

Because the UI-1 and UI-2 data sets were collected at the same site, comparison between them largely controls for ship path characteristics and bathymetry, as mentioned above. Therefore, given the 10% occurrence rate of atypically-large primary waves in the UI-1 data set, the absence of such events among the 47 UI-2 ship passages is notable. The UI-2 deployment duration was shorter (5 days) than UI-1 (22 days), so UI-2 may not have measured a fully representative range of passage characteristics. However, probability distributions of S and L for all passages at the UI site in the full years 2017 and 2022 (Figure 12) indicate changes in the ship properties between these years: traffic shifted away from mid-size container ships ($220\text{ m} < L < 340\text{ m}$) and into both smaller ($L < 220\text{ m}$) and larger ($L > 340\text{ m}$) ships. Most importantly, the distributions show that the L and S characteristics associated with most atypically large UI-1 events (white circles in Figure 12a) were less common in 2022. This change in passage characteristics may have reduced the true occurrence rate of atypically-large primary waves in 2022 compared to 2017.

Overall, the cause of atypically-large primary waves remains unclear, and this is of concern since it is the largest primary waves that are most threatening to shoreline stability, coastal ecosystems, infrastructure, and public safety. Numerical or statistical modeling, beyond the scope of this study, may lend key insight into the conditions that produce atypically-large primary waves.

Data Significance and Availability

This work provides a detailed set of primary wave observations, containing both pressure and velocity measurements of primary waves paired with comprehensive ship information, including quality-controlled and tidally-adjusted speed data, tidally varying channel characteristics, and accurate ship draft. The data are used here to examine the variability and dependencies of primary wave drivers and characteristics, as well as to assess the performance of depression prediction equations. The data also hold value for efforts in numerical modeling, primary wave prediction, and/or investigation of shallow-water primary wave behavior. The data set of primary wave drivers, including tidally-varying channel conditions, and primary wave characteristics are available in Tables S1-S4 of Supplemental Materials.

SUMMARY AND CONCLUSIONS

In this study, pressure and velocity measurements of primary waves at the margins of a tidal shipping channel are used to investigate relationships between ship properties, tidally-varying channel characteristics, and primary wave magnitudes. The study objectives are addressed by the following:

- **Estimating primary wave hydrodynamics from linear wave theory:** Pressure data are easier and less costly to measure than fluid velocity data, but the fluid velocities and dependent hydrodynamic properties are often important for practical assessments of primary wave impacts. Using wave heights and amplitudes, linear wave theory provides an estimation of fluid velocity and wave energy, but evaluations of its accuracy for primary waves are lacking. Therefore, co-located velocity and pressure data are used to compare measurements and linear wave theory estimates for peak primary wave fluid velocity and primary wave energy. Linear theory estimates of velocity and energy are correlated with the measurements ($R^2 \geq 0.89$) regardless of whether the linear wave amplitude is assigned the value of the depression magnitude or half the primary wave height. Using the depression magnitude does, however, produce a smaller fluid velocity bias (≤ 6 cm/s) than using half the wave

height (≤ 56 cm/s) for the two data sets analyzed.

- **Primary wave magnitude vs. metrics of ship size and speed:** Examination of depression and surge magnitudes alongside metrics of ship size and relative speed indicate that both wake features generally increase in magnitude for larger and faster ships, but with inconsistencies. Some events are observed in which ships with nearly the same size and speed produce wakes of considerably different magnitudes. These findings persist whether wake features are compared to dimensional parameters (S' and L) or nondimensional parameters (Fr and C_B), which more thoroughly account for tidal effects.
- **Inconsistency of primary waves produced by similar passages:** Examination of primary waves produced by groups of similar ship passages across the 2017 (UI-1) and combined 2022 (UI-2, MI and LI) data sets also reveals inconsistencies. The distributions of wave heights, depression magnitudes, and surge magnitude for ships of similar sizes and speeds differ between the 2017 and 2022 data. In general, primary waves and their features are smaller in the 2022 data sets than in the 2017 data set. Although the shipping channel was deepened between the two years, mean blockage ratios were not substantially altered, so the effect of the deepening on wave magnitude is unclear.
- **Depression prediction equations and atypically-large primary waves:** Depression magnitudes were estimated by depression prediction equations with correlation coefficients ranging from 0.61 to 0.91 and bias ranging from -23 cm to 13 cm. The Almström and Larson (2020) method has minimal bias because it uses fitted coefficients, but the variability of the coefficients among data sets underscores the importance of evaluating coefficients from observations collected precisely where predictions are desired. The unfitted methods consistently underpredicted depression magnitudes exceeding 75 cm. These underpredicted, atypically-large primary waves comprised about 10% of the UI-1 events and were not measured in other data sets.

This study reports the general features and predictability, as well as inconsistencies, of primary waves on the shallow margins of a natural, confined tidal river. The observed variability in

588 wave magnitudes for similar ship passages and the occurrence of atypically-large primary waves
589 suggest that waves in this environment are influenced by unaccounted-for factors that should be
590 investigated with future research, such as shallow water transformation processes, influences of the
591 prior trajectory of the ship, and interacting wake components. To support work on these and other
592 topics regarding primary wave behavior and modeling, the hydrodynamic, waterway, and ship data
593 presented in this paper are available in Supplemental Materials.

594 **Data Availability Statement**

595 Some or all data, models, or code that support the findings of this study are available from the
596 corresponding author upon reasonable request. In addition to the wake drivers and characteristics
597 provided in Tables S1 - S4, available data include pressure and velocity time series, ship tracks,
598 and bathymetry.

