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AERODYNAMIC ROUGHNESS AND DRAG MEASURED FROM FLIP

by

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AERODYNAMIC ROUGHNESS AND DRAG MEASURED FROM FLIP

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requirements for the degree of

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ABSTRACT

The atmospheric roughness length, z_0 , is an experimentally determined parameter that attempts to encapsulate the physics at the air-sea interface. For numerical modeling, z_0 is central to defining the exchange of momentum across the ocean for both meteorological and oceanographic forecasting. Thus, characterizing roughness over the ocean is important for the U.S. Navy marine forecasting mission. However, z_0 does not have a universal scaling with a bulk meteorological parameter, such as wind speed, sea state, etc. Using near-surface profile measurements collected from the *R/P FLIP* (Floating Instrumentation Platform), a unique platform for science applications, this research study examines the variability in z_0 as observed during the Coupled Air Sea Processes and EM ducting Research (CASPER) field study. The variability of the atmospheric friction velocity, drag coefficient, and z_0 was examined, with a particular focus on evaluating the effect vertical flux divergence had on the observed scatter. After controlling for the logarithmic wind profile and non-divergent stress, a novel parameterization for z_0 is presented and compared to widely used bulk relations. After examining the natural flux footprint variability, a conceptual approach to identifying spatial changes in z_0 is presented and the implications for feature detection are discussed. This work holds significance for air-sea interaction modeling and the bulk parameterization of ocean surface roughness.

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LIST OF ACRONYMS AND ABBREVIATIONS

CASPER	Coupled Air-Sea Processes and Electromagnetic ducting Research
COAMPS®	Coupled Ocean Atmosphere Mesoscale Prediction System
FLIP	Floating Instrumentation Platform
LES	large eddy simulation
MABL	marine atmospheric boundary layer
MASL	marine atmospheric surface layer
MOST	Monin-Obukhov Similarity Theory
NIW	non-internal wave
RANS	Reynolds Averaged Navier-Stokes
SAR	synthetic aperture radar

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EXECUTIVE SUMMARY

The atmospheric roughness length, z_0 , is an experimentally determined parameter that attempts to encapsulate the physics at the air-sea interface, in particular the momentum flux from atmosphere to ocean caused by surface wind stress. Because of the parameter's ability to reflect the conditions of the maritime environment, it is highly used in meteorological and oceanographic modeling, making it critical for the U.S. Navy mission. However, despite its usefulness, there is no universal scaling with a common meteorological parameter, making it difficult to make accurate estimates given only basic sea parameters, such as wind speed or wave height. The purpose of this thesis is to analyze the unique dataset which was observed by the R/P *FLIP* (Floating Instrumentation Platform) as part of the Coupled Air Sea Processes and EM ducting Research (CASPER) field campaign [1]. This analysis includes examining the variability of the atmospheric friction velocity, drag coefficient, and z_0 . The feature of interest in studying the *FLIP* dataset is that wind data was captured at seven different heights above the sea surface, compared to most ocean-going platforms that only collect data at one sensor height. Leveraging this feature, this analysis can also focus on evaluating the effect vertical flux divergence had on the observed scatter. These results were then compared to previous bulk parameterization relations widely used for air-sea interaction study, with the goal of developing a novel bulk parameterization method based upon the *FLIP* dataset. In addition, the variability of flux footprints was examined, aiming toward using this technique to identify spatial changes in z_0 upwind of the *FLIP*. This work holds implications for air-sea interaction modeling and the bulk parameterization of ocean surface roughness.

The sea surface roughness analysis was done specifically by calculating z_0 by the eddy covariance method and the profile method. Values of z_0 calculated by the eddy covariance method are a result of local friction velocity values, and therefore do not represent the entire wind profile. Profile method results, however, give a representation of the entire wind profile, as it was calculated by extrapolating the wind profile from the seven wind sensor heights, which could lead to more robust results. The results of these two methods were compared to find that there is a fair amount of agreement in the high wind

speed regime, but higher estimates by the profile method in the low wind speed regime. The profile method results were then compared to previous bulk parameterization methods, specifically that of Smith [2] and Edson [3], which showed agreement the bulk smooth component, and Edson producing a more favorable estimate for the bulk rough component. However, there was a notable scatter in the low wind speed regime in which z_0 had contributions leading to very high values and low values simultaneously. This phenomenon became the subject of the *FLIP* roughness investigation when developing a novel bulk parameterization method. A constant stress gradient mask was applied to the profile method results to decrease the scatter for a novel bulk parameterization fitting from *FLIP* data. After a series of various fittings, the data was discriminated into two regimes for an independent fitting of the smooth and rough components, leading to the *FLIP* bulk parameterization:

$$z_0 = \begin{cases} 0.11 \frac{v}{u_*} + \frac{0.0017U_{10} - 0.005)u_*}{g} & \text{for } u_* < 0.32 \\ 0.00177u_*^2 - 7.96 * 10^{-5} & \text{for } u_* \geq 0.32. \end{cases}$$

Lastly, a footprint analysis of the *FLIP* data was done to serve as the foundation for detecting and locating roughness contributions using a sensor. Using a MATLAB script provided by Hsieh [4], with slight modifications, the cumulative roughness at a function of distance upstream of the sensor was able to be computed. A brief analysis of the footprint analysis informed that higher speed wind events were related to cumulative contributions that were further away from the sensor. These contributions could be located directly, as distance of the contribution upstream of the sensor was one of the parameters calculated. This analysis formed the premise for a potential wake detection method involving passive sensors. Although application of this method was beyond the scope of this thesis, the principles used in the roughness and footprint analysis were put together to develop this method to input a time series of typical meteorological parameters and output practical information about locating and tracking sea roughness perturbations.

The R/P *FLIP* provided a robust dataset for sea surface roughness analysis. This work holds implications for the novel use of the *FLIP* dataset for air-sea interaction modeling and the bulk parameterization of ocean surface roughness.

References

- [1] “CASPER: Coupled Air–Sea Processes and Electromagnetic Ducting Research.” *Bull. Am. Meteorol. Soc.*, vol. 99, no. 7, 2018, Accessed: May 15, 2023 [Online]. Available: <https://journals.ametsoc.org/view/journals/bams/99/7/bams-d-16-0046.1.xml>
- [2] S. Smith, “Coefficients for sea surface wind stress, heat flux, and wind profiles as a function of wind speed and temperature,” *J. Geophys. Res. Oceans*, vol. 93, no. 12, 1988, Accessed: May 03, 2023 [Online]. Available: <https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/JC093iC12p15467>
- [3] J. Edson, V. Jampana, and R. Weller, “On the exchange of momentum over the open ocean,” *J. Phys. Oceanogr.*, vol. 43, no. 8, 2013, Accessed: May 03, 2023 [Online]. Available: <https://journals.ametsoc.org/view/journals/phoc/43/8/jpo-d-12-0173.1.xml>
- [4] C.-I. Hsieh, G. Katul, and T. Chi, “An approximate analytical model for footprint estimation of scalar fluxes in thermally stratified atmospheric flows,” *Adv. Water Resour.*, vol. 23, no. 7, pp. 765–772, Jun. 2000, doi: 10.1016/S0309-1708(99)00042-1.

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I. NAVAL RELEVANCE AND APPLICATION

The surface of the ocean is a vast interface that, through its roughness, represents the physical processes occurring above and below the surface, such as wind, waves, or undersea currents. This raw information is comprised of the small-scale waves propagating across the ocean surface, which are highly sensitive to environmental forcing and disturbances at the air-sea interface [1], [2]. These small, or short, waves respond to wind, currents, changes in bathymetry, long waves (e.g., swell, tidal bores), and maritime vessels and structures. Statistically, the distribution of these waves can be represented using the aerodynamic roughness length, z_0 , of the ocean surface. This is a cumulative parameter that represents a given ocean surface state and is critical to weather, climate, and environmental prediction in the marine battlespace. In addition to natural processes, the energy imparted by vessel wakes redistributes the short waves across the ocean. This signature is exploited for detection, typically using wake-based vessel detection methods from Synthetic Aperture Radar (SAR) backscatter data, but there could potentially be a method that leverages an understanding of z_0 to perform this detection *passively*.

This thesis analyzes a high-quality near-surface wind and wave dataset to understand the natural variability of z_0 over the ocean. Using simultaneously measured turbulence, wave, and basic micrometeorological data collected from a unique oceanic research platform, the *FLIP*, the relationship between z_0 and other atmospheric forcing on the ocean surface will be examined. This work also includes a novel air-sea interface footprint analysis—a technique to understand how locally observed turbulence is governed by the distribution of roughness upstream. This analysis is foundational to the over-arching motivation of this work: developing a passive means of detecting heterogeneous surface roughness fields, such as those found as a result of vessel wakes at the surface. In addition, having a better understanding in the variability of z_0 over the ocean can give insights to weather and climate modeling, leading to better maritime weather forecasting and a more effective U.S. naval fleet.

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II. A RELEVANT REVIEW OF THE MARINE ATMOSPHERIC BOUNDARY LAYER

A. WIND PROFILE

In general, a boundary layer velocity profile develops because of fluid flow interaction with a frictional surface. In the idealized case of an infinite half-space comprised of a horizontally homogeneous fluid moving at a constant velocity and a rough, impermeable plate, the vertical structure of the fluid moving parallel to the wall can be segregated into two parts: an external flow that often can be considered irrotational, and a near wall component highly influenced by viscous forces [3]. For turbulent flows in this viscous layer, the flow can be further segregated into a near wall, viscous sublayer, and an outer layer dominated by turbulent eddies [3]. At the leading edge of the plate, the flow velocity, U_0 , is constant and streamlines are parallel to the plate. As fluid flows over the plate, the fluid parcels near the plate are disrupted, resulting in $u(x, z)$, where x increases downstream of the leading edge and z increases away from the plate surface. Very far away from the plate, $u(x, z)$ approaches U_0 . At the plate itself, the flow approaches zero as a result of the no-slip boundary condition. This scenario creates a velocity gradient $\frac{\partial u(x, z)}{\partial z} \neq 0$ from an initially uniform steady state. The drag the fluid feels from the surface is a function of the slope of the velocity profile near the plate and the fluid's viscosity, shown by the red line in Figure 1. For laminar flow, the thickness of the boundary layer, $\delta(x)$, can be derived from assuming inertial forces and frictional forces are in equilibrium.

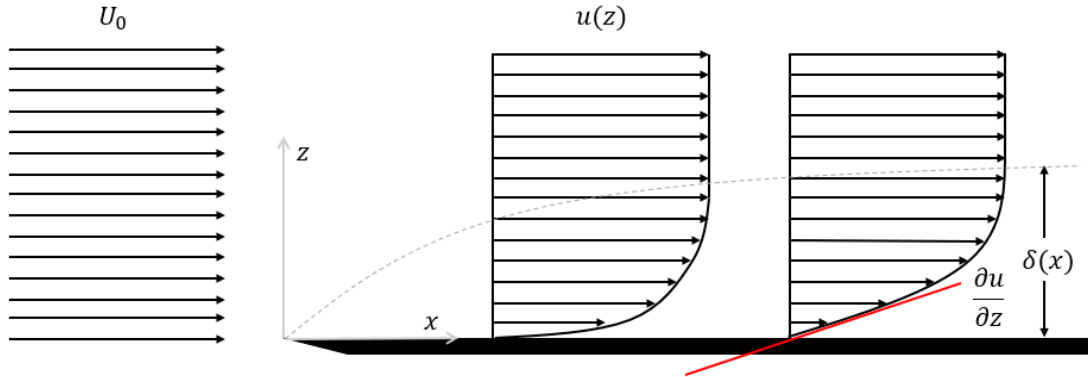


Figure 1. Basic boundary layer theory diagram with key features labeled, with the red line indicated slope tangent to the velocity profile

With some distinctions and additional terms, classical boundary layer theory is typically applied to study the interaction between the atmosphere and the Earth's surface within the layer typically referred to as the planetary boundary layer. In marine applications, the wind interacts with the ocean surface, which has the added complication of being dynamic, permeable, and deformable. To distinguish it from the general planetary boundary layer we refer to the oceanic regime as Marine Atmospheric Boundary Layer (MABL), which covers 2/3 of the planet's surface. The wind shear at the surface drives the vertical exchange of horizontal momentum between the MABL and upper ocean [4]. Wind shear can be derived from the Navier-Stokes equations [5]:

$$\frac{\partial u_i}{\partial x_i} = 0 \quad (1)$$

and

$$\frac{\partial u_i}{\partial t} + \frac{\partial}{\partial x_j} (u_i u_j) = -\frac{\partial p}{\partial x_i} + \nu \frac{\partial^2 u_i}{\partial x_j \partial x_j}. \quad (2)$$

In order to explicitly account for the role of turbulence, the Navier-Stokes equations are typically represented using Reynolds' decomposition where the mean and perturbation components of the flow are separated [5]. Here, the mean is denoted by an overbar, and the

perturbation by an apostrophe. In this form, the Navier-Stokes equations become the Reynold Averaged Navier-Stokes (RANS) equations:

$$\frac{\partial \bar{u}_i}{\partial x_i} = 0 \quad (3)$$

and

$$\frac{\partial \bar{u}_i}{\partial t} + \bar{u}_j \frac{\partial \bar{u}_i}{\partial x_j} = -\frac{\partial \bar{p}}{\partial x_i} + \nu \frac{\partial^2 \bar{u}_i}{\partial x_j \partial x_j} - \frac{\partial \tau_{ij}}{\partial x_j}. \quad (4)$$

For a more complete treatment of the RANS equations as they relate to geophysical fluid problems, the reader is directed to *Lectures on Geophysical Fluid Dynamics* [6]. With the wind shear stress being the two-dimensional component of the Reynolds stress tensor (τ_{ij}) relating the vertical (w) flux of horizontal momentum:

$$\vec{\tau} = \rho(\overline{u'w'}\hat{i} + \overline{v'w'}\hat{j}), \quad (5)$$

where ρ is the density of the fluid (air) and the term in the parentheses are components of (4), known as the air-sea momentum flux [4]. This momentum exchange is the dynamic driver of the atmosphere-ocean coupled system and critical to various applications, for example weather and climate prediction, and even electromagnetic energy propagation.

In the MABL, the intensity of the vertical momentum flux across the air-sea interface is nonlinearly linked to surface waves, atmospheric turbulence, and heat exchange at the surface. However, it is very challenging to quantify (5) in time and space across the ocean. Therefore, empirical relationships and parameterizations are used to estimate the momentum flux in terms of easier-to-measure bulk variables. It has been widely found that *Law of the Wall* predicts the relationship between this surface shear stress and the resulting mean wind profile. In the case of a neutrally stratified near-surface atmosphere, this fluid relation is given formulaically as:

$$\frac{\partial u}{\partial z} = \frac{u_*}{\kappa z}, \quad (6)$$

where u is the mean flow, u_* is friction velocity, κ is the von Kármán constant, and z is the distance transverse to the surface. Integrating this partial differential equation yields the logarithmic velocity profile,

$$u(z) = U_{surface} + \frac{u_*}{\kappa} \ln\left(\frac{z}{z_0}\right), \quad (7)$$

where u_* is the friction velocity defined in (8) and z_0 is the surface boundary condition defining the velocity at the surface. In practice, z_0 is a length scale related to the properties of the surface itself such that $u(z = z_0) = U_0 = 0$. Also, conventionally, $U_{surface} \sim 0$ over the ocean, though recent studies advocate for explicitly including ocean surface currents as a mean boundary condition, which may be especially important in low wind conditions (e.g., over the Gulf Stream) [7]. Equation (7) requires knowledge of the velocity scale u_* , which is known as the friction velocity or shear velocity. Friction velocity is defined directly from the shear stress on the surface,

$$u_* = \sqrt{\frac{\tau_0}{\rho}}, \quad (8)$$

where τ_0 is the surface shear stress. The coefficient of drag is a parameter of interest because of it encapsulates all the turbulence information in the airflow into a single number, and it does so without instruments that measure turbulence directly. Ideally, the variability of C_D is predictable for a given surface and flow regime. As such, the coefficient of drag is a useful parameter that is calculated with relatively widely available measurements. To relate average wind speed and coefficient of drag, the scalar form of shear stress can be defined as:

$$|\tau| = \rho U^2 C_D. \quad (9)$$

Equations (6)-(7) describe the velocity distribution in the absence of thermal instability or stratification. To account for thermodynamics, Monin-Obukhov Similarity Theory (MOST) must be invoked. Thermal stability refers to the vertical temperature gradient, and the resulting balance of shear and buoyancy driven turbulence production mechanisms that result from these *non-neutral* conditions. The basis of MOST requires using a new length scale [8] to define the vertical dimensions of buoyant circulations in the atmosphere,

$$L = \frac{\rho u_*^3}{\kappa g \overline{\rho' w'}}, \quad (10)$$

where $\overline{\rho' w'}$ is the vertical buoyancy flux. The Monin-Obukhov length, L , describes the distance from the surface where shear and buoyant production are in balance [9], and in the atmospheric boundary layer is typically several tens of meters [10]. As a result of the buoyancy term, L is sensitive to surface temperature changes (caused by solar radiative forcing, surface transport, etc.) and typically has a strong diurnal signal. By defining L , MOST relates the flux-gradient relationship, (6), to the balance of production terms through a new dimensionless stability parameter $\frac{z}{L}$ and re-defines the wind profile relationship using the non-dimensional shear function ϕ_M :

$$\frac{\kappa z}{u_*} \frac{\partial u}{\partial z} = \phi_M \left(\frac{z}{L} \right), \quad (11)$$

where ϕ_M is the function for momentum and only depends on stability ($\frac{z}{L}$). While MOST poses the existence of this function and is foundational to our understanding of vertical wind speed gradients, the key parameter, ϕ_M , must be empirically determined from wind and temperature gradient data [11]. Integrating (11) leads to the new form of (7),

$$u(z) = \frac{u_*}{\kappa} \left(\ln \left(\frac{z}{z_0} \right) - \psi_M \left(\frac{z}{L} \right) \right). \quad (12)$$

There are several different equations for ϕ_M and ψ_M depending on which one the many stability conditions the dataset provides. Also, notably, the von Kármán constant also

varies experimentally through different datasets. Edson [9] details which stability equation and von Kármán constant value should be used in the marine context. The coefficient of drag can then be calculated by the following equation [12]

$$C_{DzN} = \left(\frac{u_*}{u}\right)^2 = \kappa^2 / \left[\ln\left(\frac{z}{z_0}\right) - \psi_M\left(\frac{z}{L}\right) \right]^2, \quad (13)$$

where u takes the form of (12). One of the most widely used empirical techniques to observe the parameters relevant to (13) is known as the eddy covariance method, and is the basis for the analysis presented in this thesis. One of the goals of the eddy covariance method is to produce the equivalent drag coefficient at a height of 10 meters and neutral stability (C_{D10N}). This parameter is a way to standardize measurements of air-sea momentum flux (5) taken at different heights, wind speeds, and thermal stabilities. A key part of evaluating (13) is defining ψ_M , which are empirically determined with several versions available in literature [12].

B. SURFACE ROUGHNESS: GEOMETRIC AND AERODYNAMIC

The ocean's surface presents a complex fluid dynamics problem because its roughness and wind stress are nonlinearly co-dependent. The surface roughness of the ocean, which is a culmination of the short surface wave field is indicative of the various forcings on the interface because these waves respond directly to winds, currents, and long waves [4]. Surface roughness is central to understanding the frictional interactions within flow over a boundary, and there are several metrics that are used to provide quantitative information about a fundamentally abstract characteristic of surfaces. In the basic example of internal flow through a rough pipe, roughness is characterized by relative pipe roughness, $\frac{\epsilon}{d}$, which is a dimensionless parameter of the ratio of absolute roughness (a material property) and the diameter of the pipe [13]. Absolute roughness, ϵ , is simply a material property that can be found empirically through internal flow experiments. Absolute roughness is a length scale that is measured indirectly from pressure head loss experiments. These roughness measures are found in the Moody diagram, a widely used reference for internal fluid dynamics. For the atmospheric boundary layer, geometric

roughness, k , is analogous to absolute roughness. k quantifies surface roughness over different terrains and obstructions, specifically on land through careful geophysical experiments. Table 1 summarizes these various roughness metrics.

Table 1. List of common roughness length parameters and their definitions.

Roughness Parameter		Significance
<i>Absolute roughness</i>	ϵ	<i>Experimentally determined roughness of a specific material</i>
<i>Relative roughness</i>	$\frac{\epsilon}{d}$	<i>Absolute roughness normalized by pipe diameter</i>
<i>Aerodynamic roughness</i>	z_0	<i>Apparent roughness felt by air flow over a frictional surface.</i>
<i>Geometric roughness</i>	k	<i>The absolute roughness of a specific natural surface, e.g., mown grass.</i>

As compared to over land, the ocean surface is dynamic and defining k for water surfaces remains elusive. Geometric roughness is strictly surface dependent on topology, as the roughness of land changes negligibly over time. Notably, geometric roughness is independent of flow conditions. However, for the air-sea interface, the topology varies greatly due to oceanic factors such as swell and fetch (ocean surface and wind waves). Thus, an aerodynamic roughness length, z_0 , must be used to account for these complex dependencies. z_0 does not necessarily define the physical topology of the surface like the absolute roughness parameter, but rather provides a statistical metric to gauge the intensity of wind stress for a given MABL and oceanic state. To calculate z_0 , the wind profile is extrapolated, (12), to the bottom of the MABL outer layer, or by assuming a constant stress layer and measuring the turbulent properties of a given flow, as well as sea state [4].

Currently, there is no universal scaling method to estimate z_0 based upon easily measurable oceanic parameters. However, there are several methods from which z_0 can

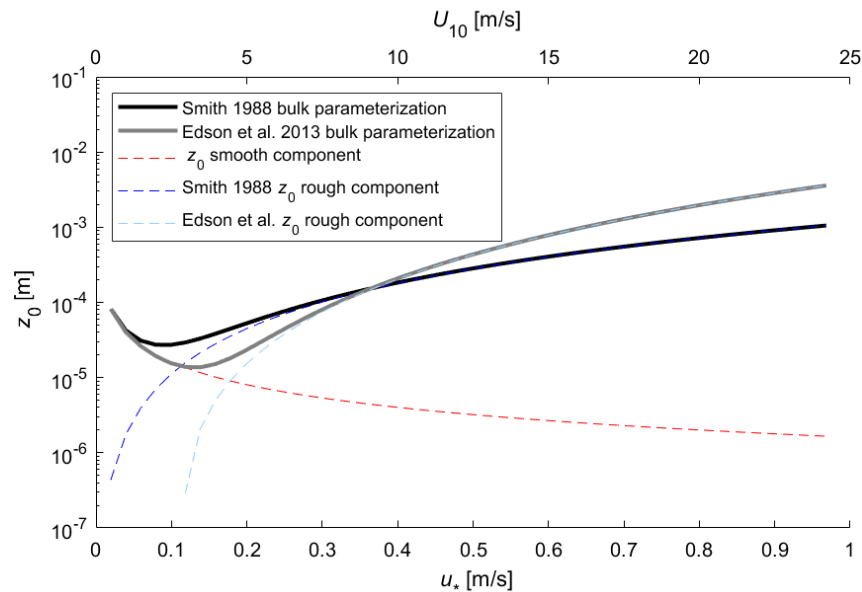
estimated. These bulk parameterizations were empirically found using various oceanic datasets [7], [14]. In general the Smith [14] formulation,

$$z_0 = 0.11 \frac{\nu}{u_*} + 0.011 \frac{u_*^2}{g}, \quad (14)$$

parameterizes roughness in terms of the friction velocity and is widely used in empirical and numerical studies, where the first term represents the smooth regime [4], and the second term represents the rough component, or the case of fully developed turbulent flow. The second bulk parameterization used in this analysis was presented by Edson [7] is

$$z_0 = 0.11 \frac{\nu}{u_*} + \frac{(0.0017U_{10} - 0.005)u_*}{g}, \quad (15)$$

where the constants were determined empirically from a linear regression. These two methods yield slightly different results in the computation of z_0 . However, it is generally accepted that the range of z_0 is within 10^{-6} and 10^{-2} m.



For demonstration purposes, u_* was defined as $\sqrt{0.0015U_{10}^2}$ [15].

Figure 2. Two examples of bulk parameterization of z_0 , formulated using (14) and (15).

There are several other bulk parameterization methods which have been shown to describe the variance in other datasets. However, there is no universally accepted method, and (14) and (15) represent the most widely used formulations. Recently, some studies have advocated adding additional independent contributions to the roughness. For example, in a surf zone study, MacMahan [16] adjusted the roughness parameterization to account for the impact of foam:

$$z_0 = z_v + z_w + z_f, \quad (16)$$

where z_v is viscous smooth flow regime, z_w is the rough component is comprised of form drag from surface waves, and z_f is the drag associated with flow separation resulting from foam [16]. Refining our approach to modeling surface roughness over the ocean remains an area of active study.

C. EDDY COVARIANCE AND FLUX FOOTPRINTS

The key connection between surface roughness being created by wind stress, while also wind being affected by surface roughness is that interface exhibits air-sea momentum transfer. This momentum transfer, in terms of per unit area, becomes momentum flux, which is felt in the MABL as drag [4]. A significant application in observing air-sea momentum transfer is footprint analysis, which gives insight into the location of origin of turbulence. The general measurement of energy transfer that footprint analysis falls under is the eddy covariance method, which uses the vertical wind component in turbulence to investigate heat, mass, and momentum transfer.

It is important to note the mechanisms that allow this flux to occur, so that such changes in momentum can be identified. The predominant method of momentum transfer is the Reynolds stress, characterized by two phase flow, and the observable indication of the transfer is the resulting wind-waves [4]. Reynolds stress is denoted by a 3x3 tensor, but the predominant components for momentum transfer for this problem are simply $\overline{u'w'}$ and $\overline{v'w'}$, or the fluctuating vertical component of velocity, and given in both dimensions of the two-dimensional surface to get an area flux. In terms of orientation, these two terms

correspond to the direction of surface wind and their covarying vertical fluctuations. The $\overline{u'w'}$ term is also referred to as the eddy covariance term [4], as u refers to the vector of prevalent wind.

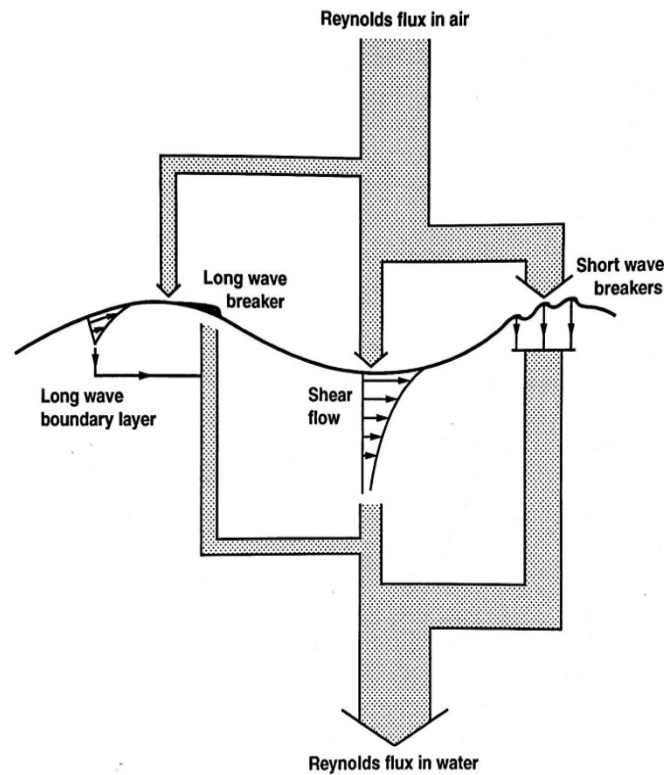


Figure 3. Drag generation mechanism diagram. Adapted from [4]

Just as momentum is captured by the interface in the form of wind-waves, the waves lose momentum quite quickly through “breaking.” Other drag mechanisms transfer to growing into longer waves that lose less momentum, while some momentum transfers directly into sheared flow. It remains unclear as to the exact fraction in which these mechanisms contribute. It is clear, however, that these short wind-waves have a significant contribution on surface drag, which is an effect that can be further investigated using techniques such as footprint analysis.

The way in which momentum exchange through the air-sea interface is quantified is through the eddy covariance method [17]. The eddy covariance method is also necessary

to identify the flux footprint, which is a statistical distribution relating the observed momentum flux at a sensor to the upwind roughness. In order to derive the mathematical basis for eddy covariance, several assumptions are applied to the fluid mechanics conservation of momentum equation, neglecting pressure gradient, viscous transport, and gravity [18] to produce

$$\frac{\partial \rho u_i}{\partial t} + \nabla(u \rho u_i) = S_i, \quad (17)$$

where u_i is the component of wind in one given direction, the first term applies to the time rate of change of the quantity, and the second term refers to advection, specifically the momentum transport from bulk flow. Lastly, the S_i term refers to the contribution of the source/sink. A Reynolds decomposition is then performed to produce [18]:

$$\frac{\partial \bar{u}}{\partial t} + \bar{u} \frac{\partial \bar{u}}{\partial x} + \bar{v} \frac{\partial \bar{u}}{\partial y} + \bar{w} \frac{\partial \bar{u}}{\partial z} + \frac{\partial \overline{u'^2}}{\partial x} + \frac{\partial \overline{v'u'}}{\partial y} + \frac{\partial \overline{w'u'}}{\partial z} = 0. \quad (18)$$

Three simplifications are then applied to (18). First is that a coordinate system is applied such that terms in the $\bar{v}$ and $\bar{w}$ direction are zero. Second, horizontal homogeneity is applied such that horizontal gradients are canceled. Third, steady state is assumed. Which leads to a vastly simplified system:

$$\frac{\partial \overline{w'u'}}{\partial z} = 0, \quad (19)$$

where $\overline{w'u'}$ is called the eddy covariance term (this is the component of the Reynolds stress aligned with the mean wind), and u specifically refers to the direction of prevailing surface wind. However, in terms of the MABL, the sea cannot necessarily be assumed to be a static surface. Therefore, data quality methods are done in order to predict the error, or alternatively, the change in the source/sink term is calculated using an array of sensors [17]. Momentum exchange can be calculated via the eddy covariance method, and footprint analysis leverages this concept to locate these areas of sea surface, specifically rough surfaces, that contribute to these fluxes.

Footprint analysis is a technique that uses the observed time series recorded at a measurement site to estimate information about the location of turbulence sources upwind of a sensor [17]. This is a statistical approach that, despite key assumptions, can nonetheless be informative about the turbulence field and surface upwind of meteorological sensors. In a terrestrial context, footprints (or flux footprints) can be used to diagnose the sources of turbulence and flux at a measurement site. Over the ocean, footprints are less often used because the surface is generally known (such as in the open ocean), though it has been used to segregate between water, tidal, and sand surfaces for coastal flux analysis [16].

Conceptually, the footprint is a statistical representation of the distribution of upwind turbulence, which has a peak localized and corresponding to some upwind surface condition [16]. The location of these footprints is predicted such that the highest contribution of flux can be attributed to a distance of x upwind of the detector sampling the advecting turbulence field at a certain height z above the interface. The contribution is a function of x , wind speed (U), and the local turbulence intensity parameterized with u_* , which is given in terms of the relative-flux-density:

$$\frac{1}{Q_0} \frac{dQ}{dx} = - \frac{U(z-d)}{u_* \kappa x^2} e^{-\frac{U(z-d)}{\kappa u_* x}}, \quad (20)$$

where Q_0 is the area flux density, U is the wind speed, x is distance upstream of the sensor, d is the height of zero displacement, and κ is the von Kármán constant [17]. In terms of analysis, the *footprint*, is this spatial-statistical function that can be order 100's of meters to several kilometers, depending on the flow speed (wind) and thermal stratification—also the intensity of the shear stress generated at the upwind roughness elements. Additionally, being able to identify the location relative to a sensor of particular area of anomalous roughness has the potential to aid in a possible target detection technique.

Specifically, the output of a footprint analysis is the cumulative flux contribution as a function of distance upstream of a sensor. This cumulative flux contribution indicates the fraction of total momentum flux from roughness that has been transferred at the air-sea interface at any distance upstream of a sensor. For example, a roughness element upstream

of the sensor caused by, say, a surface vessel wake could contribute 90% of the total air-sea momentum flux at a distance of 1 km upstream of the sensor. Also, as the cumulative flux contribution function asymptotically reaches 100%, the distance increases to infinity, because conceptually, a footprint analysis accounts for all roughness elements upstream of a sensor. Intuitively, these roughness elements extremely far from the sensor would have infinitesimal contributions to the momentum flux. Theoretically, anomalous roughness elements wakes or internal waves could be located, assuming that their contributions are differentiable from the natural variance of roughness in the area. The detection of non-driven surface roughness contributions, such as non-linear internal waves (NIWs) or subsurface vessel wakes, is discussed in detail in Section D.

D. NON-WIND DRIVEN SURFACE ROUGHNESS CONTRIBUTIONS

Surface waves with sub-meter wavelengths have short relaxation times, causing them to be sensitive to a myriad of ocean surface forcings other than the surface wind stress. For example, upper ocean internal waves propagating along the pycnocline are known to cause changes in the surface wave field and thus affect surface roughness, z_0 . The contribution of sea surface roughness that nonlinear internal waves (NIWs) produce takes the form of smooth and rough bands, creating surface roughness heterogeneity [1]. Due to this variability introduced into z_0 , bulk parameterization techniques such as (14) and (15) miss the contribution of this variance to the roughness and thus misrepresent the air-sea momentum flux. This is important to consider in a numerical scheme which must account for all major sources of flux variance and heavily relies on empirical formulae to capture the physics of the system. While this is an accepted oversimplification, the use of parameterizations in environmental forecast systems requires further attention to understanding how different processes impact the predicted surface roughness. Recent work has highlight how NIWs are an example of a previously neglected mechanisms stimulating air-sea momentum flux through modulation of surface roughness.

NIWs propagating through a wave field can be quantified in a variety of ways, however, their exact roughness contribution is unknown. However, a variety of studies have been done to observe NIWs and their effects on the MABL and air-sea interface, but

have not strictly quantified these contributions via z_0 . For example, Ortiz-Suslow observed the correlation between atmospheric turbulence and NIWs [19], and Wu observed wave slope change as a result of NIW contributions [1]. Such contributions by NIWs, which affect sea surface roughness, need to be accounted for in z_0 calculations. Accounting for this is simply a linear summation, according to (16). In order to leverage knowledge about z_0 for NIWs, work needs to be done to quantify how much roughness contribution is specifically done by NIWs. Differentiation between surface-wind driven roughness contributions and NIW roughness contributions could then be performed.

Submarine wakes, similar to ocean internal waves, act on the ocean surface waves and locally redistribute z_0 through the propagation of the wave front. The displacement of water from a sub-surface vessel creates pressure variations that lead to anisotropic turbulence that can be identified in the form of wake signatures [20]. It is currently unknown what the specific contribution to z_0 is solely from a submarine wake. Current methods identify three specific characteristics of a wake: the Bernoulli hump, Kelvin wake, and an internal wake [21]. Optical imagery is used to capture these surface perturbations. Synthetic Aperture Radar (SAR) captures these surface roughness variations and outputs an image with the resulting wave heights and geometry of the Kelvin wake. The Kelvin wake produces a relatively consistent geometry and because of this has been thoroughly investigated. Sub-surface vessels traveling in homogenous conditions typically yield a 19.5° Kelvin wedge angle, and 22.5° for linearly stratified conditions [21]. Additionally, these Kelvin wakes yield consistent wave crest perturbation heights: 0.0117 m for homogeneous conditions and 0.0206 m for stratified conditions [21]. The geometry and intensity of Kelvin wakes are also an indication of the operating conditions of the vessel. The vessel's velocity and diving depth can be directly calculated by measuring the wavelength of the Kelvin wake [21]. Besides Kelvin wakes, other turbulence wakes have been investigated. Coherent vortex structures are studied through Large Eddy Simulation (LES), where there is an emphasis on wake behavior with respect to time. Large vortices are collections of coherent structures which can take days for their energy to dissipate through turbulent energy cascade [22]. Thus, submarine wakes have distinct features that remain on the ocean surface for a significant amount of time. However, these features,

typically observed via SAR imagery, are not easily translated to the current methods of sea surface roughness analysis with z_0 . Nevertheless, submarine wakes do provide contributions to sea surface roughness, which leaves the possibility of a potential passive detection method that leverages footprint analysis. Much like NIWs, it is also unknown the exact roughness contribution is provided by surface wakes. If these contributions could be estimated, via simulating or empirically, then roughness anomalies could be identified in a time series of z_0 values, which might be leveraged to detect subsurface vessels transiting upwind of a sensing device. The aim of this thesis is to understand natural variability in surface roughness and flux footprints in order to develop a passive detection method as described above.

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III. DATA COLLECTION AND METHODS

A. CASPER: THE 2017 WEST COAST CAMPAIGN

The Coupled Air-Sea Processes and Electromagnetic ducting Research (CASPER) project was initiated to better understand atmospheric impacts on radio frequency energy propagation through the marine atmospheric boundary layer (MABL) [23].

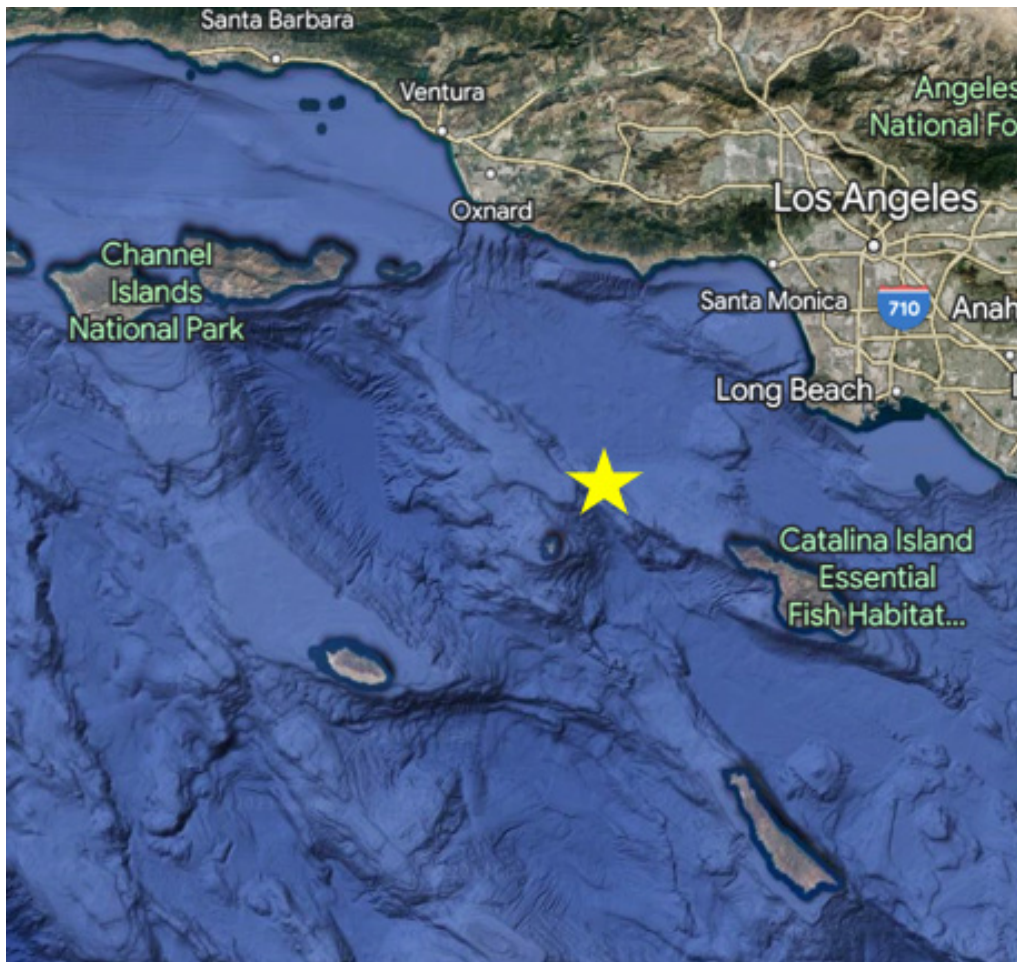


Figure 4. Location of *FLIP* during the 2017 CASPER-West campaign [19].

A key science objective for CASPER was re-evaluate Monin-Obukhov Similarity Theory (MOST) [8] and its application within a geophysical fluid boundary layer, such as the MABL. MOST provides the basis for modeling the MABL's surface layer, the marine

atmospheric surface layer (MASL), and is built into many Naval operation prediction systems and schemes, including the Coupled Ocean Atmosphere Mesoscale Prediction System (COAMPS®) and the Navy Atmospheric Vertical Surface Layer Model (NAVSLaM) [24]. MOST provides a theoretical conceptualization for high Reynolds wall-bound shear flows with thermodynamic instability. However, it requires empirical validation and input, which has been largely under-taken over land, in particular the seminal Kansas experiments [11], [25], [26]. Over water, the deformable surface creates a new regime that was not predicted by MOST and needs to be addressed empirically, as well as theoretically. This is particularly true over the ocean where surface deformation may be driven nonlinearly by wind, (non-local) waves, and currents. The impetus for CASPER was to revisit MOST in the maritime regime. In September and October 2017, CASPER conducted a field campaign in Southern California [23], which included the deployment of the Research Platform *FLIP* [19], [23]. This field effort became known as CASPER-West. The data used in this analysis comes from the CASPER-West campaign and this will be the focus of this thesis.

B. THE R/P FLIP DURING CASPER-WEST

The observations collected aboard *FLIP* during the 2017 CASPER-West campaign will be the primary focus of this thesis study. The details of this unique platform are outlined in this section.



Figure 5. Floating Instrument Platform (*FLIP*) from the CASPER-West campaign. Adapted from [19], image credit D. Khelif.

The *FLIP* was commissioned by the U.S. Navy in 1962, and originally designed for ocean acoustics research because researchers needed a very stable platform in deep water, as opposed to ships which float on the surface and resonate with a broad subrange of surface gravity waves [27]. When operating, *FLIP* inverts to the orientation seen in Figure 5. With about 85% of its length underwater while collecting oceanographic data, *FLIP* is significantly more stable to wave motion than a typical research vessel [27]. The platform has added several packages that allow it to be an asset in collecting data for meteorological research. The *FLIP* was deployed in the CASPER-West campaign between September 23 through October 25, 2017 in the Santa Monica Basin within the Southern California Bight [23].

It is important to consider the *FLIP* data processing and quality assessment in order to correctly analyze the dataset. Corrections to the dataset have been made in order to mitigate error from the platforms motion during data collection, as well as the flow

distortion from collecting wind measurements that have flowed past the hull of the vessel. Recent quantitative investigations have been done to develop a method for this data post-processing. For the purpose of calculating roughness from wind shear, the most significant data caveat is to account for skewed wind data in certain directions, specifically along the ASI mast [19]. The results of this flow contamination study were used data correction for z_0 calculations.

C. THE NPS AIR-SEA INTERACTION MAST

Using *FLIP* data is a novel approach to investigating the aerodynamic roughness length. On Figure 2, the high-resolution meteorological mast allows the FLIP to take wind and temperature measurements at various heights. For the data used in this research, the measurements were taken at a height of 2.98 m, 4.03 m, 4.94 m, 5.86 m, 8.93 m, 12.4 m, and 15.8 m. The *FLIP* collects these measurements every 0.02 s for a total time of 23 days. The collected wind measurements are the vector components of wind in the north-south direction, east-west direction, and vertical direction. Other measurements are the air temperature at each of the collection heights, the temperature of the water, and the wave height.

Because this is a novel method of observing sea surface roughness, platform specific considerations need to be made in order to yield accurate results. Due to the unique structure of the *FLIP*, a data quality analysis was done to determine the extent of flow contamination on the dataset [19]. Flow contamination, in this context, is defined as the effect the physical structure of platform has on the flux measurements [19]. The findings from this analysis was that there were certain wind directions that were distorted as a result of the *FLIP* superstructure. Any measurement that was captured with the described distortion was flagged in a MATLAB script such that the element was eliminated from the dataset. This removed ~30% of the dataset. As an initial view of the dataset, the following figure depicts all scalar wind measurements free of flow contamination as a time series.

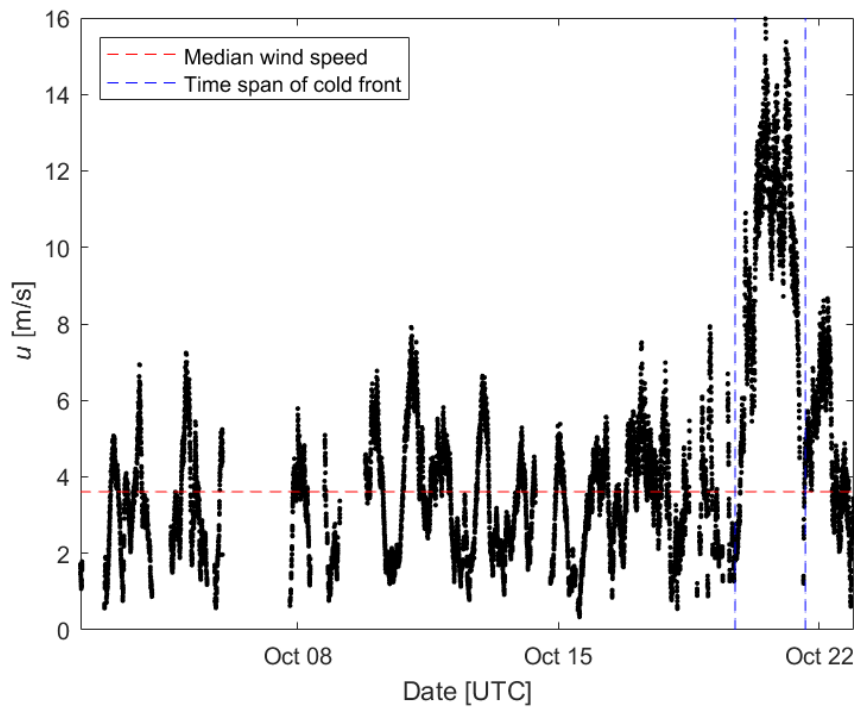


Figure 6. Wind time series with a reference line at 8 m/s

The median wind speed, ~ 3.8 m/s, is noted in Figure 6 by the red dashed line. Significant takeaways from this first look at the dataset are that there are gaps in the data as a result of flow distortion correction, and the peak in wind speed near the end of the observing window. This was the result of the passage of a cold front and a low-level jet into the Southern California bight from the west-northwest. One aspect of the data to consider in the analysis is the presence of a distinct peak in the last few days of the campaign, noted within the blue dashed lines in Figure 6. In this case, all the wind speeds above 8 m/s come from this one event and may not be generally representative. However, this does provide an important test for stronger forcing conditions. This is a limitation of the dataset and will be considered in the interpretation of the results. The rest of the measurements are quite representative of typical conditions over deep water ocean waves in Southern California in the late summer, early fall.