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APPENDIX I. NOTATION

The following symbols are used in this paper:

a	wave amplitude (cm)
A_c	channel cross-sectional area (m ²)
$A_{c,side}$	channel cross-sectional area on one side of ship (m ²)
B	ship beam (m)
c	wave celerity (m/s)
C_B	blockage ratio (-)
$C_{1,2,...,6}$	Almström and Larson (2020) depression prediction equation coefficients (-)
d	ship draft (m)
E	wave energy (J/m ²)
$\hat{E}$	estimated wave energy (J/m ²)
f	frequency (Hz)
Fr	Froude number
g	gravitational acceleration (m/s ²)
H	wave height (cm)
h	depth at instrument (m)
h_c	mean channel depth (m)
h_{SC}	shipping channel depth (m)
K	constraint factor in Hochstein (1967) depression prediction equation (-)
k	wave number (m ⁻¹)
L	ship length (m)
P	pressure (kPa)
S	absolute ship speed (m/s)
S'	relative ship speed (m/s)
T	wave period (s)
t	time (s)
t'	time relative to depression (s)

$\vec{V}$	tidal current (m/s)
V	alongshore component of tidal current (m/s)
$\vec{v}$	mid-band velocity (cm/s)
$ \hat{v} $	estimated wave velocity amplitude (cm/s)
w_c	channel top width (m)
$w_{c,side}$	channel top width from ship to shore (m)
$x_{e,n}$	east and north coordinates of ship position (m)
y	cross-shore distance between the ship and the sensor (m)
α	primary wave driver parameter (-)
β	Hochstein (1967) depression prediction equation intermediate (-)
η	mid-band water surface fluctuations (cm)
$ \eta_d $	depression magnitude (cm)
$ \hat{\eta}_d $	predicted depression magnitude (cm)
$ \eta_d _{side}$	maximum depression magnitude on side of ship with top width $w_{c,side}$ (cm)
$ \eta_d _0$	depression magnitude computed from the Schijf equation (Equation 13) (cm)
η_s	primary wave surge (cm)
κ	Maynord (1996) depression prediction equation intermediate (-)
ρ	water density (kg/m ²)
ξ	tidal stage (m)

APPENDIX II. DEPRESSION PREDICTION EQUATIONS

The Schijf (1949) depression prediction equation, derived from continuity and Bernoulli principles, assumes the depression is constant across a rectangular channel and is given by the expression

$$\frac{Bd}{A_c} + \frac{|\eta_d|}{h_{SC}} + \left(1 + \frac{2g|\eta_d|}{(S')^2}\right)^{-1/2} = 1 \quad (13)$$

where h_{SC} is the shipping channel depth, computed as the mean of the depths in the deepest 200 m of the channel cross-section. Assigning the channel depth as h_{SC} simplifies the true channel cross-section into a rectangle with area A_c and width A_c/h_{SC} .

The Hochstein (1967) depression prediction equations are given by

$$|\eta_d| = S'^2 \left(\left(\frac{A_c}{A_c - Bd} \right)^{2.5} - 1 \right) \frac{\beta'}{2g} \quad (14)$$

and

$$\beta' = \begin{cases} 0.3 \exp\left(\frac{1.8S'}{K\sqrt{gh_c}}\right) & \text{if } \frac{S'}{K\sqrt{gh_c}} \leq 0.65 \\ 1 & \text{otherwise} \end{cases} \quad (15)$$

where K is a constraintment factor approximated for each event using the curve provided by Hochstein and Adams (1989).

The Dand and White (1978) equations is

$$|\eta_d| = 8.8 \left(\frac{A_c}{Bd} \right)^{-1.4} \frac{S'^2}{2g}, \quad (16)$$

and the Bhowmik et al. (1981) equation is

$$|\eta_d| = 1.03 \frac{S'^2}{2g} \left(\frac{Bd}{A_c} \right)^{0.81} \left(\frac{L}{y} \right)^{0.31}. \quad (17)$$

where y (m) is the cross-shore coordinate of the prediction location, measured from the ship shoreward.

The Maynard (1996) equation estimates the depression at y on the side of the ship with channel top

width $w_{c,side}$ and channel cross-sectional area $A_{c,side}$ using

$$|\eta_d|(y) = |\eta_d|_{side} \sqrt{\kappa} \exp \left[\left(3.0 \ln \frac{1}{\kappa} \right) \frac{y - B}{w_{c,side} - B} \right] \quad (18)$$

where

$$\kappa = 0.75 \left(\frac{2A_{c,side}}{Bd} \right)^{0.18}, \quad (19)$$

and

$$|\eta_d|_{side} = \begin{cases} |\eta_d|_0 \left(1.65 - 1.3 \frac{w_{c,side}}{w_c} \right) & \text{if } 0 < \frac{w_{c,side}}{w_c} < 0.5 \\ |\eta_d|_0 \left(1.35 - 0.7 \frac{w_{c,side}}{w_c} \right) & \text{if } 0.5 < \frac{w_{c,side}}{w_c} < 1, \end{cases} \quad (20)$$

and $|\eta_d|_0$ is the value of $|\eta_d|$ computed with Equations 13. In this study, y is the distance from the ship to the instrument.

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TABLE 1. Deployment details.

Name	Data	Freq. (Hz)	Mode (m)	UTM coordinates (m)	$\bar{h}$ (m)	Start date mm/dd/yyyy	Duration (days)
UI-1	Pressure, velocity	1	Burst	503385 E, 3548181 N	3.52	10/06/2017	21.94
UI-2	Pressure	2	Continuous	503412 E, 3548233 N	4.09	02/10/2022	4.82
MI	Pressure	2	Continuous	504814 E, 3547163 N	4.04	02/15/2022	3.85
LI	Pressure, velocity	1	Continuous	505284 E, 3546583 N	4.41	06/07/2022	2.84

TABLE 2. Ship group definitions and characteristics in the 2017 UI-1 measurements and combined 2022 UI-2, MI, and LI measurements.

Group	Size Condition	Speed condition	Mean d (m)		Mean C_B (%)		Counts	
			2017	2022	2017	2022	2017	2022
D1	$150 \text{ m} < L < 215 \text{ m}$	$6 \text{ m/s} < S' < 7.5 \text{ m/s}$	8.5	8.6	4.2	3.8	28	32
D2	$295 \text{ m} < L < 367 \text{ m}$	$4.5 \text{ m/s} < S' < 6 \text{ m/s}$	11.4	11.7	8.4	8.2	31	21
D3	$295 \text{ m} < L < 367 \text{ m}$	$6 \text{ m/s} < S' < 7.5 \text{ m/s}$	10.9	11.7	7.5	7.7	36	19
ND1	$3\% < C_B < 6\%$	$0.5 < Fr < 0.6$	9.1	9.2	4.7	4.3	45	21
ND2	$6\% < C_B < 9\%$	$0.4 < Fr < 0.5$	11.4	11.7	7.6	7.7	42	21
ND3	$6\% < C_B < 9\%$	$0.5 < Fr < 0.6$	10.8	11.5	7.2	7.3	30	10

TABLE 3. Mean and standard deviation (STD) of primary wave drivers and characteristics for each data set.

	UI-1	UI-1	UI-2	UI-2	MI	MI	LI	LI
Drivers	Mean	STD	Mean	STD	Mean	STD	Mean	STD
S' (m/s)	6.2	0.7	5.9	0.9	6.3	0.8	6.0	0.7
L (m)	265	64	259	82	252	69	237	70
d (m)	10.1	1.7	10.0	2.2	10.0	1.9	10.2	1.7
C_B (%)	6.1	2.0	5.7	2.3	5.3	1.9	5.8	2.3
Characteristics								
$ \eta_d $ (cm)	42	27	22	15	27	16	19	14
η_s (cm)	23	13	10	8	5	5	5	4
H (cm)	65	39	32	23	32	20	24	17
Peak onshore v (cm/s)	31	23	-	-	-	-	16	13
Peak offshore v (cm/s)	28	19	-	-	-	-	17	12
Peak with-ship v (cm/s)	36	27	-	-	-	-	9	8
Peak against-ship v (cm/s)	73	40	-	-	-	-	30	20
Peak $ v $ (cm/s)	77	43	34*	23*	39*	28*	34	22
E (J/m ²)	676	677	192 [†]	248 [†]	165 [†]	208 [†]	161	235

*Estimated with Equation 9, [†] Estimated with Equation 10

TABLE 4. Coefficients used for the Almström and Larson (2020) depression prediction equation.

Data set	C_1	C_2	C_3	C_4	C_5	C_6
Almström and Larson (2020)	0.22	0.42	0.85	0.32	1.46	0.80
UI-1	0.27	0.97	1.05	0.28	1.60	0.87
UI-2	0.14	0.23	0.64	0.29	1.01	0.56
MI	0.15	0.03	0.88	0.17	1.10	0.64
LI	0.15	-0.16	0.68	0.35	0.99	0.50

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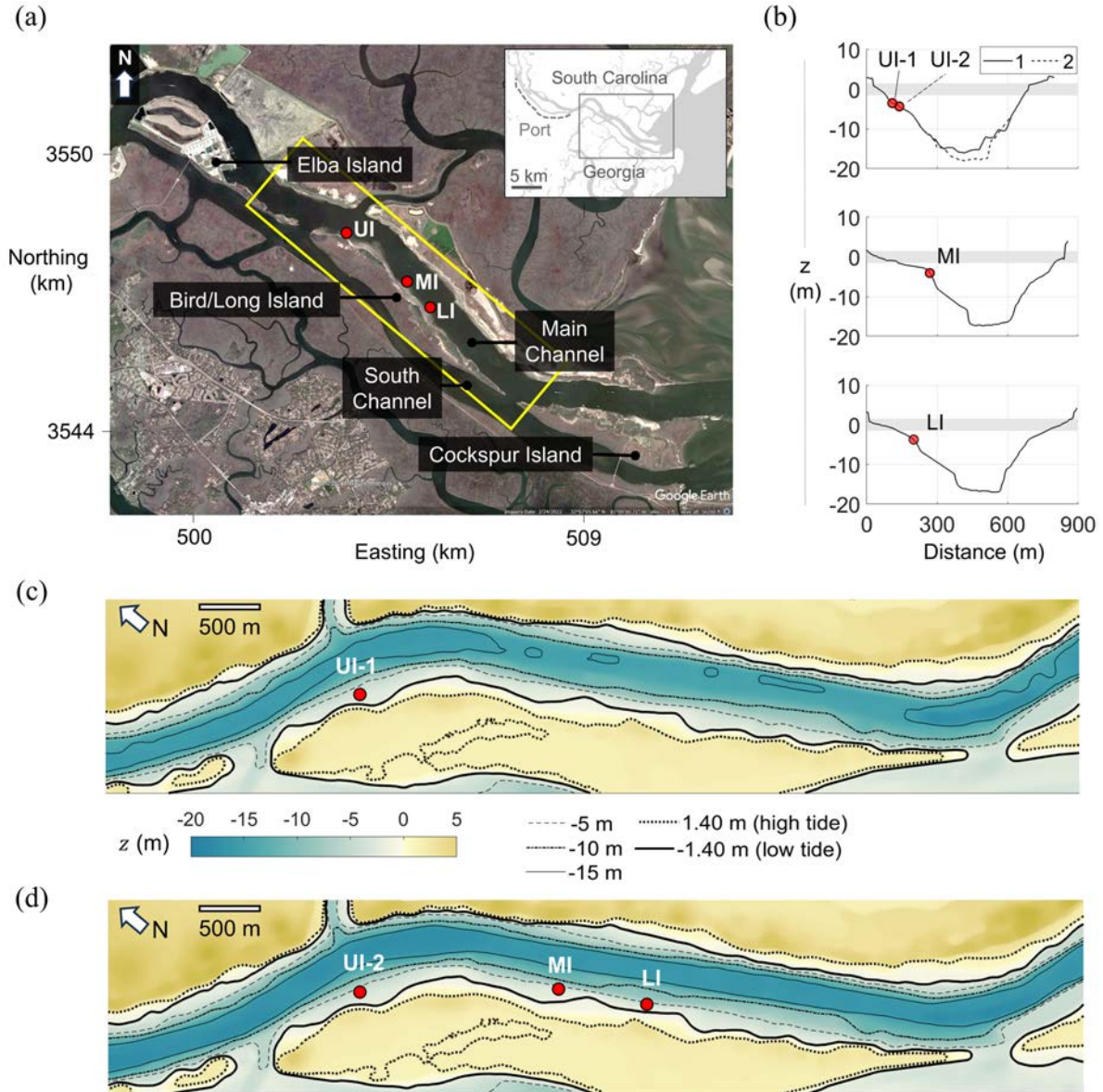