D. SURFACE ROUGHNESS FROM FLIP

The primary objective of this thesis is to use the FLIP dataset to investigate sea surface roughness variance. A specific point of emphasis within this objective is to study the relationship between the wind profile's stress gradient and the predicted roughness using conventional bulk parameterizations such as Smith's [14] and Edson's [7]. It is widely assumed in marine eddy covariance studies that the wind stress gradient is constant. In this scenario (19), the eddy covariance technique can be used to related locally measured shear stress to the shear stress at the ocean surface. However, since the NPS meteorological mast on *FLIP* collects wind data at multiple heights above the sea surface, this presumption can be directly tested and included in the data analysis as a filter.

There were two methods used to determine the sea surface roughness parameter z_0 : eddy covariance and the profile method. The eddy covariance method, which is the more typical method for determining z_0 , uses the observed shear stress (u_*) and the derived 10-m neutral wind speed and drag coefficient (13) to derive z_0 directly. Alternatively, the profile method relies on the fact that *FLIP* has wind sensors at multiple heights, and extrapolates the wind profile by using a logarithmic fit. For each 30-minute averaged wind velocity profile, we can derive an estimate of z_0 using a log-scale (on the x -axis) least squares regression. Notably, the assumption of a logarithmic wind profile implies a time averaged approximation of the outer turbulent boundary layer. Thus, the statistical model used in this analysis can be given as

$$u = A \ln(z) + B, \quad (22)$$

where, in this particular case, u is wind speed, and z is height above the surface. After performing a logarithmic fit on each timestamp, coefficients A and B (and their variance) are derived. Regression was done using a robust fitting algorithm that identifies overly-influential data points and, if any, removes them from the regression before calculating A and B .

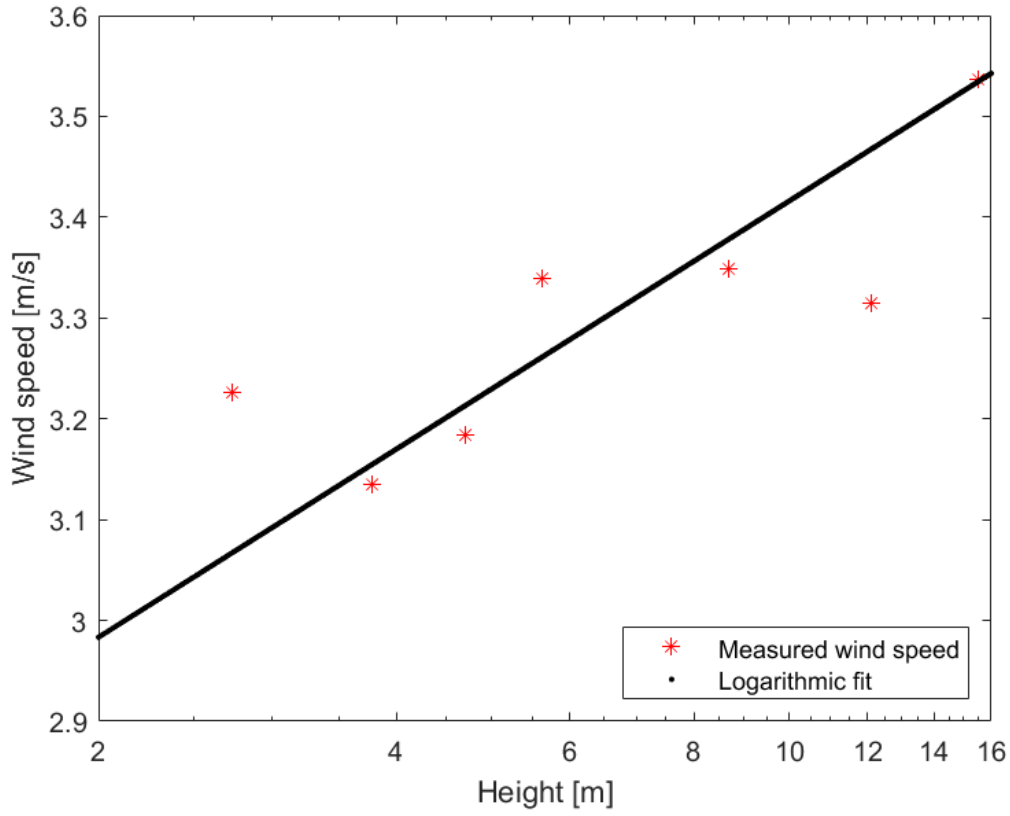


Figure 7. Sample logarithmic fitting of the wind profile at one timestamp, with $A = 0.6194$, $B = 2.7969$, and $r^2 = 0.7640$

This sample fitting shows the logarithmic curve used to calculate one set of coefficients A and B . It is notable that since the lowest height for a flux sensor was 2.98 m, the near surface portion of the wind profile is not well represented by datapoints in making the logarithmic fit. In future studies, this could be mitigated by collecting wind speed data within 1 meter of the surface. By rearranging (12), an equation for B can be produced as

$$B = -\frac{u_*}{\kappa} \psi - \frac{u_*}{\kappa} \ln(z_0) \quad (21)$$

to use to solve for a time series of z_0 values. A notable assumption that was applied was that the friction velocity was vertically uniform, as the B coefficient must be representative of the entire wind profile for one 30-minute sample. Thus, from one dataset, it is possible

to derive two independent estimates for sea surface roughness, z_0 . This allowed for the appropriate array sizes to be used in calculations.

As a further step in the analysis, the profile-derived roughness length and the eddy covariance derived friction velocity were used to test the Smith bulk parameterization [14] for surface roughness. This was done assuming that roughness was determined by a smooth and rough component (neglecting additional, independent contributions to roughness, such as sea foam) and that the coefficients in the Smith formula are constants. Mathematically, this test takes the form:

$$z_0 = \frac{C_1}{u_*} + C_2 u_*^2. \quad (22)$$

A constant stress mask was then applied in order to eliminate datapoints of divergent stress gradient. This part of the analysis is particularly unique because it evaluates the validity of the assumption that the MASL can be treated as a constant flux layer as an extension of MOST. This assumption is widely used, predominantly because many studies do not have access to multi-height sensors, such as *FLIP* [15]. A recent study found that, for momentum flux calculations using *FLIP*, only 30%-40% of measurements were found to actually be at a constant stress gradient. Using a MATLAB script from Ortiz-Suslow et al. [15], a filter was placed on the *FLIP* dataset to eliminate measurements that were not at a constant stress gradient in a process referred, in this thesis, as masking.

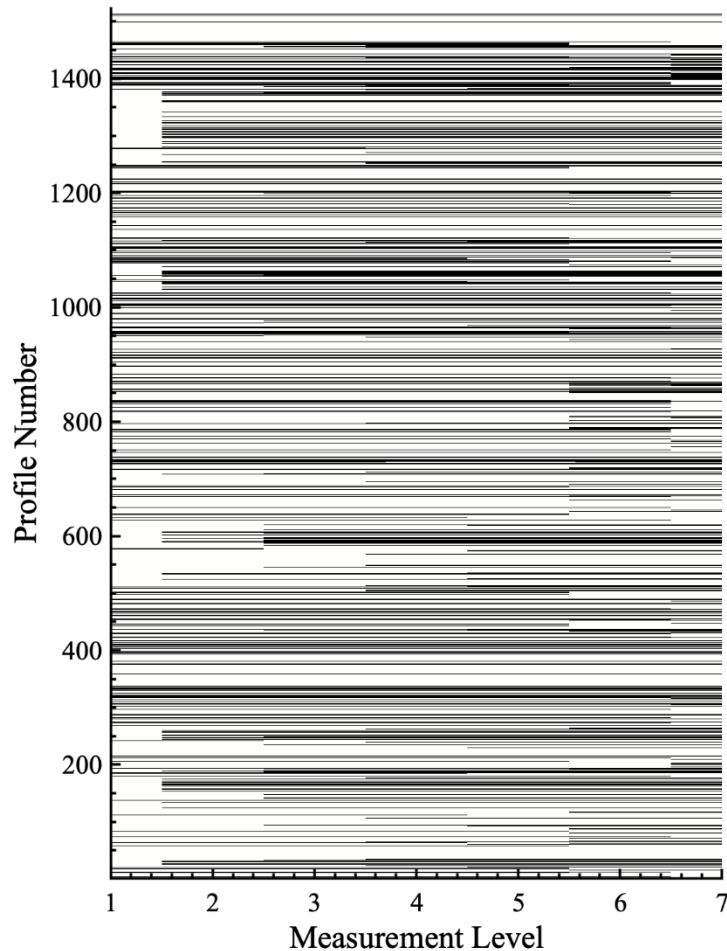


Figure 8. Stress gradient analysis for identifying time stamps of divergent stress gradient

Figure 8 portrays the amount and distribution of timestamps of a non-divergent, or constant, stress gradient (indicated in black). The measurement levels on the x -axis refers to the seven sensors at different heights aboard the *FLIP*, and the profile number refers to the averaged measurements from a 30-minute time frame. Note, the algorithm used to test for non-divergent stress may only identify a portion of the observed profile. The difference in scatter between the original data and masked data was observed for the parameters of friction velocity, coefficient of drag, neutral 10-meter coefficient of drag, and z_0 . Results

from the use of this mask poses implications for studies that use a single height sensor for flux measurements, therefore using the constant flux layer assumption.

E. FLUX FOOTPRINT ANALYSIS

The purpose of performing a flux footprint analysis is to leverage the understanding of z_0 from the *FLIP* dataset to provide the foundation for measuring flux contributions upstream of a sensor for a potential passive wake detection application. This analysis is done using a MATLAB script adapted from Hsieh et al. 2000 [28]. The function takes inputs of friction velocity, sensible heat, mean air temperature, sensor height, and local z_0 value. These values, particularly friction velocity and temperature values, pertain to turbulence characteristics, which dictate the extent of the footprint. The algorithm works by calculating the intensity of a turbulent eddy based upon local measurements, then estimating the distance upstream of the sensor that the eddy developed. Additionally, the algorithm uses these parameters to calculate stability using z/L , with L being the Monin-Obukhov length (10). To initialize using the Hsieh algorithm for flux footprint analysis, several data quality and compatibility steps were taken. Specifically, the algorithm outputs the cumulative source contribution upstream of the sensor and the distance upstream of the sensor of maximum flux contribution. The cumulative source contribution can be manipulated to calculate the distance at which a given percentage of the contribution is achieved. For instance, if it is desirable to know the location at which 90% of the total flux contribution occurs, the distance is found simply by finding the point on the cumulative source contribution curve where 90% contribution intersects at some distance.

To initialize using the Hsieh algorithm for flux footprint analysis, several data quality and compatibility steps were taken. For example, this included removing null values and restructuring the temperature profiles. The temperature adjustments are necessary because the *FLIP* did not have temperature sensors at the same height as the flux sensors. Therefore, in order to input a corresponding pair of temperature and flux measurements, an assumption was applied to correspond the temperature data closest in height to each flux sensor. For context, the greatest height difference between a flux sensor and the temperature sensor was ~ 0.1 m. There are NaN values that periodically appear in

the *FLIP* dataset. For NaN value removal, the script does not accept NaN values. Therefore, for any timestamp where one of the inputs contained a NaN value, the data for the entire timestamp was not included in the footprint analysis. This eliminated 90 timestamps from the dataset.

After the data reformatting, a statistical analysis of the footprints was performed to better understand the flux contributions in the *FLIP* dataset. Contributions at different wind conditions was observed, and probability density functions of the distance of various percent contributions were developed. Lastly, trends in distance of peak contribution was observed in regards to wind speed and sensor height.

Notably, a minor modification was made to the script. The variable labeled “Mu” was changed from the original [100, 500, 2000] to remove any restrictions on the maximum flux footprint. The variable “Mu” was used to determine the minimum and maximum distance values used in the bin, based upon the stability condition. Depending on the value of z/L , one of the three values of “Mu” would be used. These stability conditions were as follows:

$$\text{Mu} = \begin{cases} 100 & \text{for } z/L < -0.04 \\ 500 & \text{for } |z/L| < 0.04 \\ 2000 & \text{for } z/L > 0.04. \end{cases} \quad (23)$$

This restriction that resulted in smaller bin ranges was not practical for the *FLIP* footprint analysis as parameters of interest, such as distance at which 90% cumulative contribution occurs, would not be present within a small bin range. This might be suitable for terrestrial measurements where footprints might be much shorter due to larger surface roughness in absolute terms. Over the ocean, the distance for this parameter could be up to 10 km [17]. As such, these bin size bounds were expanded such that this distance was captured. The final parameters of note that were included in histogram production were distance of 90% cumulative contribution and distance of peak contribution, which is the same as the parameters of interest in the footprint analysis done by Hsieh [28].

F. CASE STUDY OF INTERNAL WAVE FRONT DETECTION

The purpose of this case study is to provide a theoretical foundation for detecting roughness contributions originating from under the sea surface for the potential for a passive detection method of undersea vessels using instruments typically used for meteorological applications. From this brief case study, a methodology to construct a feasibility study for this complex problem of passive wake detection was developed, and a graphic on how the method works was produced. The actual performance of this feasibility study, however, is beyond the scope of this thesis.

Based upon footprint analysis of the *FLIP* dataset, it is possible to locate the distance upstream of the sensor of the greatest flux contribution. This premise provides the foundation for detecting perturbations in the sea surface via meteorological instruments. The way for this method to prove effective is if an undersea perturbation would be detected above the natural noise of other sea surface roughness parameters, and to be able to locate the source of this contribution as a time series of locations to provide a tracking fix. This would be possible to test because, during the 2017 CASPER-West campaign, the *FLIP* captured a strong undersea wave event in its dataset.

The second part of this case study would be designing a practical understanding of this wake detection method under the premise that the wakes could be detected by a downstream sensor. The crux of the problem is taking very limited inputs (i.e., a time series of wind speed and wave height) from a meteorological sensor, and interpreting these results in a practical way to map underwater perturbations based upon their wake.

IV. RESULTS

A. SURFACE ROUGHNESS, MOMENTUM FLUX, AND DRAG OBSERVED FROM FLIP

The primary objective of this thesis is to observe the natural variance in surface roughness as measured by *FLIP*. Areas of interest within this objective are observing trends in various bulk parameters such as friction velocity and coefficient of drag to understand the *FLIP* dataset more completely. Additionally, comparing the performance of the eddy covariance method and the profile method in calculating z_0 . A key part of this analysis will be accounting for conditions of divergent stress gradients where the underlying principles for MOST, eddy covariance, etc., no longer apply. This builds on previous studies using this dataset, but has not been applied to the study of momentum flux and surface roughness. The results can then be compared to existing bulk parameterization models.

Using (5) and (8), a u_* value for each timestamp and flux height was calculated in Figure 9.

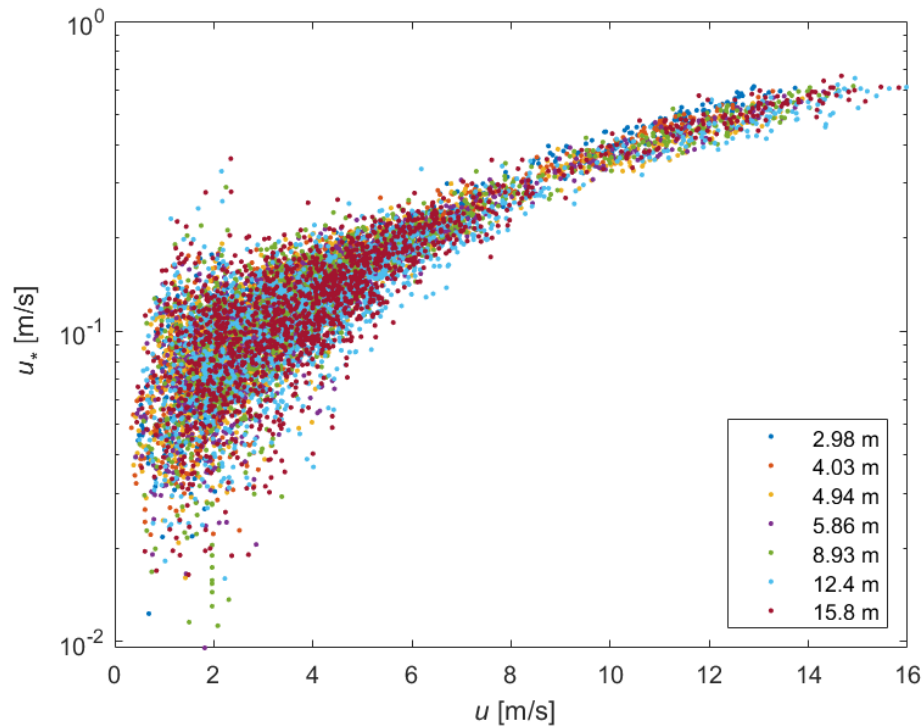


Figure 9. Observed values of friction velocity over wind speed at each sensor height above the mean water level

As expected, the locally observed friction velocity at each measurement level increases monotonically with wind speed. On a log-log scaled plot, the distribution is quasi-linear beyond 3–4 m/s, below which u_* tends to decrease rapidly with wind speed. In general, variability in u_* seems inversely proportional to wind speed. For instance, the scatter in these data, regardless of sensor location, increases significantly as u goes to zero. By inspection, there is no clear dependence of u_* on height above the surface. Additionally, the datapoints are sparser in the higher wind speed regime of the dataset because measurements above 8 m/s came from one cold front event (see Figure 6). The eddy covariance drag estimates (13) were also analyzed in terms of local variables (e.g., not accounting for logarithmic profile or stability). The rationale behind Figs. 9–10 is to show the local variables measured via eddy covariance from *FLIP*, which are the direct estimates of air-sea momentum flux and drag coefficient. The remainder of the analysis will focus on more empirical values (C_{DN} , z_0 , etc.) with various forms and known deficiencies.

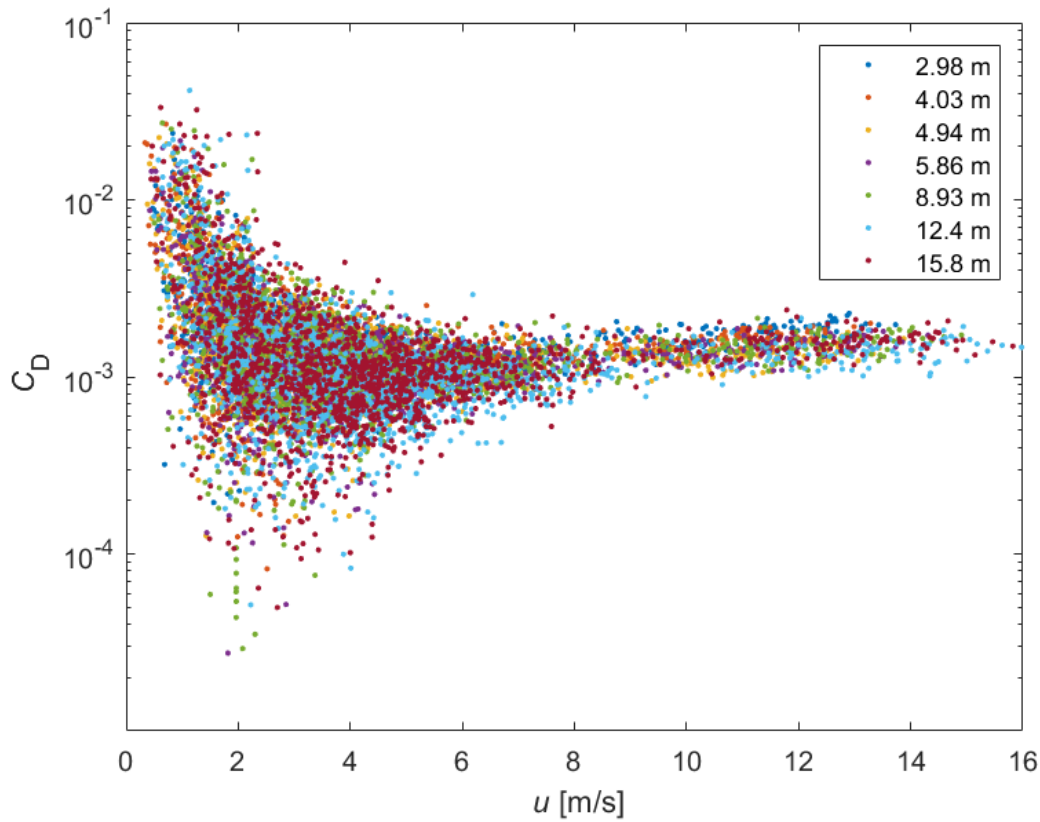


Figure 10. Local values of the drag coefficient (dimensionless) as a function of wind speed at each sensor height

Figure 10 shows a wide scatter in the low wind speed regime, which is expected and commonly found in other oceanic datasets. As the wind speed increases, there is a relatively less scatter compared to low winds, with a somewhat linear trend of increasing drag with an increase in wind speed. Quantifying the amount of scatter, the distribution of C_D below 6 m/s had a mean of $1.268\text{E-}3 \pm 1.449\text{E-}3$ (1x the standard deviation), and above 6 m/s had a mean of $1.796\text{E-}4 \pm 4.785\text{E-}4$. Additionally, in higher wind cases, the drag distribution begins to separate by sensor height, indicating a vertical dependence in the observed momentum flux. This is driven in part by natural variability and the logarithmic profile (12), but may be due to slight systematic differences across sensors.

Conventionally, the observed drag coefficient derived from eddy covariance methods is referenced to a standard 10-m height and corrected to neutral stability using a

similarity relationship, such as MOST. In this sense, drag measurements across datasets from different instruments, using the same techniques can be compared directly. These 10-meter, neutral equivalent drag coefficients are shown in Figure 11, plotted as a function of the corresponding 10-m, neutral equivalent wind speed.