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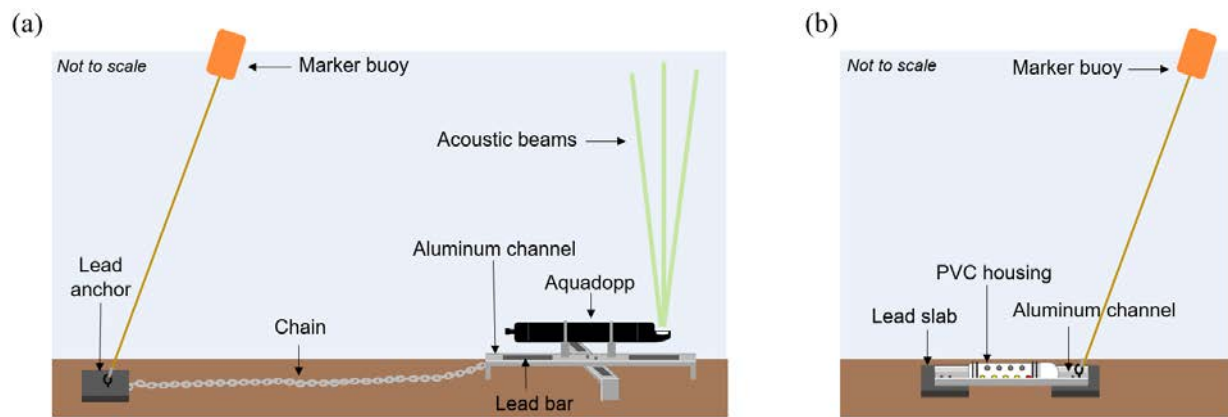


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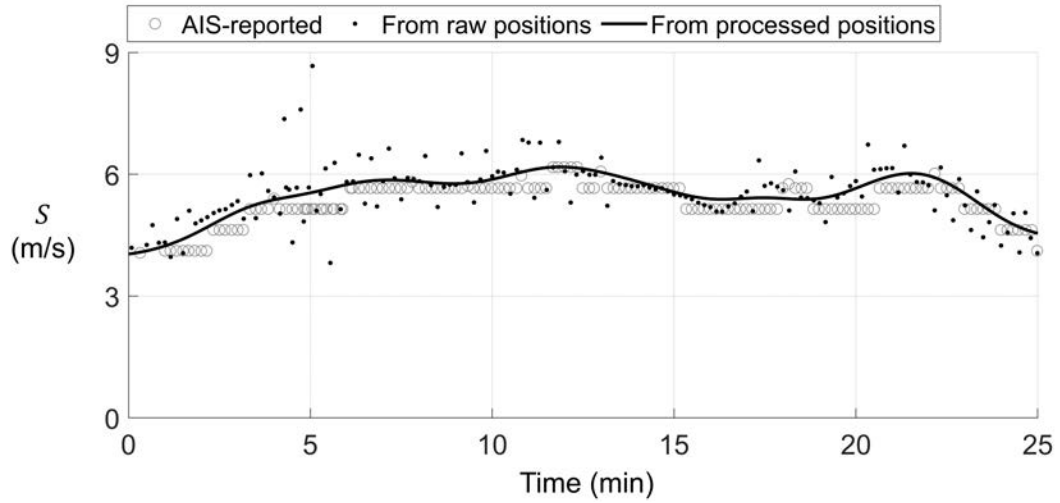


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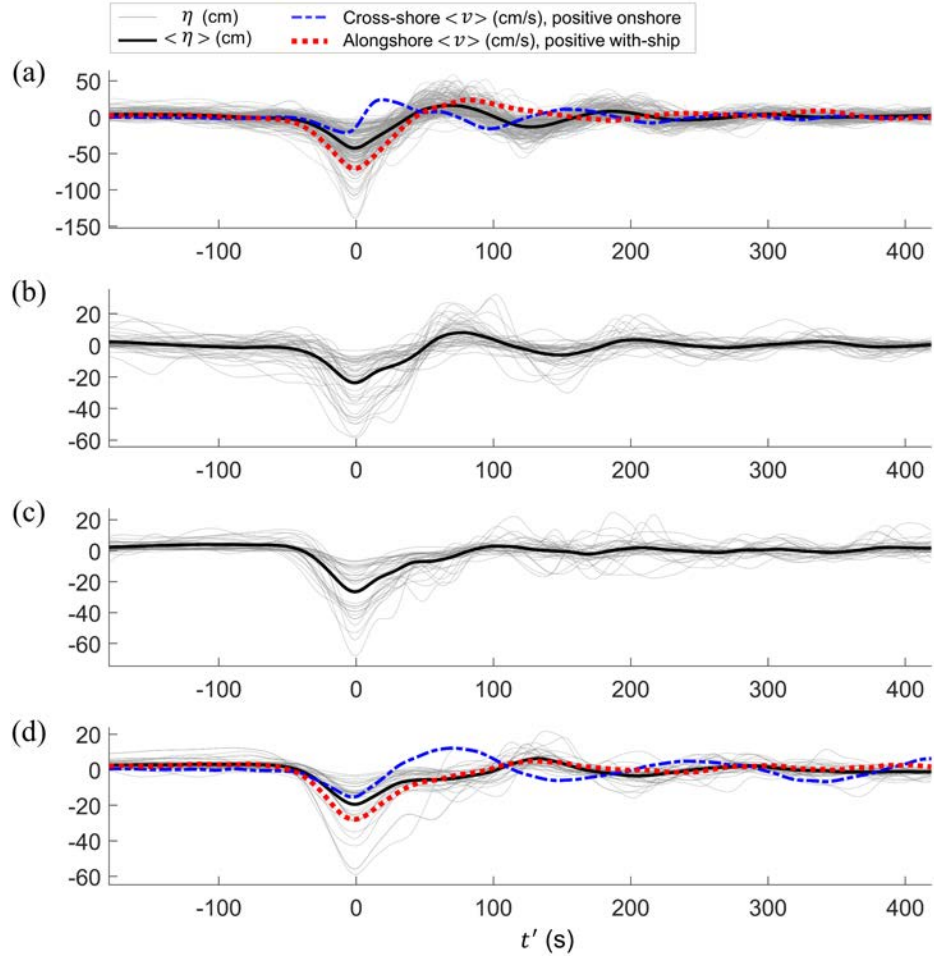


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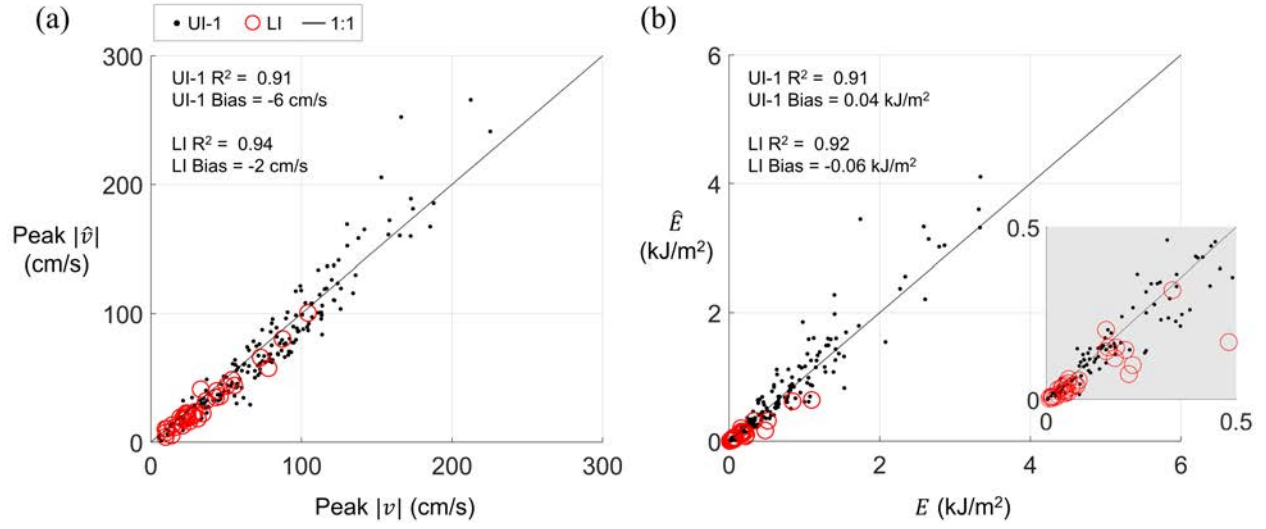


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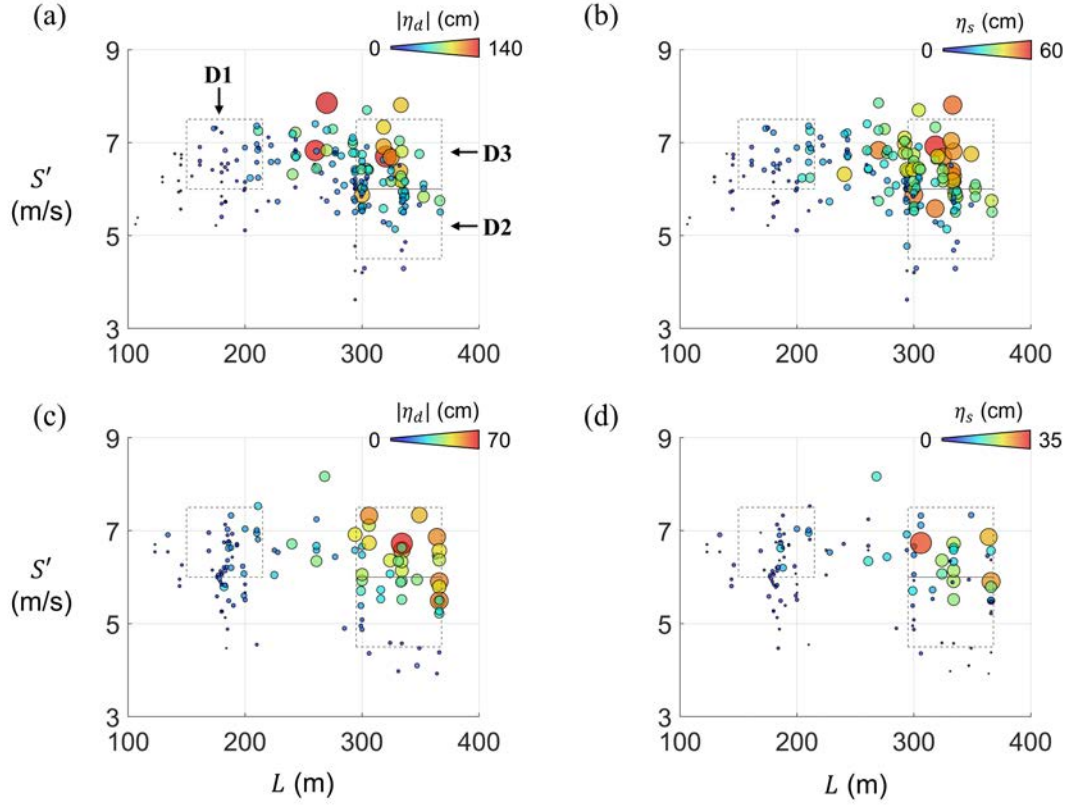