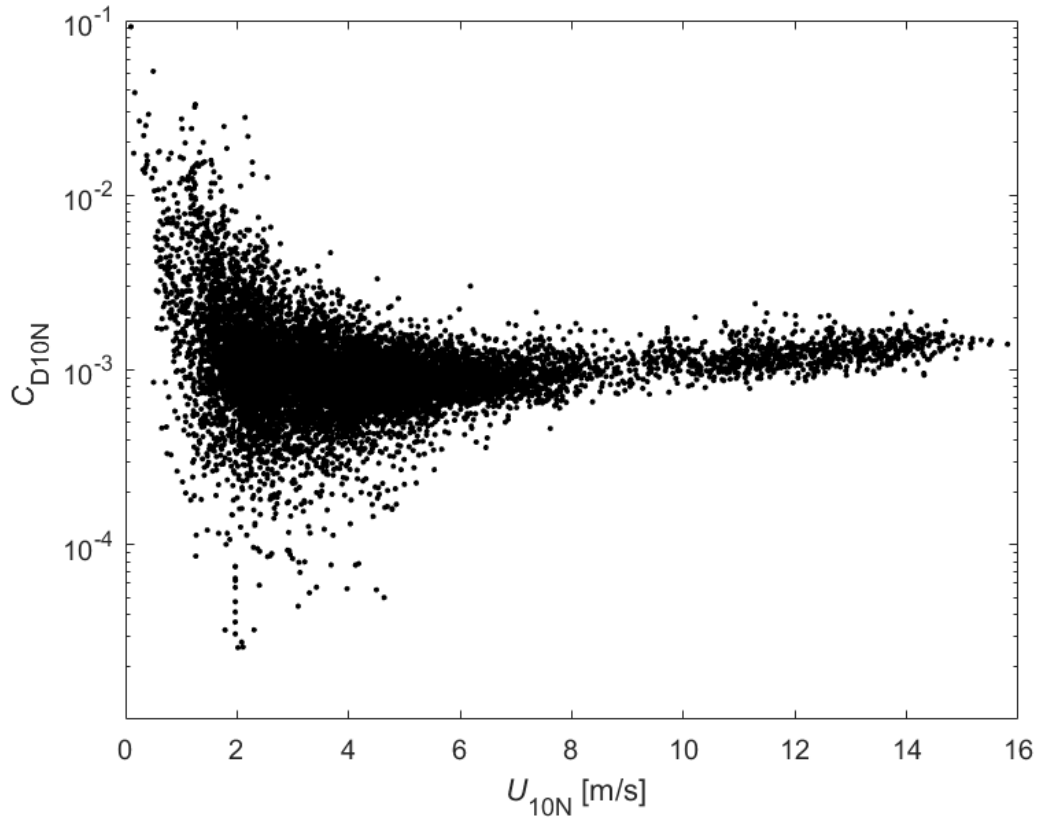


Figure 11. The neutral 10-meter coefficient of drag over the neutral 10-meter wind speed for all measurements from *FLIP*

While the stability adjustment accounts for some of the scatter, there is still significant variance for a given wind speed, especially below 6 m/s. The mean of C_{D10N} below 6 m/s was $1.046\text{E-}3 \pm 7.429\text{E-}4$. Above 6 m/s, the mean was $1.102\text{E-}3 \pm 3.889\text{E-}4$.

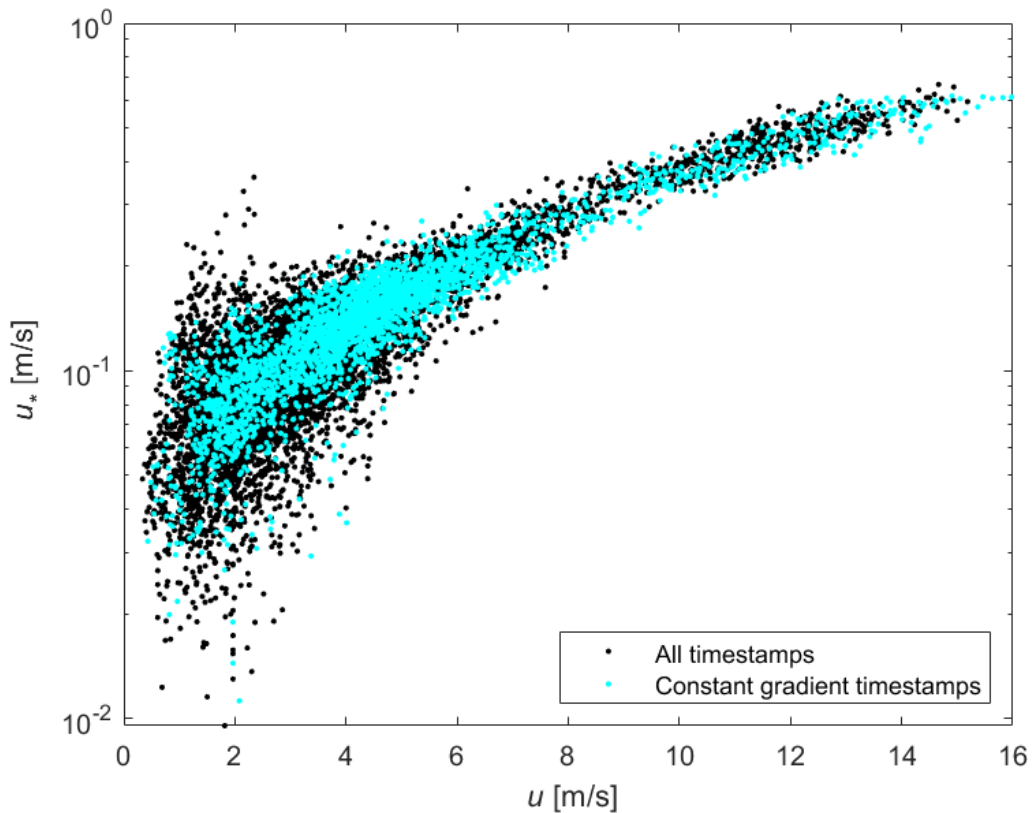


Figure 12. Friction velocity data with the constant stress gradient mask applied

The constant stress gradient mask was applied to the friction velocity values in Figure 9 to produce Figure 12. This mask directly accounts for cases in the data where the constant flux layer assumption would be valid. From inspection, the variability in friction velocity is less for the masked versus unmasked data samples, especially for the lower wind speeds observed. Above 6–8 m/s, accounting for the presence of a constant stress gradient does not seem to affect the variance or mean trend in friction velocity. For winds below 6 m/s, the mean of the unmasked observations was $0.1038 \pm 5.603\text{E-}2$, for the masked observations it was $0.1261 \pm 4.276\text{E-}2$. For above 6 m/s, the mean of the unmasked observations was $4.634\text{E-}2 \pm 0.1282$ for the masked observations it was 0.3697 ± 0.1310 . In lower wind speeds, the variance is reduced by masking. However, in higher winds, the masking increases the variance.

For analysis of the neutral 10-meter coefficient of drag, the same mask can be applied, as seen in Figure 13.

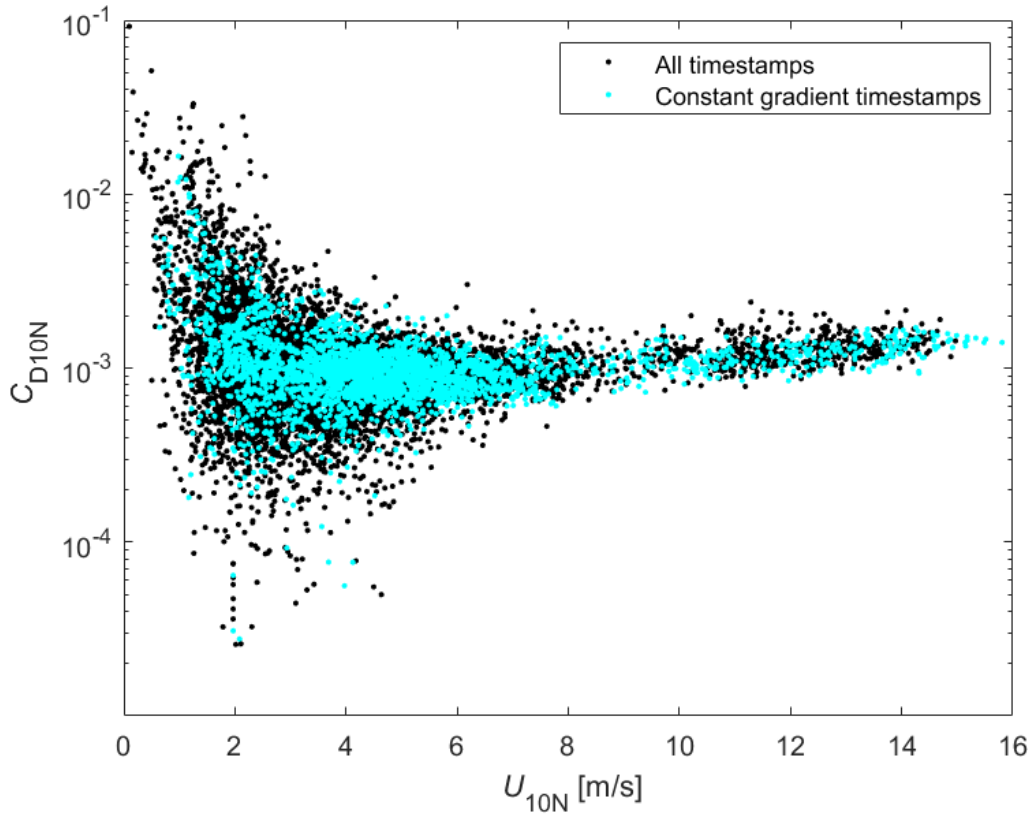


Figure 13. Neutral 10-meter coefficient of drag values with a constant stress gradient mask applied

After applying the mask for C_{D10N} , the difference in drag for the unmasked versus masked observations were compared. For winds below 6 m/s, the trend for C_{D10N} increasing at lower wind speeds was preserved for data with the mask applied. Interestingly, there is a significant amount of data, below 2 m/s, where the stress gradient was apparently constant. Typically, it is believed that in very low winds over ocean waves, the wavy motion distorts the mean velocity profile. Fully understanding the relationship between wind, stress, and surface waves should be the topic of future study, especially in this low wind condition. At higher wind speeds, a linear increase in C_{D10N} is observed as wind speed increases. The

standard deviations of the masked and unmasked data were compared in Figure 13. For winds below 6 m/s, the mean of the unmasked observations was $1.046\text{E-}3 \pm 7.007\text{E-}4$, for the masked observations it was $1.002\text{E-}3 \pm 6.334\text{E-}4$. For above 6 m/s, the mean of the unmasked observations was $1.102\text{E-}3 \pm 2.208\text{E-}4$, for the masked observations it was $1.129\text{E-}3 \pm 2.261\text{E-}4$. The masking resulted in reduced variance in the lower wind speed regime, and the variance at higher wind speeds was unaffected.

The constant stress gradient mask has removed profiles with potential systematic bias in the vertical distribution of C_{D10N} . Thus, the masked 30-minute profiles can be aggregated into a single mean with random variance. The dependence of these aggregated samples on wind speed is shown in Figure 14.

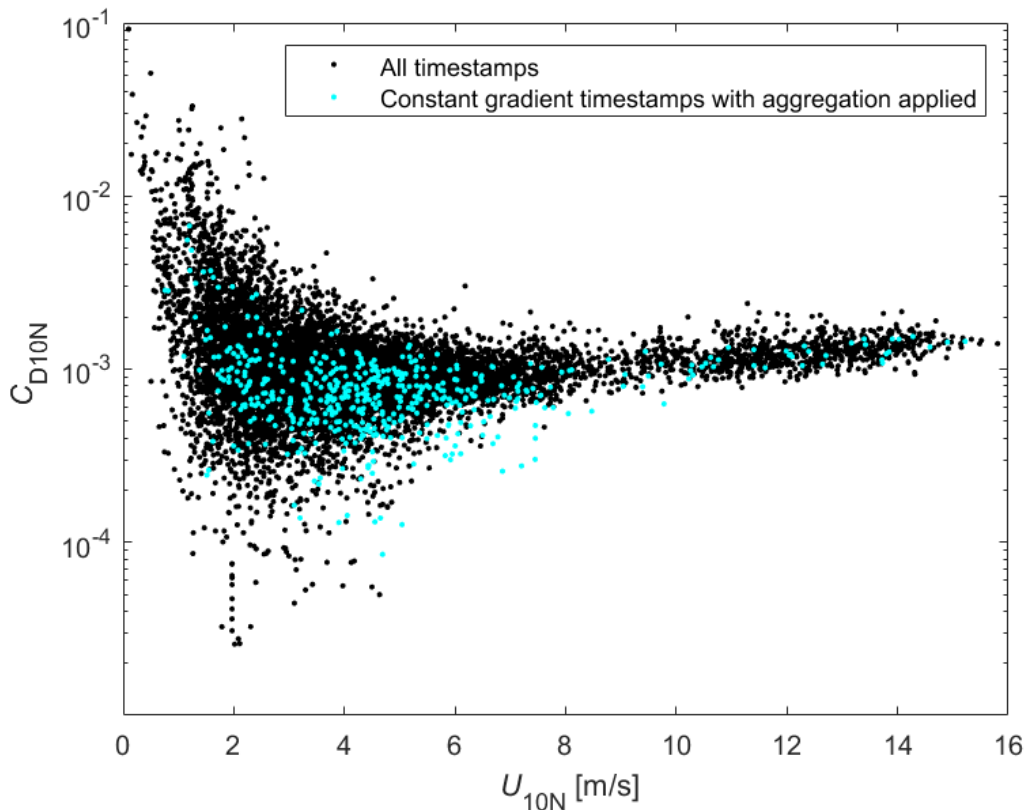


Figure 14. Neutral 10-meter coefficient of drag values with a constant stress gradient mask and aggregation applied

After the mask was applied to the data, the trend of C_{D10N} increasing at lower wind speeds, as well as the trend of C_{D10N} linearly increasing at higher wind speeds, was preserved. The reduction in variance observed between the two distributions directly comes from the fewer samples in the aggregated data. It was noted that the mean drag tended to decrease, particularly between 3–8 m/s. For wind speeds below 6 m/s, the mean of the masked data was $8.479\text{E-}4 \pm 6.504\text{E-}4$. For wind speeds above 6 m/s, the mean of the masked data was $9.451\text{E-}4 \pm 3.161\text{E-}4$. The means in both wind regimes decreased as a result of the mask. By inspection, the masking appeared to preferentially eliminate data in the higher end of the distribution below 6 m/s.

In order to fully encapsulate this thesis's goal of leveraging a multifaceted understanding of the air-sea interface for surface wake detection, the focus now shifts from drag and momentum flux, to the analysis of the surface roughness length, z_0 .

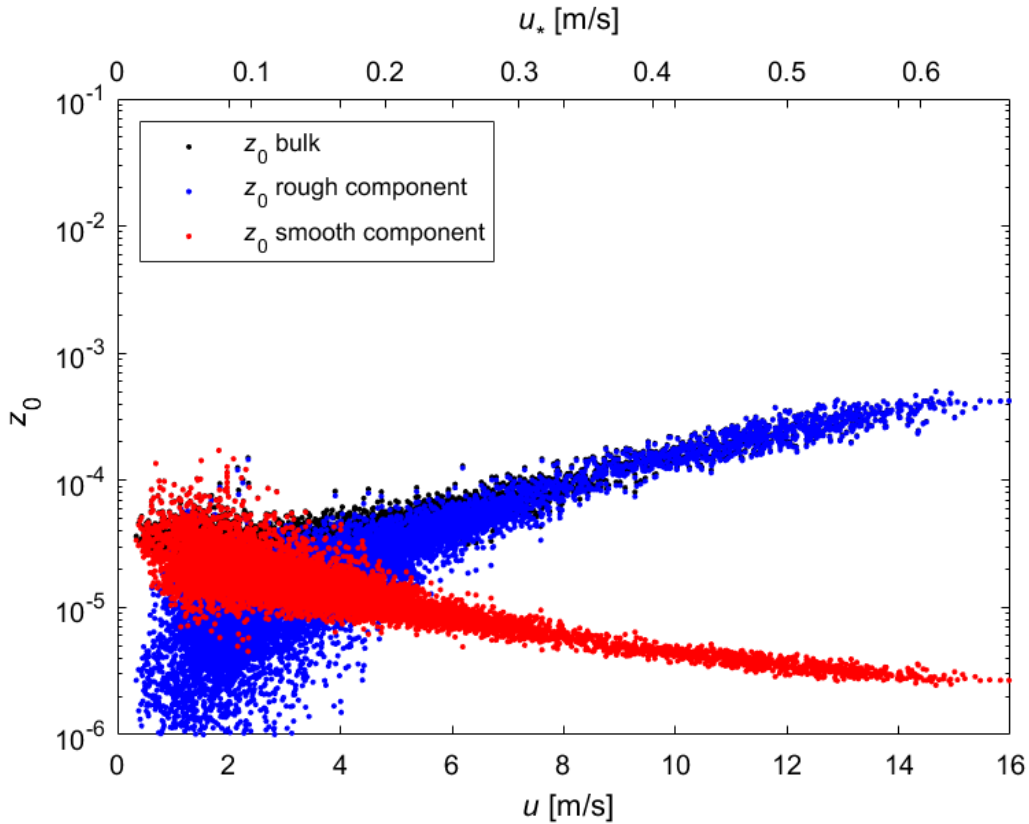


Figure 15. Application of the Smith bulk parameterization using *FLIP* data (all observations)

The Smith bulk parameterization [14] (14) was applied to the *FLIP* dataset, in particular using the eddy covariance friction velocity (Figure 9). In a sense, the variance in Figure 15 is the result of inputting observational data into the analytical relationships in Figure 2 and the scatter includes sample variance and uncertainty, as well as natural processes not accounted for in the parameterization.

The logarithmic wind profile (12) can be inverted to estimate z_0 directly from the eddy covariance u_* , observed wind speed, and MOST empirical functions. The results of this are shown in Figure 16. There is scatter in the eddy covariance derived roughness, especially at lower wind speeds, where the range spanned from approximately 1 to 10^{-15} m (figure axes were truncated to allow for comparison with other figures). With the generally accepted value range for z_0 being within 10^{-6} and 10^{-2} , the results in the low

wind speed regime are not within reason. In part, this large range of values reflects how z_0 is calculated in the eddy covariance method, and how the equation is inverted to solve for z_0 . Physically, this can be interpreted as the ocean surface becoming so smooth that the roughness is not well defined. It also highlights a limitation in the eddy covariance method for quantifying z_0 because the relationship is highly sensitive to several assumptions and empirical relationships.

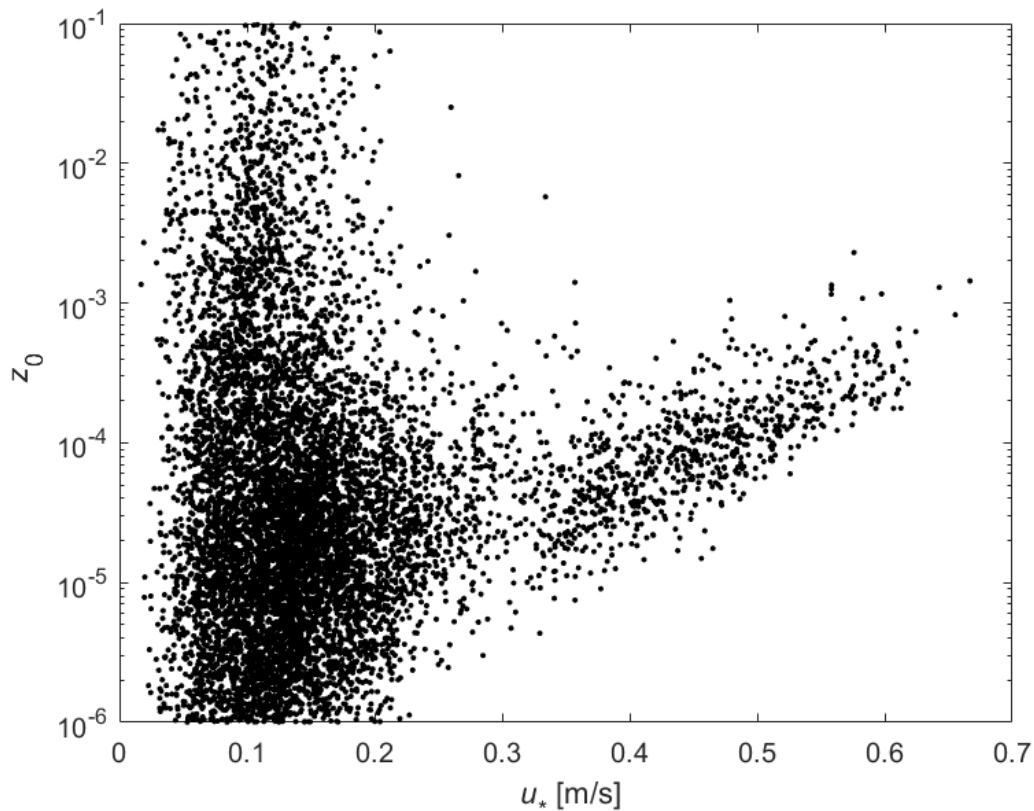


Figure 16. Aerodynamic roughness length results using the eddy covariance method

Using the profile method outlined in Section III, another estimate of z_0 values was derived from the *FLIP* data. Additionally, it is important to consider that, unlike previous results, these values are quantified using the entire wind profile, rather than generating

local estimates at each measurement height. Thus, the profile method provides one estimate of z_0 for each 30-minute analysis window (1433 individual profiles).

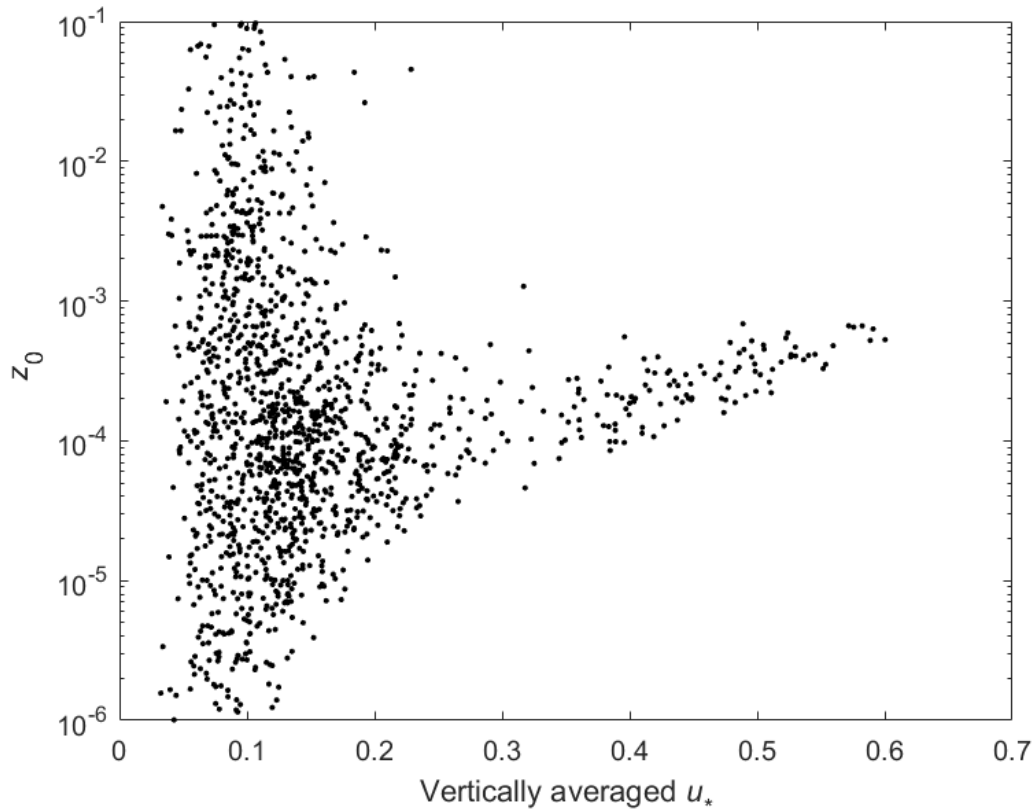


Figure 17. Aerodynamic roughness length results using the profile method

The profile-based estimates of roughness length showed considerably less scatter and range than the eddy covariance derived estimates. In terms of the regression, Figure 18 summarizes the performance using Pearson's correlation coefficient for the success of fit. In terms of the dependence based upon friction velocity, the profile method z_0 shows consistent behavior with the Smith bulk parameterization. In particular, as friction velocity approaches zero, z_0 tends to increase sharply, which is expected by theory of the smooth flow regime. It is also noted that there was a trend in the data showing *decreasing* z_0 with *decreasing* wind forcing, which counters the expected behavior. With increasing wind speed, the expected quasi-linear (on a semi-log axis) trend was recovered. Similar to the

results of friction velocity and drag coefficient, there was a clear trend in variance with wind speed observed.