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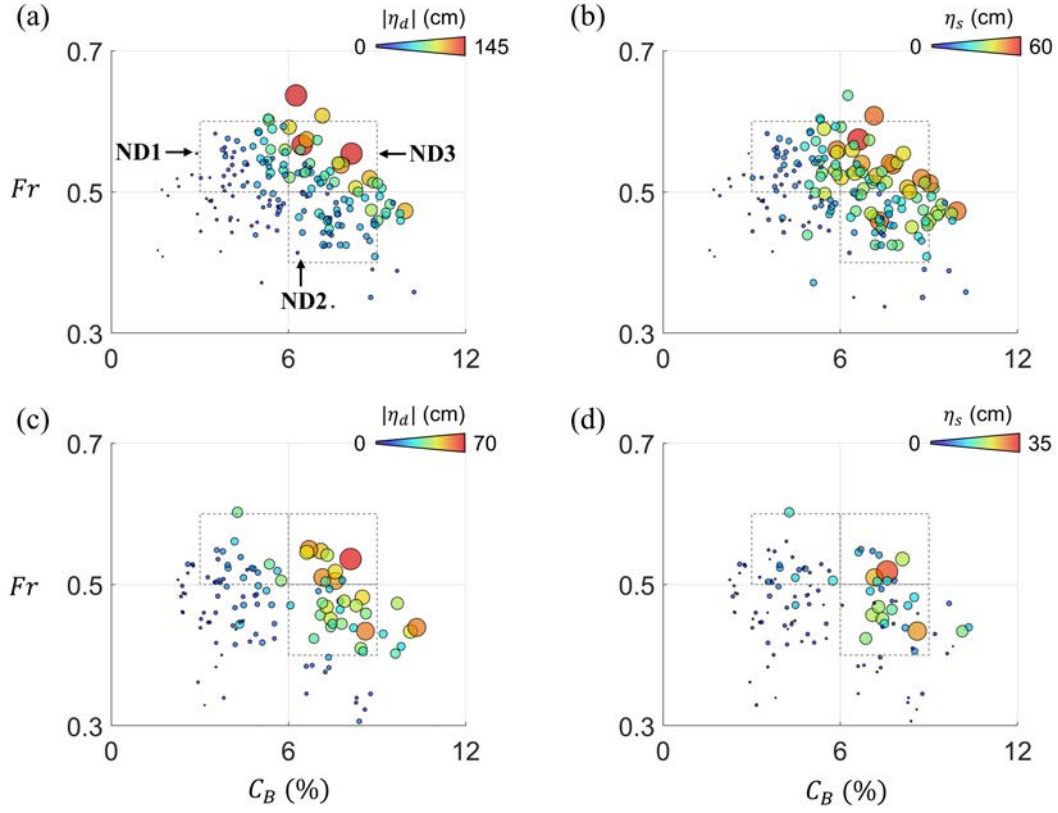


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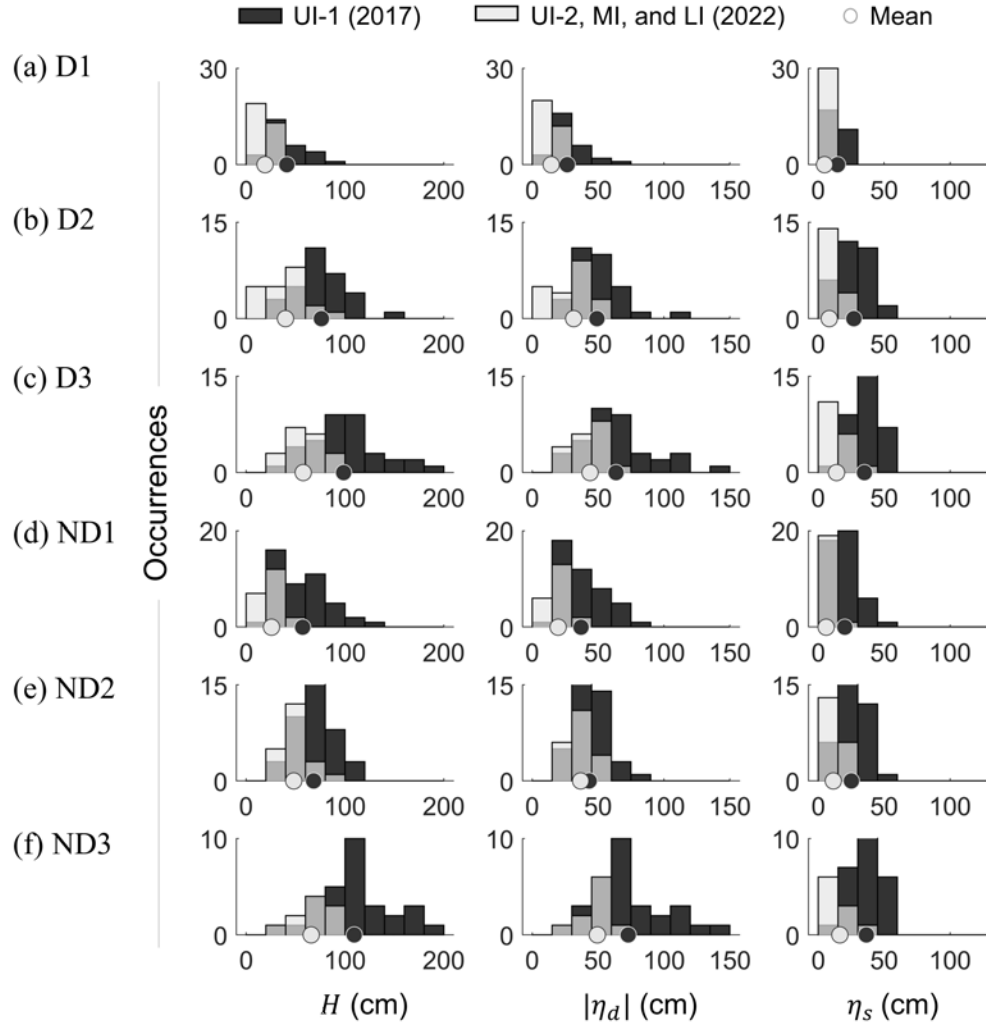


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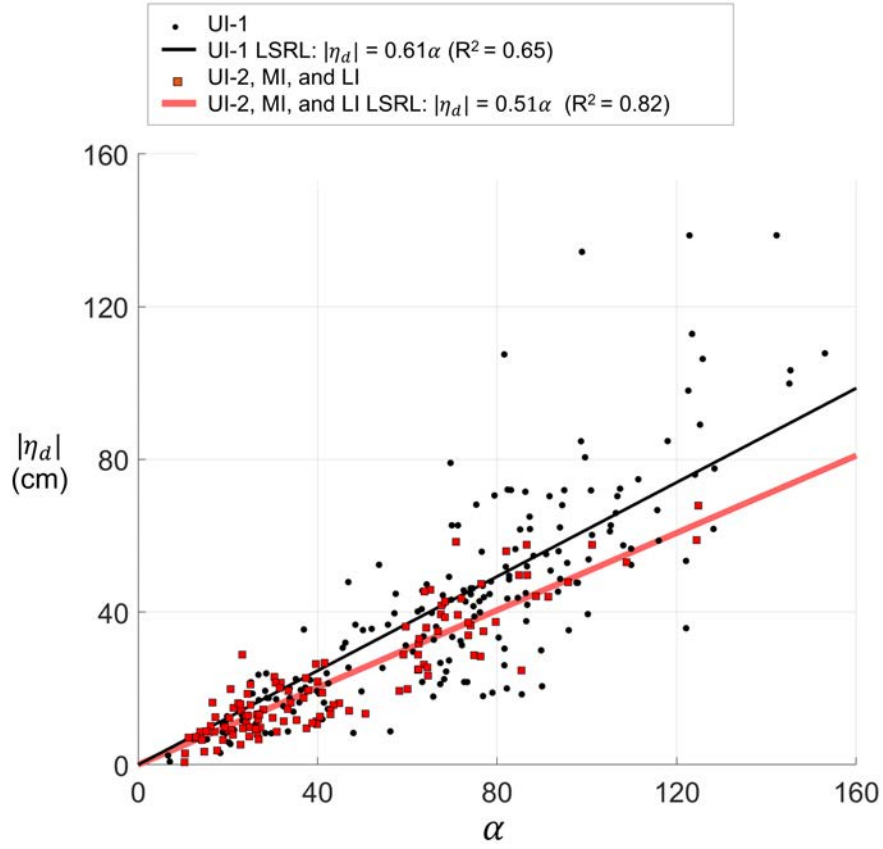


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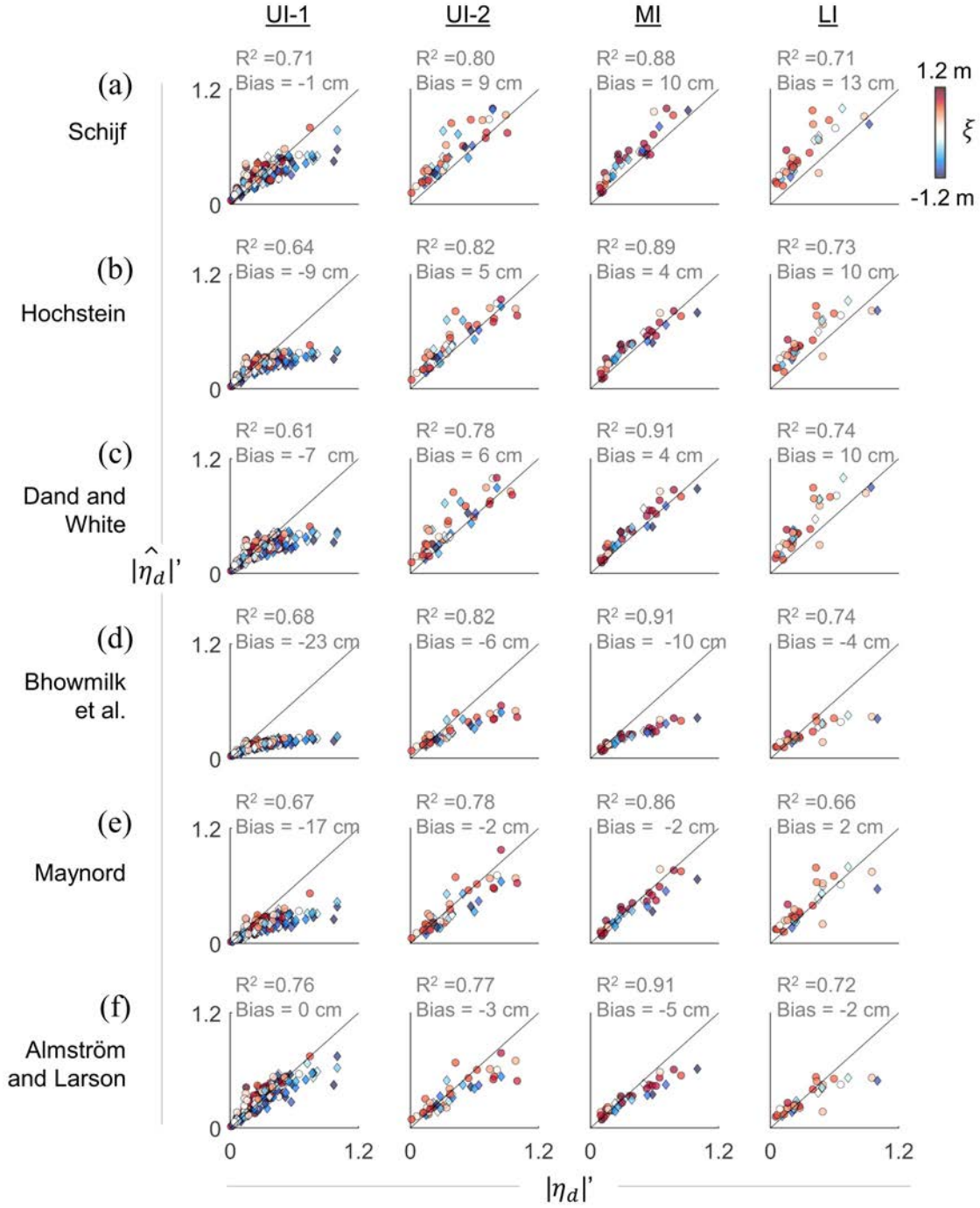