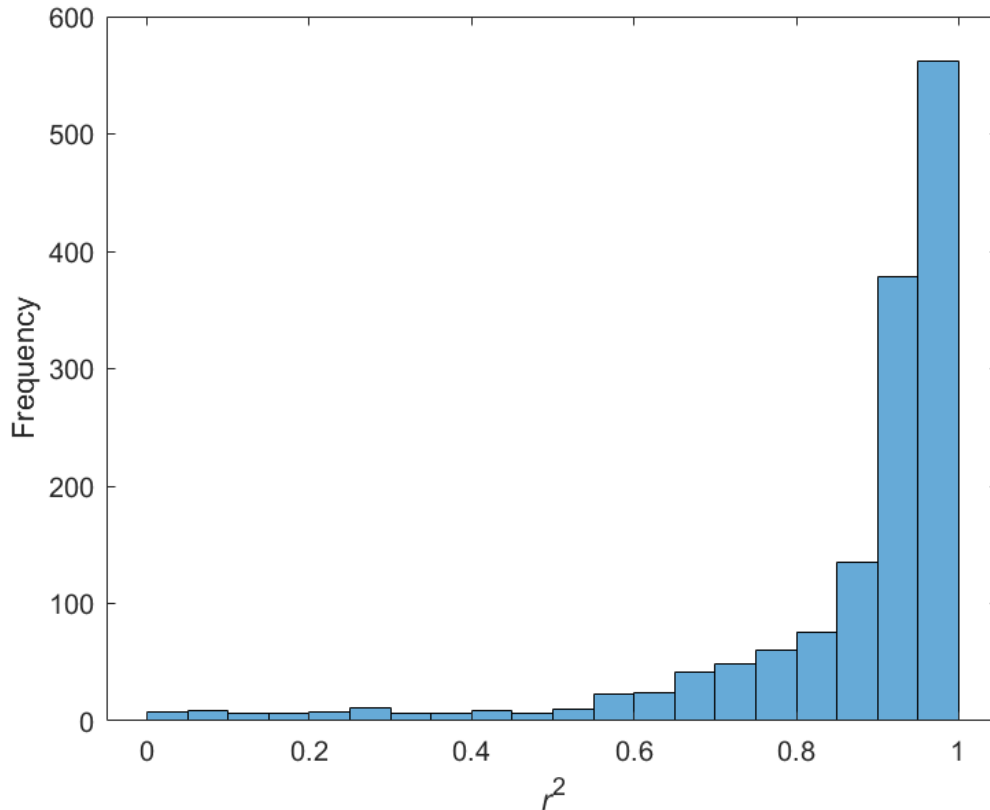


Figure 18. Histogram of r^2 values for profile method logarithmic fits

Some regressions did not accurately describe the wind gradient, as seen in Figure 18 with some cases of correlation coefficient well below 0.6. This suggests that there were many samples that did not follow the expected logarithmic wind profile. However, the vast majority of profiles show very strong correlation with a median r^2 of 0.93, and the mean of 0.87.

Figure 19 compares profile method results to the bulk parameterization methods introduced with Figure 2.

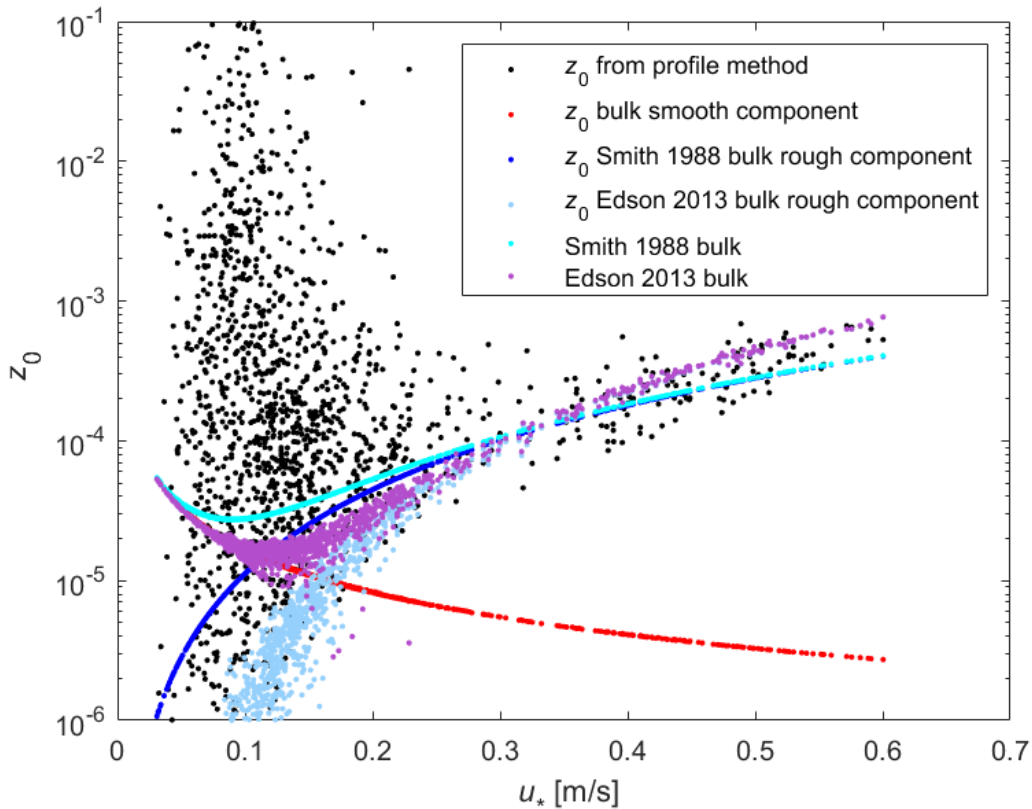


Figure 19. Various bulk parameterization methods and their components plotted over profile method aerodynamic roughness length values

Using the z_0 values obtained from the profile method, as well as bulk parameterization results obtained from the local friction velocity and wind measurements, the performance of the profile method can be compared to the Smith and Edson models. The Edson bulk rough component produces a scatter of z_0 values because it is a function of 10-meter wind speed. Neither parameterization captures the sharp increase in z_0 at low friction velocities that was observed using the profile method. It was also noted that z_0 increases with decreasing wind forcing earlier than predicted by the smooth regime's $z_0 \propto \nu u_*^{-1}$ behavior. By inspection, there is a local minimum in the observed value between 0.1-0.2 m/s, whereas the bulk methods tend to have a local minimum closer to 0.1.

Much like the analysis of u_* and the coefficient of drag, the constant stress gradient mask can be applied to z_0 values calculated with the profile method. In this sense, we can

isolate cases where the wind profile is logarithmic (as expected by the Law of the Wall) and cases where the stress gradient is non-divergent (as expected by MOST).

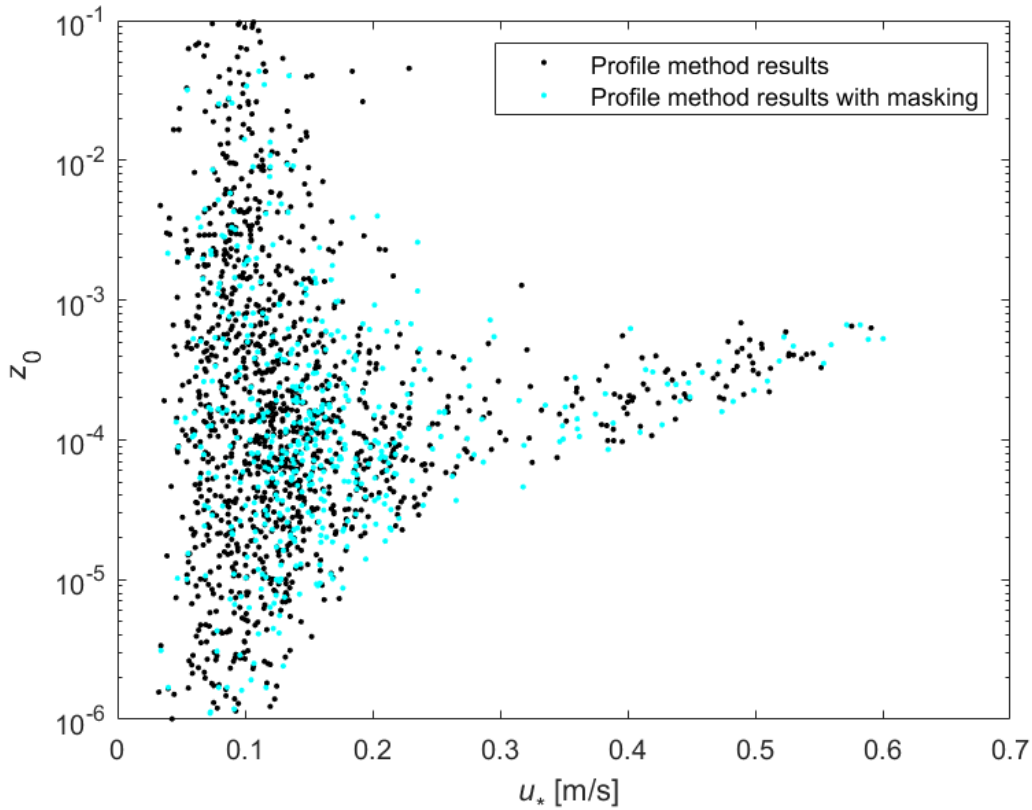


Figure 20. Profile method z_0 results with constant stress gradient mask applied

When observing *FLIP* surface roughness metrics, the question that remains is what the source of extremely high and low z_0 values at low wind speeds is. The constant stress gradient mask reduced the amount of data from 1433 datapoints to 510 datapoints, which is consistent with the trend of 30–40% of samples coming from constant stress gradient conditions [15]. After applying the mask in Figure 20, it is evident that this has no meaningful impact on the profile-derived roughness length, from a statistical perspective. Because the mask had no impact on the structure of the distribution, it can be presumed that other unaccounted for processes might be impacting the observed variability, e.g., surface waves.

The roughness derived from the eddy covariance method and the profile method were directly compared, and the results are given in Figure 21. With the profile method being less available for calculating z_0 over the ocean, it is important to compare the results to the widely used eddy covariance method. The profile method roughness was compared to the eddy covariance method roughness at a height of 8.93 m above the surface, as well as the vertically averaged roughness. Further, results were compared with and without the stress gradient mask applied.

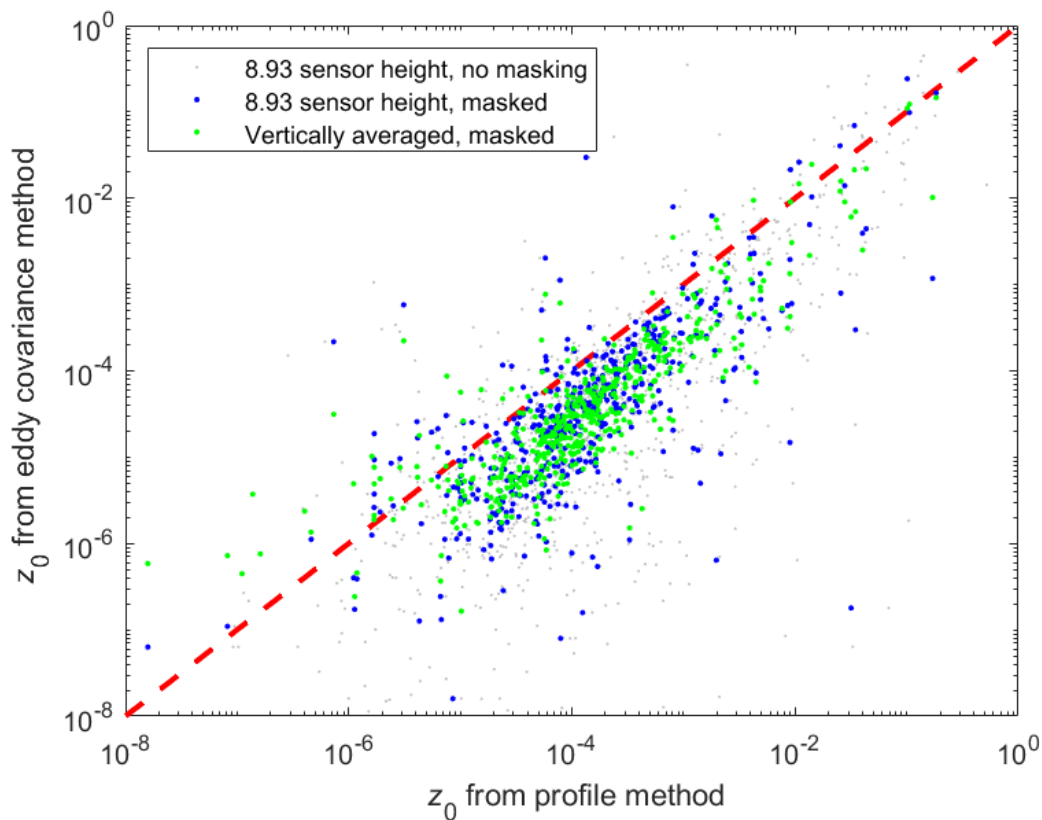


Figure 21. Comparison of eddy covariance method to the profile method with varying sensor height treatment and constant stress gradient mask application. Red shows the 1:1 line.

The two methods are strongly correlated with each other, but there is a clear mean offset where the profile method roughness is roughly an order of magnitude greater than the eddy covariance method roughness, in a mean sense for all roughness lengths. It appears that

there is a bias between the two methods such that the distributions either converge or cross at high roughness lengths, but it difficult to determine without a wider range in the data or a more in-depth statistical analysis. The results from the single measurement level and the vertically average profile show little difference. To quantify the differences, a log-log regression was performed on each distribution in Figure 21. For the 8.93 m sensor with no masking (gray markers), the regression had a slope of 1.03 ($r^2 = 0.73$). For the 8.93 sensor with masking (blue markers), the bias between the two methods increased with a regression slope of 1.14 ($r^2 = 0.98$). Lastly, for the vertically averaged and masked data (green markers), the regression had a slope of 0.90 ($r^2 = 0.95$). This decrease in slope below 1, may be driven by a cluster of samples where eddy covariance roughness was significantly higher than the profile method (10^{-8} to 10^{-5} , i.e., the smallest roughness lengths). From this analysis, it could indicate that using vertically averaged and masked data could provide more agreement between the two methods, compared to masked local values. It was noted, the unmasked local values had the slope closest to unity, but with markedly poor regression performance, indicating that this result may simply be driven by the higher variance.

As a final analysis for z_0 estimation, a novel bulk parameterization of z_0 was developed by fitting the constant stress gradient masked z_0 to the form of Equation 18. Using a fit function in MATLAB resulted in unphysical results when solving for both C_1 and C_2 in Equation 24. However, the assumption that bulk parameterization of the smooth component of z_0 was the same as Smith and Edson (which is the assumption that Edson makes when presenting the COARE roughness scheme), such that we only needed to parameterize the rough component. Using this assumption, the difference of the profile method z_0 and the smooth component of z_0 was fitted to produce the C_2 coefficient. This method also produced poor results due to the points of high z_0 values in the lower wind speed regime influencing the fit such that it did not accurately parameterize the quasi-linear portion of the data ($u_* > \sim 0.3$). As such, the approach was slightly altered. This new approach involved defining a threshold value of u_* that marked the beginning of the quasi-linear subrange of samples. The results of this approach are portrayed in Figure 22.

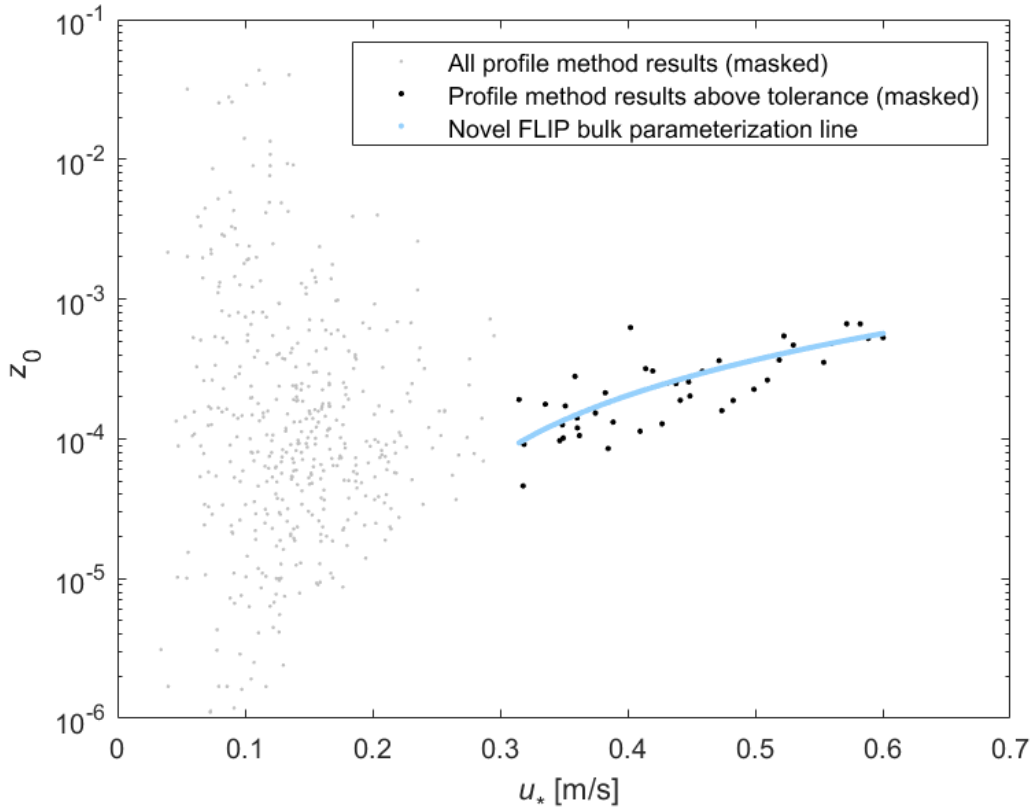


Figure 22. Fitting of the quasi-linear regime for the rough component of *FLIP* bulk parameterization

The resulting fit function for Figure 22 is

$$z_{0,\text{rough}} = 0.00177u_*^2 - 7.96 * 10^{-5}, \quad (24)$$

where the coefficients were solved by MATLAB's `fit` function. Notably, there are only 41 datapoints that were considered in this fit. This small number of datapoints considered is a result of three factors: (1) the original dataset only contained data in this regime from one cold front wind event (Figure 6), (2) the profile method requires a vertical averaging of data, which reduced the data by a factor of 7, and (3) the constant stress gradient mask reduces datasets by 60–70% [15]. Nevertheless, the remaining scatter produced a fit (22) with a confidence 95% bounds for the first coefficient being (0.001314, 0.002218) and the second being (-1.745e-4, 1.535e-5). Adding the common smooth component (shown in red

in Figure 23), yielded results that did not capture the scatter outside of the quasi-linear regime.

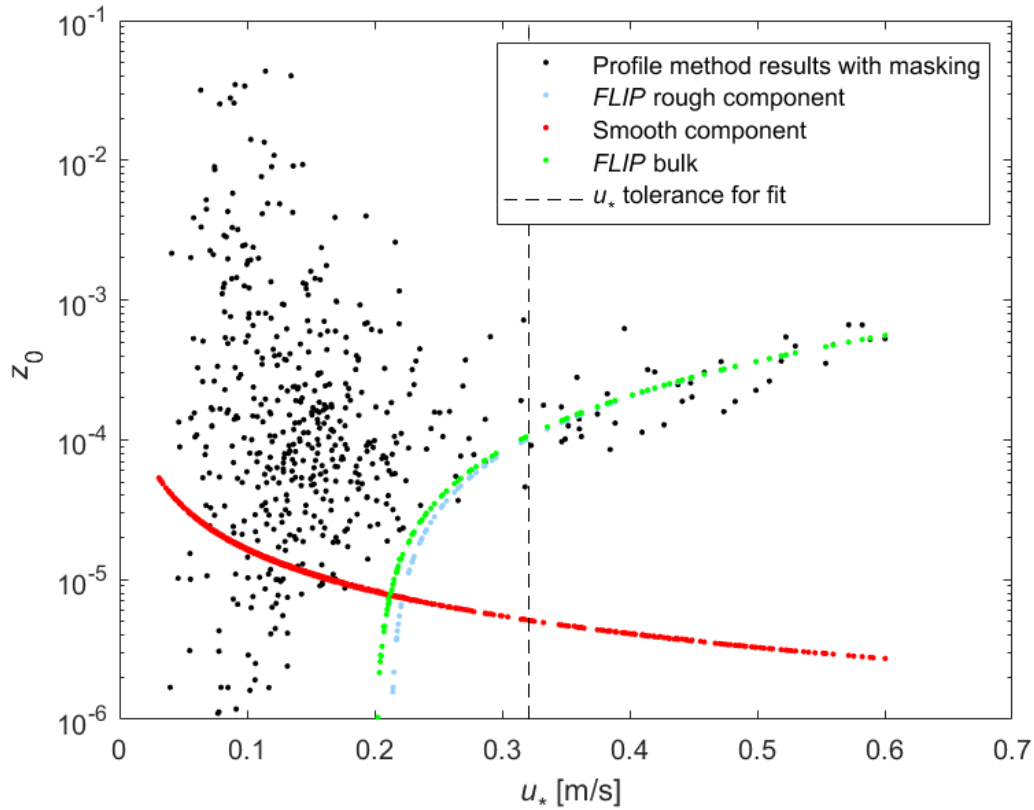


Figure 23. Unfavorable *FLIP* bulk parameterization using conventional smooth component to the fitted rough component, with tolerance for fit indicated (dashed line)

From Figure 23, it is evident that the initial *FLIP* bulk parameterization of the sum of the smooth component and the fitted roughness results in a poor representation of the data below the threshold. A further approach was made to make z_0 piece-wise about the threshold where the lower friction velocity regime would be dictated either or Smith or Edson's formula. Figure 24 compares both parameterizations to the *FLIP* rough component fit.