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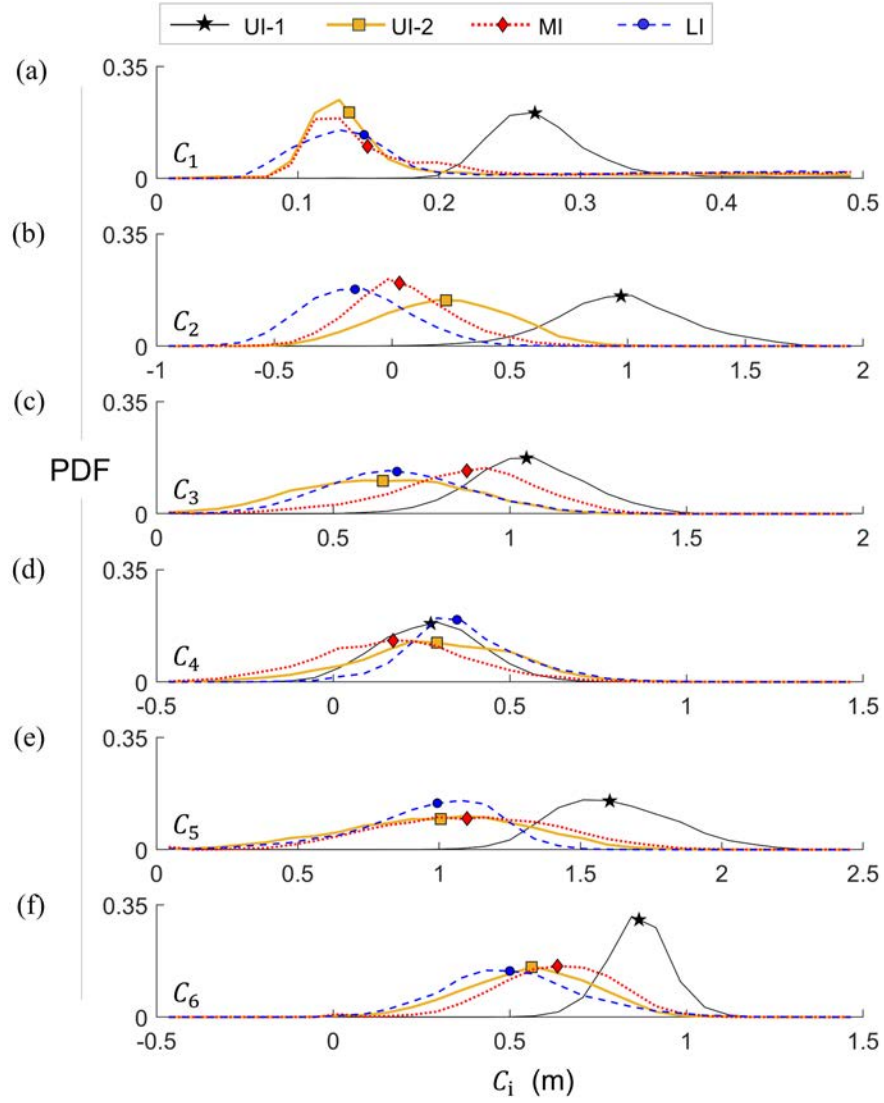


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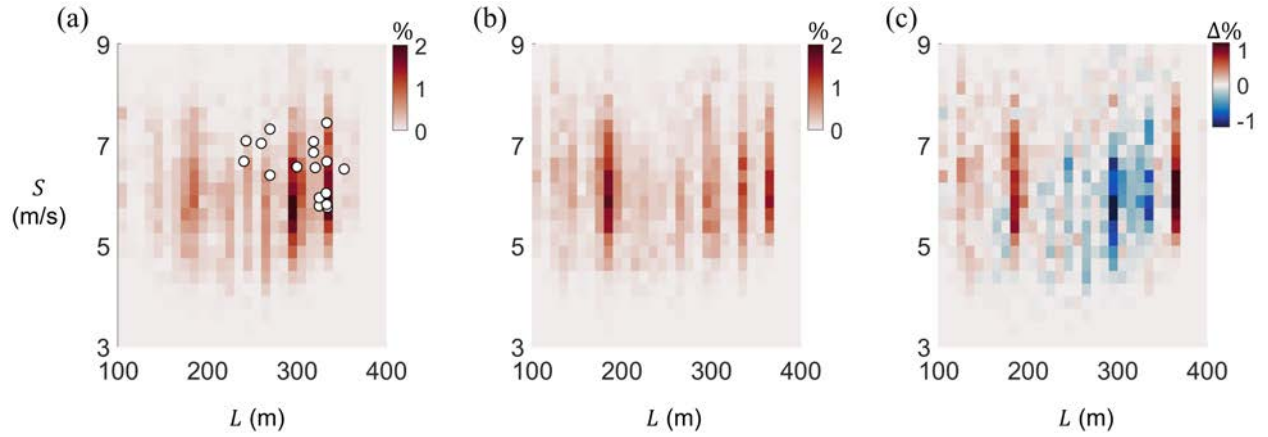


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