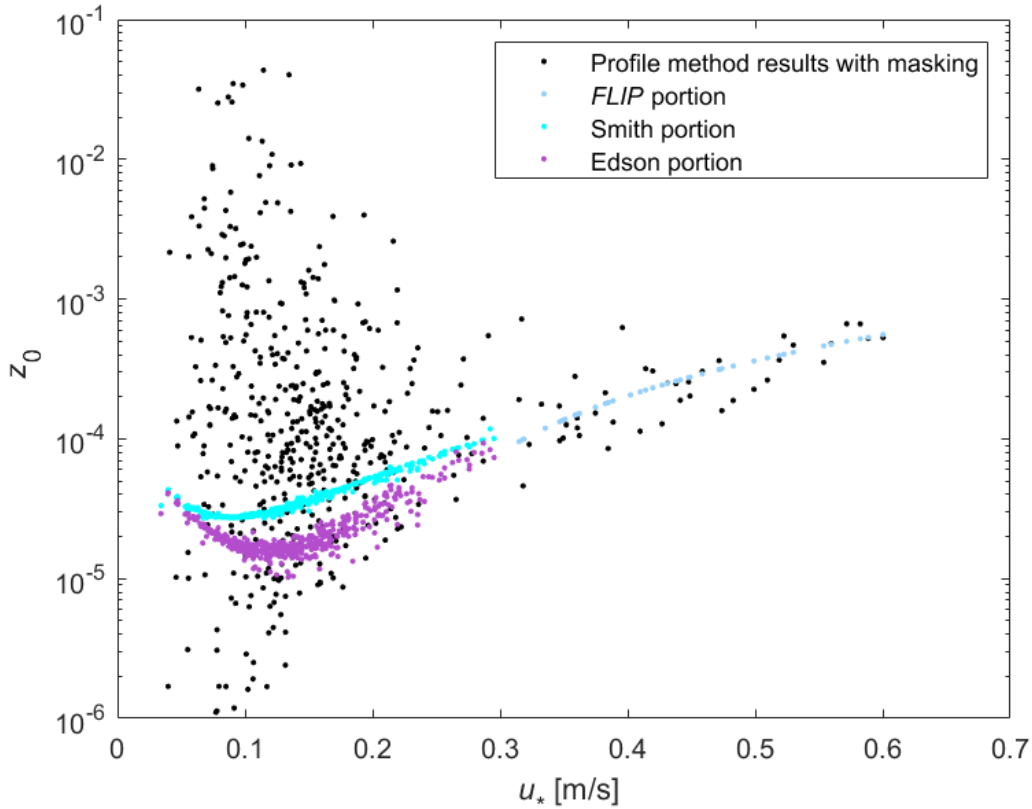


Figure 24. Comparison of bulk parameterizations in the non-linear regime to the *FLIP* rough component of roughness

Figure 24 shows the two potential options for the piecewise function: the Smith (cyan) and Edson (purple) bulk parameterizations. The Edson parameterization shows a much more favorable transition from the low friction velocity to quasi-linear regime as the Smith parameterization has a more abrupt change after the discontinuity. As a result, the *FLIP* piece-wise parameterization will be defined as:

$$z_0 = \begin{cases} 0.11 \frac{v}{u_*} + \frac{(0.0017U_{10} - 0.005)u_*}{g} & \text{for } u_* < 0.32 \\ 0.00177u_*^2 - 7.96 * 10^{-5} & \text{for } u_* \geq 0.32. \end{cases} \quad (25)$$

This bulk parameterization can be considered an initial attempt of fitting masked profile method data, but judging from the results of the profile method (introduced in Figure 17), there are most likely contributions to roughness, particularly seen in the range of 0.1 m/s <

$u_* < 0.2$ m/s, that are unaccounted for by the parameterization methods studied in this thesis. Nevertheless, by leveraging knowledge on the profile method and constant stress gradient, an expression was derived from the *FLIP* data that is both physically and statistically robust, given that it isolated samples where both the Law of the Wall and MOST were valid. This has implications for numerical and empirical models incorporating roughness parameterization.

B. OBSERVATIONS OF ATMOSPHERIC FOOTPRINTS

In the previous section the variability of momentum flux and sea surface roughness in the *FLIP* dataset was observed. In order to leverage this information on the natural variability of these parameters, footprint analysis can be performed to further glean information about the air-sea interface. Performing footprint analysis and observing the variability in these footprints can give insights into the field of roughness upwind of the sensor. It should be emphasized that footprint analysis is a statistical approach to approximating this field using a time series of flow data, e.g., wind velocity, wind stress, heat flux, etc. In order to understand how the outputs of a footprint analysis are interpreted, the momentum flux contributions from roughness were portrayed via cumulative source contribution functions and histograms. The cumulative source function represents the fraction of total flux contributions from roughness elements upstream of the sensor. In order to identify basic trends in flux contribution, an analysis of three wind speed cases was performed.

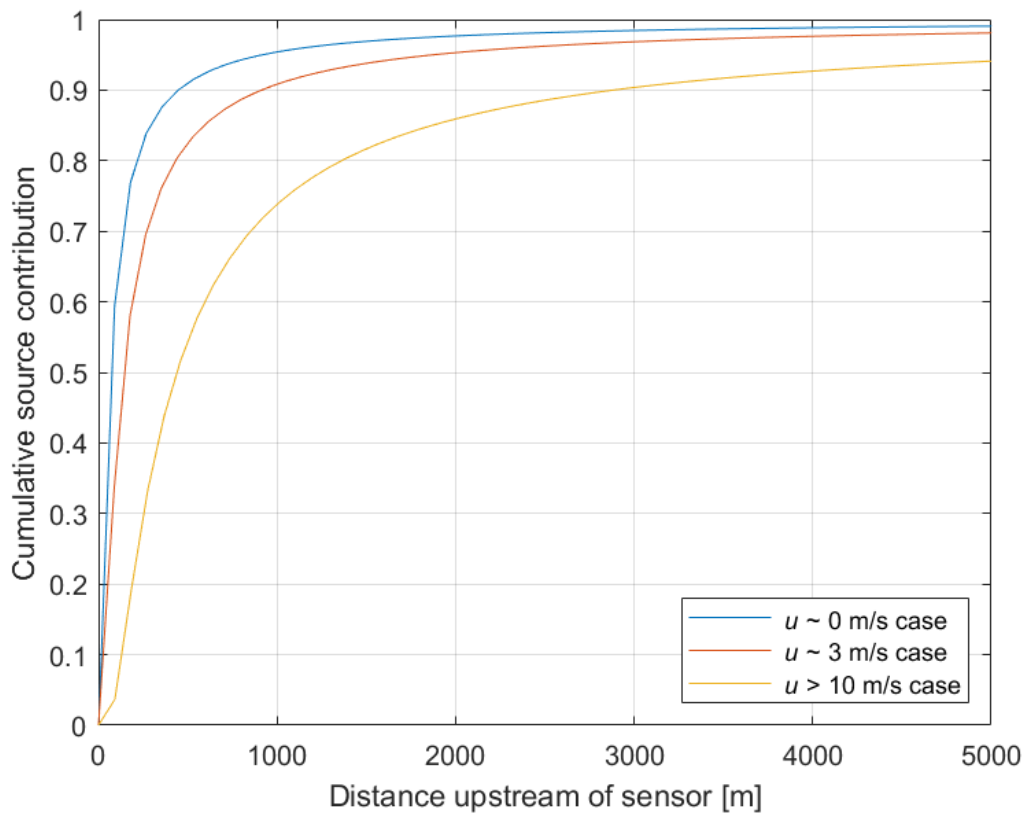


Figure 25. Cumulative source distribution of momentum flux from roughness as a function of distance upstream of the sensor for three different 30-minute samples of data at different mean wind speeds. All curves calculated from the $z = 8.93$ m measurement level.

In Figure 25, 3 individual samples (from the $z = 8.93$ m level) were selected from the *FLIP* dataset to portray the general trend for the cumulative source function under different wind regimes. As expected, footprints tended to be larger for higher wind speeds, as quantified by the intersection between the source function and the 90th percentile. For example, in the >10 m/s wind speed case, the distance upstream of the sensor at which 90% cumulative contribution occurs is $\sim 3,000$ m, whereas the ~ 0 m/s wind speed case results in a distance of ~ 500 m.

Histograms of distances for various contribution levels were then produced to summarize the footprint analysis from *FLIP*. The first parameter of interest to be analyzed

was the distance (x) to reach 90% of the observed flux at the sensor. Technically, every footprint extends out to $x \rightarrow \infty$.

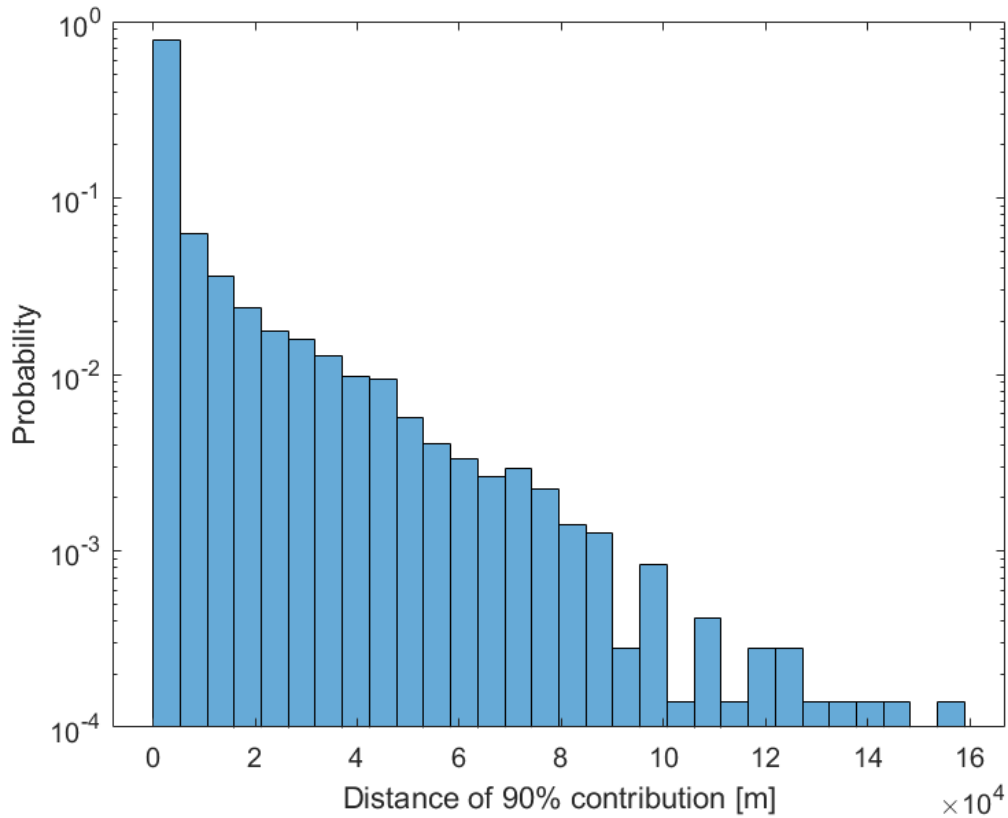


Figure 26. Histogram of the distance of 90% flux contribution

From Figure 26, 10.7% of the footprints exhibit 90% flux contributions within 500 m upstream of the sensor, 31.2% of the footprints within 500–1000 m, 23.7% within 1–2 km, and the remaining 34.4% of footprints exceeding 2 km. Note the log-log scale in Figure 26. The distance of peak contribution was also analyzed. Distance of peak contribution is defined as the peak distance from the measuring point to the maximum contributing source area, given in Figure 27.

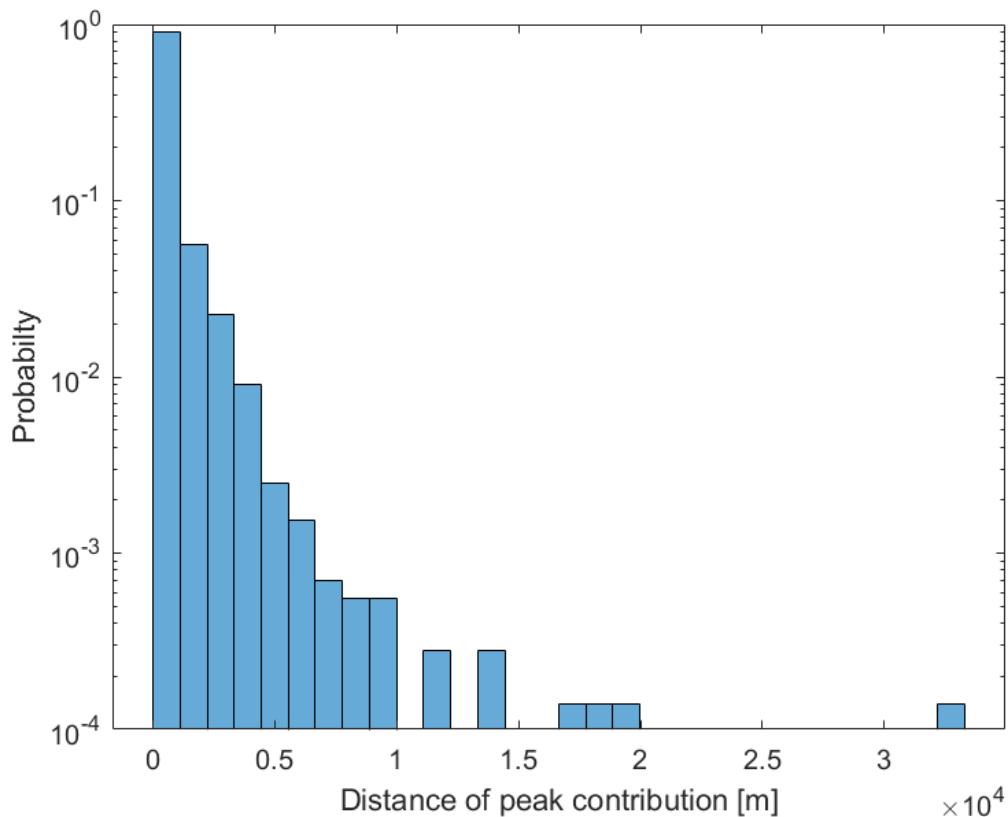


Figure 27. Histogram of the distance of peak contribution

From this analysis, we found that 83.4% of the footprints exhibit peak flux contributions within 500 m upstream of the sensor, 6.3% within 500 m-1000 m, 5.7% within 1–2 km, and the remaining 4.6% of footprints exceeding 2 km. Lastly, trends were investigated between distance of peak contribution and the parameters sensor height and wind speed.

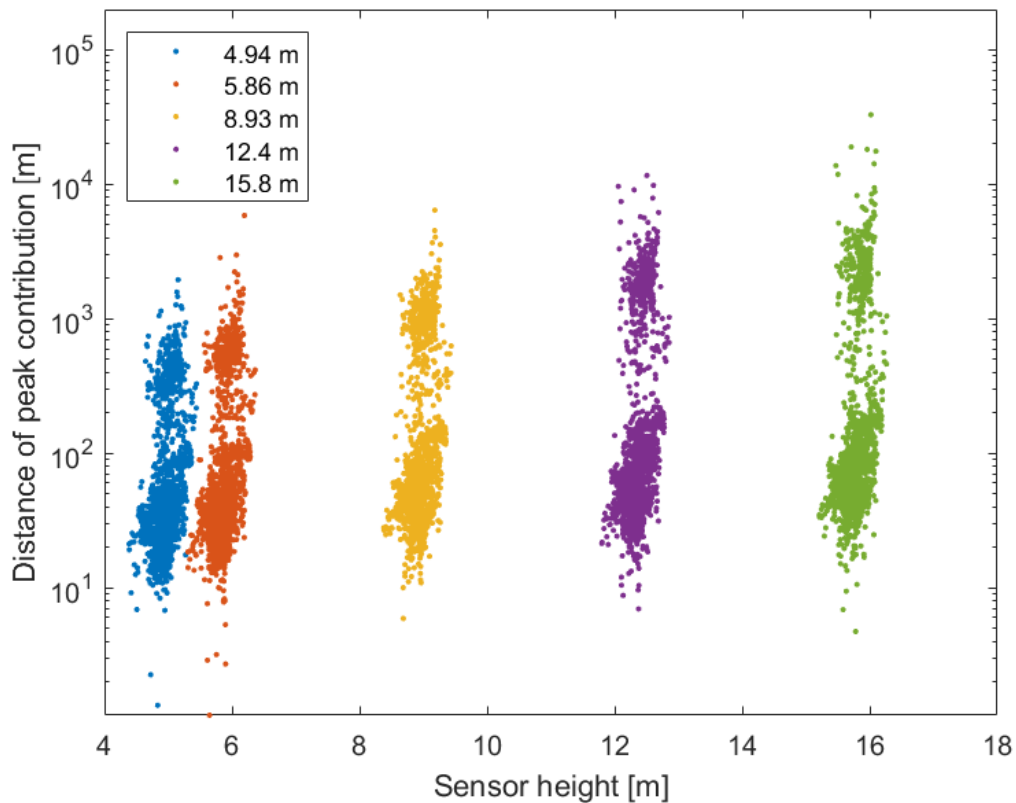


Figure 28. Distance of peak flux contribution plotted with the instantaneous sensor height

To investigate how footprint varies with height above the surface, the distance to peak flux was examined for the 5 measurement levels between 5–16 m above the surface. These distributions are given in Figure 28, note the variability in sensor height is caused by using the instantaneous altitude of each level, where variance is caused by the mean tilt and draft of *FLIP* over a 30-minute period. The first thing to note is that there appears to be a mean trend in the distance to peak flux with height above the surface. Further, it appears that this distance, for each level, is bimodal, where there is a cluster of data with peak distances between 10–100 m, and a cluster around 500–1500 m. This bimodal distribution was observed for each measurement level. Finally, it was noted that the mean trend with height held for both clusters of peak distance within the data.

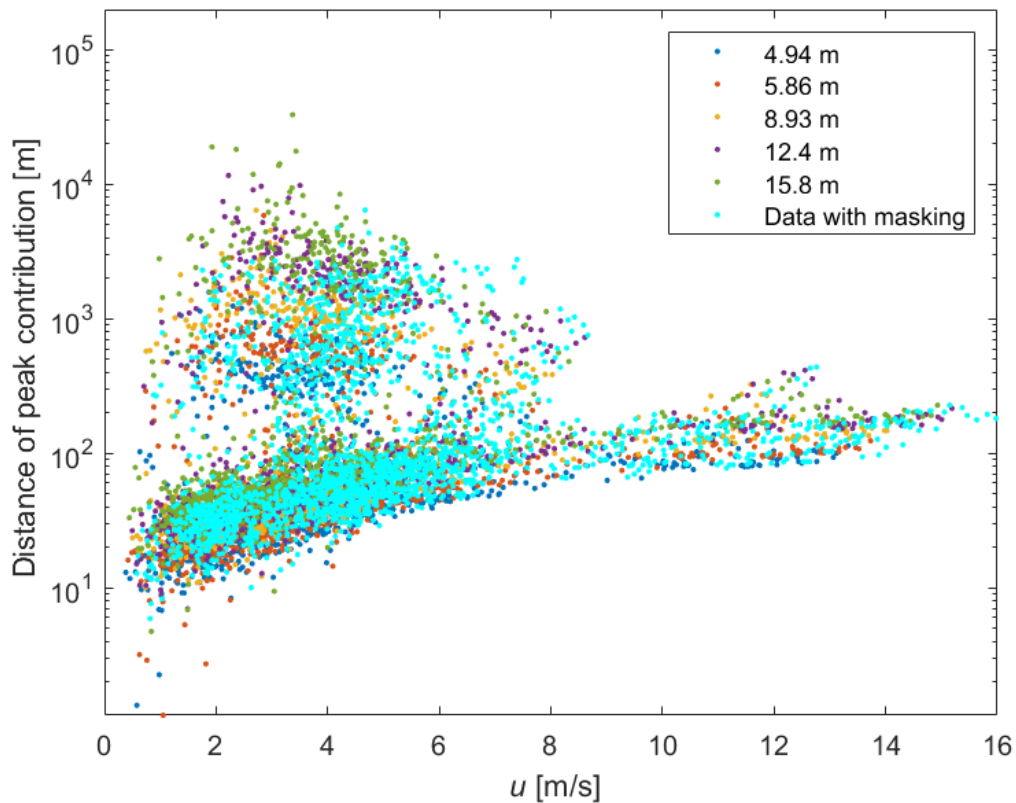


Figure 29. Distance of peak flux contribution plotted with measured wind speed, with constant stress gradient masking applied

Wind speed's effect on the distance of peak contribution was then analyzed in Figure 29. It is clear that in the wind regime higher than 8 m/s, there are no instances of exceptionally high distance of peak contribution. The trend in the low wind speed regime is that there is a peak in the scatter at ~ 3 m/s. Much like Figure 28, the contributions for each sensor are bimodal, whereby the majority of the peak distances around 1000 m occur between and 2–8 m/s for all levels. Outside of this cluster of data, there is a strong quasi-linear relationship between peak distance and wind speed.

The constant stress gradient mask was also applied to the data in Figure 29. Noticeably, there are more datapoints that remain after the masking in Figure 29 compared to Figure 20. This is because when the mask is applied in conjunction with the profile method, the vertical averaging of friction velocity greatly reduces the number of datapoints

(from 1981 datapoints of constant stress gradient to 510 datapoints). For the 1981 constant stress gradient datapoints in Figure 29, the masked data scatter indicates that the longer distance contributions seen in the grouping above the quasi-linear scatter is not a result of the constant flux layer assumption, as masked data appears in both modes. However, the furthest distances to peak flux tend to occur when the constant flux layer is not valid. For example, there were very few cases of non-divergent stress above 5 km.

C. A HYPOTHESIS FOR THE DETECTION OF SURFACE ROUGHNESS HETEROGENEITY USING FOOTPRINTS

The following diagram was designed to outline the method in which the knowledge of sea surface roughness, as well as the footprint method, could be used to implement a passive wake detection system. However, due to feasibility and time constraints, executing this portion of the research objective fell beyond the scope of this thesis.

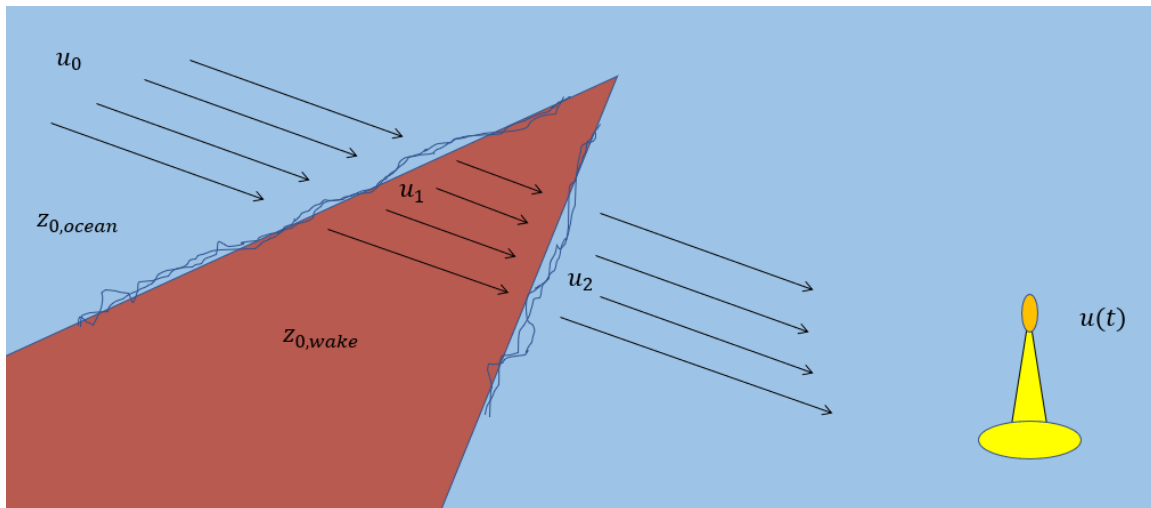


Figure 30. A conceptual diagram of air flow over a vessel-induced wake upstream of a sensor monitoring wind flow

The purpose of this section is to outline this hypothesis. It has been demonstrated in Section A that near-surface, fast-response anemometers can measure natural variability of surface roughness. It has also been shown that roughness varies with wind forcing and potentially other variables such as sea state. Furthermore, Section B highlighted how

statistical models can be used to estimate the upwind contributions to the observed flux measured at these sensor locations from the upwind field of roughness. Previous studies have shown that the surface roughness and atmospheric conditions can respond to discontinuity and heterogeneity. For example, this was shown in previous observational and numerical study into the impact of internal waves on the ocean surface [2], [1]. These internal waves result in a distinct transition between rough and smooth ocean surface appearance caused by the currents generated by the internal wave. This transition can be very sharp $O(1\text{ m})$ with individual rough/smooth bands being $O(10\text{ m})$. These features also transit with the propagating wave. This provides a natural example similar to the impact vessel wakes have on surface roughness. Thus, the hypothesis that I sought to test is: the flux footprint calculated from a wind data at the sensor should be sensitive to an upwind discontinuity in the roughness field and be able to indicate the relative movement of that discontinuity to the sensor. As a first step, this hypothesis could be tested using the *FLIP* data with internal waves captured during the experiment, which were well documented using a camera, radar system, and temperature string. Further investigations into this hypothesis could use laboratory-based experiments, a controlled field test, or computation fluid dynamics models.

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V. SUMMARY

From the results of the sea surface roughness analysis, specifically from the eddy covariance and profile methods, there is a great amount of scatter in the very low wind speed regime. Some of these z_0 values were outside the range expected from the literature and reported in other datasets. When compared to the Smith and Edson bulk parameterizations in Figure 19, this could indicate that there are other factors or processes, both natural and methodological, at play that are not accounted in the wind profile equation (12). These factors can drive both extremely high values of z_0 and extremely low values of z_0 within the same dataset. Further study is needed to investigate the potential biases in the reported roughness lengths using both eddy covariance and profile methods. For example, further study should focus on the statistical analysis to address this scatter, and what statistical methods could constrain this distribution. This has implications for refining the new *FLIP* bulk parameterization presented in this thesis and help to develop a model that directly includes the low wind speed regime.

The application of the constant stress gradient mask to various drag parameters is a unique aspect of the analysis presented here. Since the majority of existing work on sea surface roughness (using eddy covariance methods) come from single point measurements, investigators tend to assume the constant flux layer is widely valid. However, thanks to the unique capabilities of *FLIP*, and the NPS meteorological mast in particular, this assumption could be directly tested within the analysis. By accounting for the cases where the stress gradient was constant, it was shown that this significantly reduced the variance in the overall distributions (Figs. 12–14 and 20), as compared to the entire dataset. This type of analysis was only possible by having a vertical stack of meteorological sensors, which lead to a more physically robust dataset. This also allowed for direct comparison between the eddy covariance method and the profile method for estimate surface roughness. The study of agreement between the two methods is given in Figure 21. By inspection, it appears as if the agreement between the two methods increases with higher values of z_0 , but it is difficult to tell if this indicates a systematic bias crossing the 1:1 line, or a convergence

between the two approaches in this size range. This question could be resolved with more data of higher z_0 values.

As for the passive detection method for subsurface vessel wake signatures, it should not be seen as an emerging technology, but rather an interesting concept that leverages existing sensing capability the maritime domain for a novel application in the future. In the maritime domain, virtually every aspect of a platform can be exploited, from its radar emissions to its undersea noise. These factors can be mitigated, but it would be virtually impossible to mitigate the displacement of water, causing a wake. Being able to leverage this physical vulnerability could be the technological edge needed for the U.S. naval fleet.

It is important to discuss some limitations to the dataset presented in this thesis. In particular, the scope of the data represents one month (Sep-Oct) offshore of southern California. This data, of course, is not representative of the entire ocean, or even the year-round conditions of the coastal Pacific. Furthermore, and as with any experimental dataset, the relatively small number of datapoints that remained after accounting for flow contamination, masking, and aggregation. The sparse scatter shown in Figure 22 shows that a great number of datapoints were eliminated after the described steps. This sample size has some impact on the statistical analysis and may not generally represent the flow conditions. Possible solutions to addressing this, including re-evaluating the data quality control strategies applied to the data, should be the focus on continued work using this dataset. For example, perhaps filling in gaps in the 30-minute wind profiles might preserve more samples and provide more samples for developing the *FLIP* bulk parameterization. Other limitations are a result of the bulk parameterization methods studied in this thesis. The Smith and Edson bulk parameterization methods are commonly used, but there is the possibility that other methods could more accurately represent the data in the lower friction velocity regime seen in Figure 23. Lastly, due to the unique nature of the *FLIP*, there are relatively few resources that discuss the profile method. During the use of the profile method, a fairly significant assumption to use the vertical average of friction velocity was applied. There is the possibility that this could be a suboptimal assumption. A statistical analysis could be done to confirm the best selection for u_* for the profile method.

Furthermore, additional insights from cases where the profile method is typically used, for example over land, would help improve the use of this method for this case.

From a fluid mechanics perspective, the MABL is an extremely complex system of atmospheric and oceanic influences that, at first glance, may appear highly random. However, through careful analysis, it is possible to see patterns emerge in this complicated environment. Using data from the R/P *FLIP* the natural variability in the sea surface roughness was explored and compared to bulk parameterizations widely used in empirical and numerical research. The footprint analysis using *FLIP* data revealed the vast amount of information that can be gleaned from passively measuring the atmospheric state and turbulence. Weather and surf forecasting rely on having accessible and accurate predictions to these parameters. Having a better understanding of the air-sea interface at the base of the MABL leads to a more complete understanding of the maritime domain, and therefore, a more effective U.S. Navy.

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APPENDIX

A. WIND TIME SERIES

Produce the wind time series

```
clear; close all; clc
```

Load in data

```
load FLIPflux30.mat  
load constant_stress.mat
```

Get psi from eddycorrFLIP.m

```
psi = NaN(2180,7);  
for i = 1:2180  
    for j = 1:7  
        psi(i,j) = psiU(zeta(i,j));  
        % General source for this is Edson et al. 2004, Edson et al. 2013,  
        % COARE Algorithm (coare35vn.m)  
    end  
end
```

Data correction

flow distortion

```
for i = 1:7  
    ustcorr(:,i) = ust(clean_profiles,i); % Only take indices from clean_profiles  
    profucorr(:,i) = profu(clean_profiles,i);  
    CD10Ncorr(:,i) = CD10N(clean_profiles,i);  
    U10Ncorr(:,i) = U10N(clean_profiles,i);  
    psicorr(:,i) = psi(clean_profiles,i);  
    profzfcrr(:,i) = profzf(clean_profiles,i);  
    profTcorr(:,i) = profT(clean_profiles,i);  
    z0corr(:,i) = z0(clean_profiles,i);  
end  
  
proftimecorr = proftime(clean_profiles,1);
```

NaN elimination

Identify profucorr indices where NaN, and delete the value at that index and also the profzfcrr value at that index

```
ind = ~isnan(profucorr(:,5)); % this is 5 because the only NaN indices are
                             % in column 5
profucorr1 = profucorr(ind,:);
profzfcrr1 = profzfcrr(ind,:);
proftimecorr1 = proftimecorr(ind);

ind2 = ~isnan(profzfcrr1(:,6)); % only NaN indices in column 6 (for profzf)
profucorr2 = profucorr1(ind2,:);
profzfcrr2 = profzfcrr1(ind2,:);
proftimecorr2 = proftimecorr1(ind2);
```

Other variables

```
g = 9.81; % gravitational constant [m/s^2]
K = 0.41; % von Karman constant
z = [2.98, 4.03, 4.94, 5.86, 8.93, 12.4, 15.8]; % [m]
```

Figure

```
t = proftimecorr2 - proftimecorr2(1);
thour = t.*2;
reflinex = linspace(min(thour),max(thour),length(thour));
refliney = linspace(8,8,length(thour));

figure
plot(thour,profucorr2,'k.')
hold on
xlabel('Time [h]')
ylabel('{\it u} [m/s]')
plot(reflinex,refliney,'r--')
xlim([min(thour) max(thour)])
hold off
```

B. SMITH AND EDSON EXAMPLE BULK PARAMETERIZATIONS

Analytical test and comparison of z_0 function for rough + smooth conditions

```
clear; close all; clc
addpath C:\Users\2022\Desktop\Thesis\toolbox\toolbox
```

Constants

```
visc = 1.461e-5; % [m^2/s] kinematic viscosity of air assumed at 15C
% https://www.engineeringtoolbox.com/air-absolute-kinematic-viscosity-d_601.html
g = 9.81; % [m/s^2] gravitational constant
C1 = 0.0015; % value from Ortiz-Suslow et al. 2021 for rule-of-thumb relationship
U = linspace(0,25,50); % [m/s] array of wind vectors
ust = sqrt(C1*U.^2); % friction velocity
%
U(1) = [];
ust(1) = [];
```

Governing Equations

Wind Stress p42

```
z0smooth = 0.11*visc./ust;
z0rough = 0.011*(ust.^2)/g;
z0total1 = z0smooth + z0rough;

% COARE 3.5 wind only
C2 = 0.0017; % constant from COARE 3.5 wind only (coare35vn.m)
c2 = 0.017; % constant from JPO Edson et al. 2013 paper (abstract)

% [0.0017519 -0.0055696] this is m & b from eq. 13 fitted to Figure 6 between U = 7 and
18 m/s

C3 = 0.005; % constant from COARE 3.5 wind only (Edson et al. 2013)
B0 = ((C2.*U - C3).*ust.^2)/g;
z0total2 = z0smooth + B0;
z0total3 = z0smooth + ((C2.*U - C3).*ust.^2)/g;
B0(B0 < 0) = nan;
```

Figure presentation

```
figure('name','z0 test','Position',[1887 49 618 321])
```

```
figure
hold on
```

```

hp(1) = plot(ust,z0total1,'k','linewidth',2); % wind Stress p42
hp(2) = plot(ust,z0smooth,'r--');
hp(3) = plot(ust,z0rough,'b--');
hp(4) = plot(ust,z0total2,'color',[.5 .5 .5],'linewidth',2);
hp(5) = plot(ust,B0,'color',[.5843 .8157 .9882],'LineStyle','--');
% hp(6) = plot(ust,z0total3,'color',[.3 .3 .3],'linewidth',2);

set(gca, 'YScale', 'log', 'YLim',[1e-7 1e-1], 'Position',[0.13 0.12 0.775 0.73625])
xlabel('\it u_* [m/s]')
ylabel('\it z}_0 [m]')

% legend(gca,...
% '\it z}_0 from Smith 1988',...
% 'Smooth component of {\it z}_0',...
% 'Rough component of {\it z}_0 from Smith 1988',...
% '\it z}_0 from COARE 3.5 wind Only',...
% 'Rough component of {\it z}_0 from COARE 3.5 wind Only',...
% 'location','Northwest')

legend(hp([1 4 2 3 5]),...
['Smith 1988 bulk parameterization'],...
['Edson et al. 2013 bulk parameterization'],...
['{\it z}_0 smooth component'],...
['Smith 1988{\it z}_0 rough component'],...
['Edson et al.{\it z}_0 rough component'],...
'location','Northwest')

hold off

secondaxis
plot(ax2,U,ust,'x','Color','none','LineStyle','none')
set(ax2,'YColor','none','XColor',get(ax1,'XColor'),'Xlim',[0
max(U)],'Ylim',get(ax1,'Ylim'),'Position',get(ax1,'Position'))
xlabel('\it U}_{10} [m/s]')
axes(ax1)
set(ax1,'Color','none')

```

C. PROFILE METHOD ANALYSIS

Profile method to solve for z_0

Solves for z_0 as a system of equations of wind profiles from data at different heights
26MAR2023

```
clear; close all; clc
```

Script information

Data presented as 2185x7 doubles ASSUMING... Col 1: Flux00 RMY Col 2: Flux00
CSAT Col 3: Flux01 Col 4: Flux02 Col 5: Flux03 Col 6: Flux04 Col 7: Flux05

Load in data

```
load FLIPflux30.mat  
load constant_stress.mat
```

Get psi from eddycorrFLIP.m

```
psi = NaN(2180,7);  
for i = 1:2180  
    for j = 1:7  
        psi(i,j) = psiu(zeta(i,j));  
        % General source for this is Edson et al. 2004, Edson et al. 2013,  
        % COARE Algorithm (coare35vn.m)  
    end  
end
```

Data correction

flow distortion

```
for i = 1:7  
    ustcorr(:,i) = ust(clean_profiles,i); % Only take indices from clean_profiles  
    profucorr(:,i) = profu(clean_profiles,i);  
    CD10Ncorr(:,i) = CD10N(clean_profiles,i);  
    U10Ncorr(:,i) = U10N(clean_profiles,i);  
    psicorr(:,i) = psi(clean_profiles,i);  
    profzfcrr(:,i) = profzf(clean_profiles,i);  
    profTcorr(:,i) = profT(clean_profiles,i);  
    z0corr(:,i) = z0(clean_profiles,i);  
end
```

Reasonable value cutoff

```
for i = 1:length(CD10Ncorr)
    for j = 1:7
        if CD10Ncorr(i,j) < 10E-6
            CD10Ncorr(i,j) = nan;
            U10Ncorr(i,j) = nan;
            profucorr(i,j) = nan;
            ustcorr(i,j) = nan;
            profzfcrr(i,j) = nan;
            profTcorr(i,j) = nan;
            z0corr(i,j) = nan;
        end
    end
end

clear i
clear j
```

Mask ust in order to get a z0pm mask

```
constant_stress_mask = cfarray > 0;

ust_conststress = ustcorr.*constant_stress_mask;
ust_conststress(ust_conststress == 0) = nan;
N_CS = sum(sum(isnan(ust_conststress)));
```

NaN elimination

identify profucorr indices where NaN, and delete the value at that index and also the profzfcrr value at that index

```
ind = ~isnan(profucorr(:,5)); % this is 5 because the only NaN indices are
                             % in column 5
profucorr1 = profucorr(ind,:);
profzfcrr1 = profzfcrr(ind,:);

ind2 = ~isnan(profzfcrr1(:,6)); % only NaN indices in column 6 (for profzf)

profucorr2 = profucorr1(ind2,:);
profzfcrr2 = profzfcrr1(ind2,:);

% Then same thing for ustcorr and psicorr (and temperature and
% getFLIPflux.m z0 values)
ind3 = ~isnan(ustcorr(:,6));

ustcorr1 = ustcorr(ind3,:);
ust_CS1 = ust_conststress(ind3,:);
```

```

psicorr1 = psicorr(ind3,:);
profTcorr1 = profTcorr(ind3,:);
z0corr1 = z0corr(ind3,:);
U10Ncorr1 = U10Ncorr(ind3,:);

```

```

ind4 = ~isnan(psicorr1(:,5));

```

```

ustcorr2 = ustcorr1(ind4,:);
ust_CS2 = ust_CS1(ind4,:);
psicorr2 = psicorr1(ind4,:);
profTcorr2 = profTcorr1(ind4,:);
z0corr2 = z0corr1(ind4,:);
U10Ncorr2 = U10Ncorr1(ind4,:);

```

Other variables

```

g = 9.81; % gravitational constant [m/s^2]
K = 0.41; % von Karman constant
z = [2.98, 4.03, 4.94, 5.86, 8.93, 12.4, 15.8]; % [m]

```

Testing to see if exponent is within ~[-6, -2]

Test case

```

for i = 700 % ***USER INPUT BETWEEN 1 AND 1433***
    [rfittedcheck(i), rawcheck(i)] = rlogfit(profzfcorr2(i,:), profucorr2(i,:), 'logx');
    expcheck = -rfittedcheck(i).coeffs(1)*K/(mean(ustcorr2(i),2)) + mean(psicorr2(i),2);
end
Acheck = rfittedcheck(i).coeffs(2);
Bcheck = rfittedcheck(i).coeffs(1);

xcheck = linspace(0,16,length(profzfcorr2));
ycheck = Acheck*log10(xcheck) + Bcheck;

figure
plot(profzfcorr2(i,:), profucorr2(i,:), 'r*')
xlabel('Height [m]')
ylabel('wind speed [m/s]')
hold on
plot(xcheck, ycheck, 'k.')
legend('Measured wind speed', 'Logarithmic fit', 'location', 'southeast')
hold off

```

Solving for z0 using B from fit

```

x0 = 0.0001;
% Big assumption: using vertical averages for ust and psi

```

```

ustavg = mean(ustcorr2,2);
psiavg = mean(psicorr2,2);

ustavg_CS = mean(ust_CS2,2);
psiavg_CS = mean(psicorr,2);

% no mask
for i = 1:length(profzfcrr2)
    [rfitted(i),~] = rlogfit(profzfcrr2(i,:),profucrr2(i,:), 'logx');
    B(i) = rfitted(i).coeffs(1);
    exponent = -B(i)*K/mean(ustcorr2(i,:)) + mean(psicorr2(i,:));
    % z0comp(i) = 2.718281828^exponent;
    z0comp(i) = exp(exponent);
end

z0pm = z0comp';

clear B
clear exponent
clear rfitted

% with mask
for i = 1:length(profzfcrr2)
    [rfitted(i),~] = rlogfit(profzfcrr2(i,:),profucrr2(i,:), 'logx');
    B(i) = rfitted(i).coeffs(1);
    exponent = -B(i)*K/mean(ust_CS2(i,:)) + mean(psicorr2(i,:));
    z0compCS(i) = exp(exponent);
end

z0pm_CS = z0compCS';

```

Figures

```

figure
semilogy(ustavg,z0pm,'k.')
xlabel('Vertically averaged {\itu}_*')
ylabel('{\it z}_0')

```

Smith bulk parameterization

```

Ta_avg = mean(profTcorr2,2);

visc = visair(Ta_avg); % dynamic viscosity of air [Ns/m^2]
z0_smooth = 0.11.*(visc./ustavg);
z0_rough = 0.011.*(ustavg.^2)/g;

```

COARE bulk parameterization

COARE 3.5 wind only

```
C2 = 0.0017; % constant from COARE 3.5 wind only (coare35vn.m)
c2 = 0.017; % constant from JPO Edson et al. 2013 paper (abstract)
U10Navg = mean(U10Ncorr2,2);

% [0.0017519 -0.0055696] this is m & b from eq. 13 fitted to Figure 6 between U = 7 and
18 m/s

C3 = 0.005; % constant from COARE 3.5 wind only (Edson et al. 2013)
B0 = ((C2.*U10Navg - C3).*(ustavg.^2))/g; % COARE rough component
```

Figure of given z0 over avgust

```
% no mask
ust_plot = ustcorr(1:length(z0corr),:);
ustavg_plot = mean(ust_plot,2);

figure
semilogy(ustavg,z0pm,'k.')
xlabel('{\it u}_{*}')
ylabel('{\it z}_{0}')
hold on
semilogy(ustavg,z0_smooth,'r.')
semilogy(ustavg,z0_rough,'b.')
semilogy(ustavg,B0,'color',[.5843 .8157 .9882],'marker','.', 'linestyle','none')
semilogy(ustavg,z0_smooth+z0_rough,'c.')
semilogy(ustavg,z0_smooth+B0,'color',[.7 .3 .8],'marker','.', 'linestyle','none')
legend('{\it u}_{0} from profile method','{\it z}_{0} bulk smooth component','{\it z}_{0} Smith
1988 bulk rough component','{\it z}_{0} Edson 2013 bulk rough component',' Smith 1988
bulk',' Edson 2013 bulk')
hold off
% ADD IN SMOOTH+ROUGH LINES FOR SMITH AND COARE

% just plotting z0corr
figure
semilogy(ustavg_plot,z0corr,'k.')
xlabel('vertically averaged {\it u}_{*}')
ylabel('{\it z}_{0}')
ylim([1e-15 1e0])

figure
loglog(z0pm,z0corr2(:,5),'k.')
% THIS IS NOT AVG u*... IT USES FLUX LEVEL # IN (:,#)
hold on
xlabel('{\it z}_{0} from profile method')
ylabel('{\it z}_{0} from eddy covariance method')
xlim([1e-8 1e0])
```

```
ylim([1e-8 1e0])
plot([1e-8 1e0],[1e-8 1e0],'r--','linewidth',2)
```

Figure z0pm over z0corr WITH MASKING

```
figure
loglog(z0pm_CS,z0corr2(:,5),'k.')
% THIS IS NOT AVG u*... IT USES FLUX LEVEL # IN (:,#)
hold on
xlabel('{\it z}_0 from profile method')
ylabel('{\it z}_0 from eddy covariance method')
xlim([1e-8 1e0])
ylim([1e-8 1e0])
plot([1e-8 1e0],[1e-8 1e0],'r--','linewidth',2)

z0corr_avg = mean(z0corr2,2); % effective roughness length for 10-m wind

figure
loglog(z0pm_CS,z0corr_avg,'k.')
% THIS FIGURE USES u* VERTICAL AVG
hold on
xlabel('{\it z}_0 from profile method')
ylabel('{\it z}_0 from eddy covariance method')
xlim([1e-8 1e0])
ylim([1e-8 1e0])
plot([1e-8 1e0],[1e-8 1e0],'r--','linewidth',2)
```

Novel FLIP bulk parameterization from z0pm

```
% fit of z0 over ust with form  $z_0 = (a*ust^{-1}) + (b*ust^2)$ 
x_wnan = ustavg_CS;
y_wnan = z0pm_CS;

x = rmmissing(x_wnan);
y = rmmissing(y_wnan);

startcoef = [1 1];
% startcoef = [1e-6 5e-4];
% chosen as lower bound conservative estimates based upon Smith 1988
% a_guess < 0.11*1.4e-5, where 1.4e-5 is a low estimate for visc air
% b_guess < 0.011/9.81, where 9.81 is gravity
```

```

bulkEQ = '(a * x^-1) + (b * x^2)';
f1 = fit(x,y,bulkEQ,'Start', startcoef);
fprintf('A = %g\nB = %g\n\n',f1.a,f1.b)

% check calculated coefficients
% xbulkcheck = linspace(0, max(ustavg_CS .* visc), length(x));
% ybulkcheck = (f1.a .* visc .* xbulkcheck.^-1) + (f1.b * g^-1 .* xbulkcheck.^2);
xbulkcheck = linspace(0, max(ustavg_CS), length(x));
ybulkcheck1 = (f1.a .* xbulkcheck.^-1) + (f1.b .* xbulkcheck.^2);

Av = f1.a ./ visc; % curious to see how close it is to Smith's 0.11
Bg = f1.b .* g; % how close it is to Smith's 0.011

figure
semilogy(xbulkcheck,ybulkcheck1,'g--')
xlabel('u_*')
ylabel('z_0')
hold on
semilogy(x,y,'k.')
legend('Novel FLIP bulk parameterization line','Profile method results')
hold off

```

```

A = 9.67564e-05
B = 7.00638e-06

```

Trying a polynomial

```
f2 = fit(x,y,'poly6'); ybulkcheck2 = f2(xbulkcheck);
```

```

figure semilogy(xbulkcheck,ybulkcheck2,'g--') xlabel('u_*') ylabel('z_0') hold on
semilogy(x,y,'k.') legend('Novel FLIP Bulk Parameterization Line','Profile Method
Results') hold off

```

FLIP bulk, with the following assumptions

-smooth component the same -just going to take a fit of $z_{0pm} - z_{0smooth}(smith)$ to solve for the coefficient for the z_{0rough} component

```

z0_smoothCS = 0.11.*(visc./ustavg_CS);

z0_roughCS = z0pm_CS - z0_smoothCS;

x3 = x;
y_wnan3 = z0_roughCS;
y3 = rmmissing(y_wnan3);

```

```

roughEQ = '(b * x^2)';
startcoef3 = 1;

f3 = fit(x3, y3, roughEQ, 'start', startcoef3);

bulk_rough = (f3.b .* xbulkcheck.^2);

ybulkcheck3 = bulk_rough + y3;

figure
semilogy(xbulkcheck, ybulkcheck3, 'g--')
xlabel('u_*')
ylabel('z_0')
hold on
semilogy(x, y3, 'k.')
legend('Novel FLIP bulk parameterization line', 'Profile method results')
hold off

b3 = f3.b;
fprintf('B coefficient from rough fit is %g\nB*g = %g\n', b3, b3*g)

z0_roughFLIP = b3 .* (ustavg.^2);

figure
semilogy(ustavg, z0pm, 'k.')
xlabel('{\it u}_* [m/s]')
ylabel('{\it z}_0')
hold on
semilogy(ustavg, z0_smooth+z0_rough, 'c.')
semilogy(ustavg, z0_smooth+B0, 'color', [.7 .3 .8], 'marker', '.', 'linestyle', 'none')
semilogy(ustavg, z0_smooth+z0_roughFLIP, 'g.')
legend('{\it z}_0 from profile method', 'Smith 1988 bulk', 'Edson 2013 bulk', 'FLIP bulk')
hold off

visc_const = 1.461e-5;
ustavg_CSplot = linspace(0.02, max(ustavg_CS), length(ustavg_CS));
z0_bulkFLIP = 0.11.*(visc_const./ustavg_CSplot) + b3 .* (ustavg_CSplot.^2);

figure
semilogy(ustavg_CSplot, z0_bulkFLIP, 'g-')
xlabel('{\it u}_* [m/s]')
ylabel('{\it z}_0')
hold on
semilogy(ustavg_CS, z0pm_CS, 'k.')
legend('Novel FLIP bulk parameterization line', 'Profile method results with masking')
hold off

figure
semilogy(ustavg, z0pm, 'k.')

```

```
xlabel('\it u_* [m/s]')
ylabel('\it z_0')
hold on
semilogy(ustavg_CS,z0pm_CS,'c.')
legend('Profile method results','Profile method results with masking')
hold off
```

B coefficient from rough fit is 0.00163877
 $B \cdot g = 0.0160763$

D. CONSTANT STRESS MASKING AND FLIP BULK PARAMETERIZATION

Using constant_stress.mat

Figure production Big question: Is it valid to assume stress gradient is zero near the surface? We test this because we can determine if the stress gradient is actually zero because we take flux measurements at multiple heights due to the mast on FLIP.
 20MAR2023

```
clear; close all; clc
```

Script information

Data presented as 2185x7 doubles ASSUMING... Col 1: Flux00 RMY Col 2: Flux00
 CSAT Col 3: Flux01 Col 4: Flux02 Col 5: Flux03 Col 6: Flux04 Col 7: Flux05

Load in data

```
load FLIPflux30.mat
load constant_stress.mat
```

Data correction

```
for i = 1:7
ustcorr(:,i) = ust(clean_profiles,i); % Only take indices from clean_profiles
profucorr(:,i) = profu(clean_profiles,i);
ustcorrmask(:,i) = ust(clean_profiles,i);
CD10Ncorr(:,i) = CD10N(clean_profiles,i);
CD10Ncorrmask(:,i) = CD10N(clean_profiles,i);
U10Ncorr(:,i) = U10N(clean_profiles,i);
ustcorrdiv(:,i) = ust(clean_profiles,i);
end
```

Outlier elimination

```

for i = 1:length(CD10Ncorr)
    for j = 1:7
        if CD10Ncorr(i,j) < 10E-6
            CD10Ncorr(i,j) = nan;
            CD10Ncorrmask(i,j) = nan;
            U10Ncorr(i,j) = nan;
            ustcorr(i,j) = nan;
            ustcorrmask(i,j) = nan;
            profucorr(i,j) = nan;
            ustcorrddiv(i,j) = nan;
        end
    end
end
end

```

Constant stress mask

```

constant_stress_mask = cfarray > 0;
divergent_stress_mask = cfarray < 0;

ust_conststress = ustcorrmask.*constant_stress_mask;
ust_divstress = ustcorrddiv.*divergent_stress_mask;

ust_conststress(ust_conststress == 0) = nan;
ust_divstress(ust_divstress == 0) = nan;
N_isnan = sum(sum(isnan(ust_conststress)));

CD10N_conststress = CD10Ncorrmask.*constant_stress_mask;
CD10N_conststress(ust_conststress == 0) = nan;

```

Plotting

```

i = 1:7; % just in case I want to display only one flux level
figure
semilogy(profucorr(:,i), ustcorr(:,i),'k.')
hold on
semilogy(profucorr(:,i), ust_conststress(:,i),'c.')
legend('All timestamps',' ',' ',' ',' ',' ',' ','...
       'Convergent timestamps','location','southeast')
xlabel('{\it u} [m/s]')
ylabel('{\it u}_* [m/s]')
hold off

figure
semilogy(U10Ncorr(:,i), CD10Ncorr(:,i),'k.')
hold on
semilogy(U10Ncorr(:,i), CD10N_conststress(:,i),'c.')
legend('All timestamps',' ',' ',' ',' ',' ',' ','...

```

```

    'Convergent timestamps','location','northeast')
xlabel({'\it U}_1_0_N [m/s]')
ylabel({'\it C}_D_1_0_N')
hold off

```

Aggregation of constant stress gradient mask

averages each timestamp over the 7 flux levels (ASSUMPTION)

```

CD10Naggmask = mean(CD10N_conststress , 2);
U10Nagg = mean(U10Ncorr , 2);

% Figure with aggregation and constant stress gradient mask

figure
semilogy(U10Ncorr(:,i), CD10Ncorr(:,i),'k.')
hold on
semilogy(U10Nagg, CD10Naggmask,'c.')
xlabel({'\it U}_1_0_N [m/s]')
ylabel({'\it C}_D_1_0_N')
ylim([1e-5 1e1])
legend('All timestamps','','','','','','','Convergent timestamps with aggregation applied')
hold off

```

Figure with eliminated divergent stress ONLY

```

figure
semilogy(profucorr(:,i), ustcorr(:,i),'k.')
hold on
semilogy(profucorr(:,i),ust_divstress,'r.')
xlabel('u')
ylabel('u_*')
legend('All Data','','','','','','','Eliminated divergent stress gradient datapoints')

```

E. FOOTPRINT ANALYSIS

Profile method to solve for z_0

Solves for z_0 as a system of equations of wind profiles from data at different heights Big assumption: with these calculations, we need to assume that z_0 is constant even when dealing with wind data at different flux levels 26MAR2023

```
clear; close all; clc

% Script information
% Data presented as 2185x7 doubles
% ASSUMING...
% Col 1: Flux00 RMY
% Col 2: Flux00 CSAT
% Col 3: Flux01
% Col 4: Flux02
% Col 5: Flux03
% Col 6: Flux04
% Col 7: Flux05
```

Load in data

```
load FLIPflux30.mat
load constant_stress.mat
```

Get psi from eddycorrFLIP.m

```
psi = NaN(2180,7);
for i = 1:2180
    for j = 1:7
        psi(i,j) = psiU(zeta(i,j));
        % General source for this is Edson et al. 2004, Edson et al. 2013,
        % COARE Algorithm (coare35vn.m)
    end
end
```

Data correction

```
for i = 1:7
    ustdcorr(:,i) = ust(clean_profiles,i); % Only take indices from clean_profiles
    profucorr(:,i) = profu(clean_profiles,i);
    CD10Ncorr(:,i) = CD10N(clean_profiles,i);
    U10Ncorr(:,i) = U10N(clean_profiles,i);
    psicorr(:,i) = psi(clean_profiles,i);
    SHFcrr(:,i) = SHFc(clean_profiles,i);
```

```

profTcorr(:,i) = profT(clean_profiles,i);
profzfcrr(:,i) = profzf(clean_profiles,i);
z0corr(:,i) = z0(clean_profiles,i);
end

for i = 1:13
profTcorr(:,i) = profT(clean_profiles,i);
end

```

Reasonable value cutoff

```

for i = 1:length(CD10Ncorr)
    for j = 1:7
        if CD10Ncorr(i,j) < 10E-6
            CD10Ncorr(i,j) = nan;
            U10Ncorr(i,j) = nan;
            profUcorr(i,j) = nan;
            ustcorr(i,j) = nan;
        end
    end
end

clear i
clear j

```

Other variables

```

visc = visair(ustcorr); % dynamic viscosity of air [Ns/m^2]
g = 9.81; % gravitational constant [m/s^2]
K = 0.41; % von Karman constant
z = [2.98, 4.03, 4.94, 5.86, 8.93, 12.4, 15.8]; % [m]

```

Converting profT to closest heights

```

T = NaN(length(ustcorr),7);
T(:,3) = profTcorr(:,1); % column numbers selected based upon closest heights from
                        % profzT compared to flux heights
T(:,4) = profTcorr(:,3);
T(:,5) = profTcorr(:,6);
T(:,6) = profTcorr(:,10);
T(:,7) = profTcorr(:,13);

```

Removing NaN's

```

ind = ~isnan(ustcorr(:,5));
ustcorr1 = ustcorr(ind,:);
SHFccorr1 = SHFccorr(ind,:);
T1 = T(ind,:);
profzfcrr1 = profzfcrr(ind,:);
z0corr1 = z0corr(ind,:);
profucorr1 = profucorr(ind,:);

ind2 = ~isnan(ustcorr1(:,6));
ustcorr2 = ustcorr1(ind2,:);
SHFccorr2 = SHFccorr1(ind2,:);
T2 = T1(ind2,:);
profzfcrr2 = profzfcrr1(ind2,:);
z0corr2 = z0corr1(ind2,:);
profucorr2 = profucorr1(ind2,:);

```

START OF FOOTPRINT ANALYSIS

```

clear x
xfoot = cell(length(ustcorr2),7);
Fcfoot = cell(length(ustcorr2),7);
fpfoot = cell(length(ustcorr2),7);

for i = 1:length(ustcorr2)
    for j = 3:7
        [cc, pp, xx,L(i,j),xp(i,j),F2H(i,j)]=footprint_hsieh(ustcorr2(i,j)...
            ,SHFccorr2(i,j),T2(i,j),profzfcrr2(i,j),z0corr2(i,j));

        xfoot{i,j} = xx;
        Fcfoot{i,j} = cc;
        fpfoot{i,j} = pp;

    end
end

```

Figure for 3 cases of flux contribution

*** User Inputs ***

```

tplot1 = 816; % time stamp (choose from 1 through 1433)
zplot1 = 5; % flux sensor height (choose 1 through 7)

tplot2 = 361;
zplot2 = 5;

tplot3 = 1217;
zplot3 = 5;
% *****

```

```

figure
plot(xfoot{tplot1,zplot1},Fcfoot{tplot1,zplot1},'c.')
hold on
xlabel('Distance upstream of sensor [m]')
ylabel('Cumulative source contribution')
plot(xfoot{tplot2,zplot2},Fcfoot{tplot2,zplot2},'r.')
plot(xfoot{tplot3,zplot3},Fcfoot{tplot3,zplot3},'g.')
xlim([0 5000])
legend('{\it u} ~ 0 m/s case','{\it u} ~ 3 m/s case','{\it u} > 10 m/s case','location','southeast')

```

Statistics

cut out flux0 and flux1 (all zeros)

```

xp_hist = xp(:,3:7);
Fcfoot_hist = Fcfoot(:,3:7);
xfoot_hist = xfoot(:,3:7);

```

Calculate x at which a defined percent of cumul. cont. occurs

```

xperc_ind = NaN(length(Fcfoot_hist),5);

% ***User defined percentage from 0.01 to 0.99***
perc = 0.9;
% *****

for i = 1:length(Fcfoot_hist)
    for j = 1:5
        Fcmat = Fcfoot_hist{i,j};
        Fcmat_flag = (Fcmat > perc); % if value is 1 or greater, than a contribution
                                     % of >=0.8 exists
        if sum(Fcmat_flag) >= 1
            xperc_ind(i,j) = find(Fcfoot_hist{i,j} >= perc, 1);
            % finds the first index where
            % contribution is greater than 80%
        else
            xperc_ind(i,j) = nan;
        end
    end
end

clear Fcmat

xperc = NaN(length(xfoot_hist),5);
% apply indices to make
for i = 1:length(Fcfoot_hist)
    for j = 1:5

```

```

        xmat = xfoot_hist{i,j};
        if isnan(xperc_ind(i,j))
            xperc(i,j) = nan;
        else
            xperc(i,j) = xmat(xperc_ind(i,j));
        end
    end
end

```

Statistics figures

look up paper to see justification for Mu maybe a lognormal pdf to make it more gaussian

```

% xpeak
figure
histogram(xp_hist,'normalization','pdf')
xlabel('Distance of peak contribution [m]')
ylabel('pdf')

% x at which a certain percentage cumul. cont. occurs
figure
histogram(xperc,'normalization','pdf')
xlabel(sprintf('Distance of %g%% contribution [m]',perc*100))
ylabel('pdf')

```

Other figures

xpeak over u

```

u_trun = profucorr2(:,3:7);

figure
plot(u_trun,xp_hist,'.')
hold on
xlabel('{\it u} [m/s]')
ylabel('Distance of peak contribution [m]')
legend('4.94 m','5.86 m','8.93 m','12.4 m','15.8 m')
ylim([0 2e4])
hold off

% xpeak over t

% xpeak over z
z_trun = profzfcrr2(:,3:7);
figure
plot(z_trun,xp_hist,'.')
hold on

```

```

xlabel('Sensor height [m]')
ylabel('Distance of peak contribution [m]')
legend('4.94 m','5.86 m','8.93 m','12.4 m','15.8 m','location','northwest')
ylim([0 2e4])
hold off

% xpeak over z/L
L_trun = L(:,3:7);
zL = z_trun./L_trun;
figure
plot(zL,xp_hist,'.')
xlabel('z/L [ ]')
ylabel('Distance of peak contribution [m]')
legend('4.94 m','5.86 m','8.93 m','12.4 m','15.8 m')

```

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LIST OF REFERENCES

- [1] J. Wu, D. G. Ortiz-Suslow, X. Hao, Q. Wang, and L. Shen, “A model sensitivity study of ocean surface wave modulation induced by internal waves,” *Earth Space Sci.*, vol. 9, no. 11, p. e2022EA002394, 2022, doi: 10.1029/2022EA002394.
- [2] D. G. Ortiz-Suslow *et al.*, “Interactions between nonlinear internal ocean waves and the atmosphere,” *Geophys. Res. Lett.*, vol. 46, no. 15, pp. 9291–9299, 2019, doi: 10.1029/2019GL083374.
- [3] D. Chung, N. Hutchins, M. P. Schultz, and K. A. Flack, “Predicting the drag of rough surfaces,” *Annu. Rev. Fluid Mech.*, vol. 53, no. 1, pp. 439–471, 2021, doi: 10.1146/annurev-fluid-062520-115127.
- [4] I. Jones and Y. Toba, *Wind Stress Over The Ocean*. Cambridge, United Kingdom: Cambridge University Press, 2001.
- [5] G. Alfonsi, “Reynolds-Averaged Navier–Stokes Equations for Turbulence Modeling,” *Appl. Mech. Rev.*, vol. 62, no. 040802, Jun. 2009, doi: 10.1115/1.3124648.
- [6] R. Salmon, *Lectures on Geophysical Fluid Dynamics*. OUP USA, 1998.
- [7] J. Edson, V. Jampana, and R. Weller, “On the exchange of momentum over the open ocean,” *J. Phys. Oceanogr.*, vol. 43, no. 8, 2013, Accessed: May 03, 2023 [Online]. Available: <https://journals.ametsoc.org/view/journals/phoc/43/8/jpo-d-12-0173.1.xml>
- [8] A. S. Monin and A. M. Obukhov, “Basic Laws of Turbulent Mixing in the Surface Layer of the Atmosphere,” *Tr Akad Nauk SSSR Geophiz.*, vol. 24, no. 151, p. 30, 1954.
- [9] J. B. Edson, C. J. Zappa, J. A. Ware, W. R. McGillis, and J. E. Hare, “Scalar flux profile relationships over the open ocean,” *J. Geophys. Res. Oceans*, vol. 109, no. C8, 2004, doi: 10.1029/2003JC001960.
- [10] H. Tennekes and J. L. Lumley, *A First Course in Turbulence*. Cambridge, MA: The MIT Press, 1972. doi: 10.7551/mitpress/3014.001.0001.
- [11] J. A. Businger, Y. Izumi, E. F. Bradley, and J. C. Wyngaard, “Flux-Profile Relationships in the Atmospheric Surface Layer,” *J. Atmospheric Sci.*, vol. 28, p. 9, 1971.
- [12] E. Andreas, L. Mahrt, and D. Vickers, “A new drag relation for aerodynamically rough flow over the ocean,” *J. Atmospheric Sci.*, vol. 69, no. 8, 2012, Accessed: Jan. 23, 2023 [Online]. Available: <https://journals.ametsoc.org/view/journals/atsc/69/8/jas-d-11-0312.1.xml>

- [13] K. A. Flack, M. P. Schultz, and J. M. Barros, “Skin friction measurements of systematically-varied roughness: probing the role of roughness amplitude and skewness,” *Flow Turbul. Combust.*, vol. 104, no. 2, pp. 317–329, Mar. 2020, doi: 10.1007/s10494-019-00077-1.
- [14] S. Smith, “Coefficients for sea surface wind stress, heat flux, and wind profiles as a function of wind speed and temperature,” *J. Geophys. Res. Oceans*, vol. 93, no. 12, 1988, Accessed: May 03, 2023 [Online]. Available: <https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/JC093iC12p15467>
- [15] D. G. Ortiz-Suslow, J. Kalogiros, R. Yamaguchi, and Q. Wang, “An evaluation of the constant flux layer in the atmospheric flow above the wavy air-sea interface,” *J. Geophys. Res. Atmospheres*, vol. 126, no. 8, p. e2020JD032834, 2021, doi: 10.1029/2020JD032834.
- [16] J. MacMahan, “Increased aerodynamic roughness owing to surfzone foam,” *J. Phys. Oceanogr.*, vol. 47, no. 8, 2017, Accessed: Nov. 20, 2022 [Online]. Available: <https://journals.ametsoc.org/view/journals/phoc/47/8/jpo-d-17-0054.1.xml>
- [17] P. Schuepp, M. Leclerc, and J. Macpherson, “Footprint prediction of scalar fluxes from analytical solutions of the diffusion equation.,” Accessed: Nov. 20, 2022 [Online]. Available: https://www.researchgate.net/publication/44084861_Footprint_Prediction_of_Scalar_Fluxes_From_Analytical_Solutions_of_the_Diffusion_Equation
- [18] M. Aubinet, T. Vesala, and D. Papale, *Eddy Covariance: A Practical Guide to Measurement and Data Analysis*. New York City, NY: Springer. Accessed: Jan. 09, 2023 [Online]. Available: <https://link.springer.com/book/10.1007/978-94-007-2351-1>
- [19] D. G. Ortiz-Suslow *et al.*, “The data processing and quality control of the marine atmospheric boundary layer measurement systems deployed by the Naval Postgraduate School during the CASPER-West Field Campaign,” Naval Postgraduate School, Monterey, CA, Technical Report, Mar. 2019. Accessed: Nov. 20, 2022 [Online]. Available: <https://calhoun.nps.edu/handle/10945/61638>
- [20] F. Huang, Q. Meng, L. Cao, and D. Wan, “Wakes and free surface signatures of a generic submarine in the homogeneous and linearly stratified fluid,” *Ocean Eng.*, vol. 250, p. 111062, Apr. 2022, doi: 10.1016/j.oceaneng.2022.111062.
- [21] F. Xue, W. Jin, S. Qiu, and J. Yang, “Wake features of moving submerged bodies and motion state inversion of submarines,” *IEEE Access*, vol. 8, pp. 12713–12724, 2020, doi: 10.1109/ACCESS.2020.2966005.
- [22] G. R. Spedding, “Wake signature detection,” *Annu. Rev. Fluid Mech.*, vol. 46, no. 1, pp. 273–302, Jan. 2014, doi: 10.1146/annurev-fluid-011212-140747.
- [23] Q. Wang *et al.*, “CASPER: Coupled Air-Sea Processes and Electromagnetic (EM) ducting Research,” *Bull. Am. Meteorol. Soc.*, vol. 99(7), pp. 1449–1471, Nov. 2018, doi: 10.1175/BAMS-D-16-0046.1.

- [24] P. Frederickson *et al.*, “Evaluating the Use of Different Flux-Gradient Functions in NAVSLaM during Two Experiments,” *2018 IEEE Antennas Propag. Soc. Int. Symp. Usn. Natl. Radio Sci. Meet. APSURSI 2018 – Proc.*, pp. 885–886, 2018, doi: 10.1109/APUSNCURSINRSM.2018.8608225.
- [25] J. C. Kaimal, J. C. Wyngaard, Y. Izumi, and O. R. Cote, “Spectral Characteristics of Surface-Layer Turbulence,” *Q. J. R. Meteorol. Soc.*, vol. 98, no. 417, 1972.
- [26] C. A. Paulson, “The Mathematical Representation of Wind Speed and Temperature Profiles in the Unstable Atmospheric Surface Layer,” *J. Appl. Meteorol.*, vol. 9, no. 6, pp. 857–861, Dec. 1970, doi: 10.1175/1520-0450(1970)009<0857:TMROWS>2.0.CO;2.
- [27] University of California, San Diego, “Research Platform FLIP (FLoating Instrument Platform),” *Scripps Institution of Oceanography*. <https://scripps.ucsd.edu/ships/flip> (accessed May 15, 2023).
- [28] C.-I. Hsieh, G. Katul, and T. Chi, “An approximate analytical model for footprint estimation of scalar fluxes in thermally stratified atmospheric flows,” *Adv. Water Resour.*, vol. 23, no. 7, pp. 765–772, Jun. 2000, doi: 10.1016/S0309-1708(99)00042-1.

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