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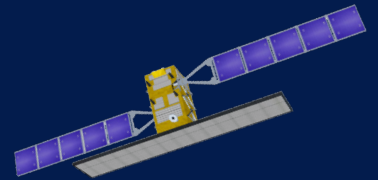
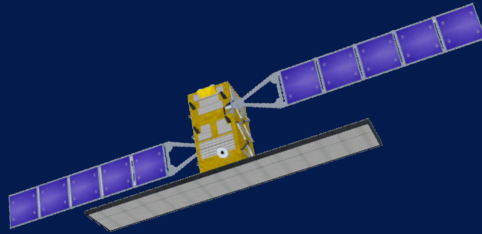
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# FLUXES AND FLOWS

Characterizing the Air-Sea Interface with Spaceborne Radars

Owen O'Driscoll



Invitation to attend the  
public defence of the  
thesis

## Fluxes and Flows

Characterizing the Air-Sea Interface  
with Spaceborne Radars

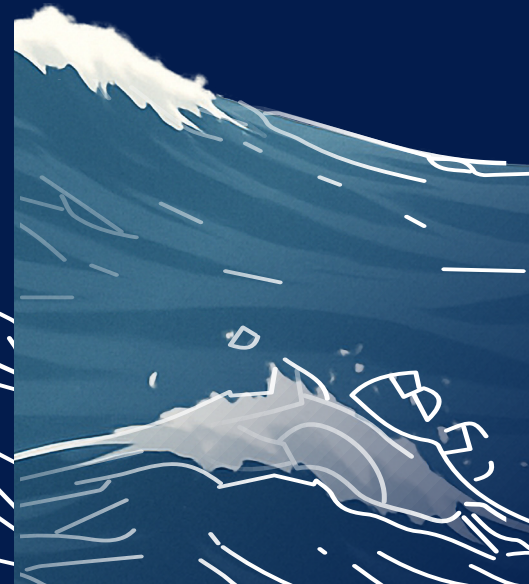
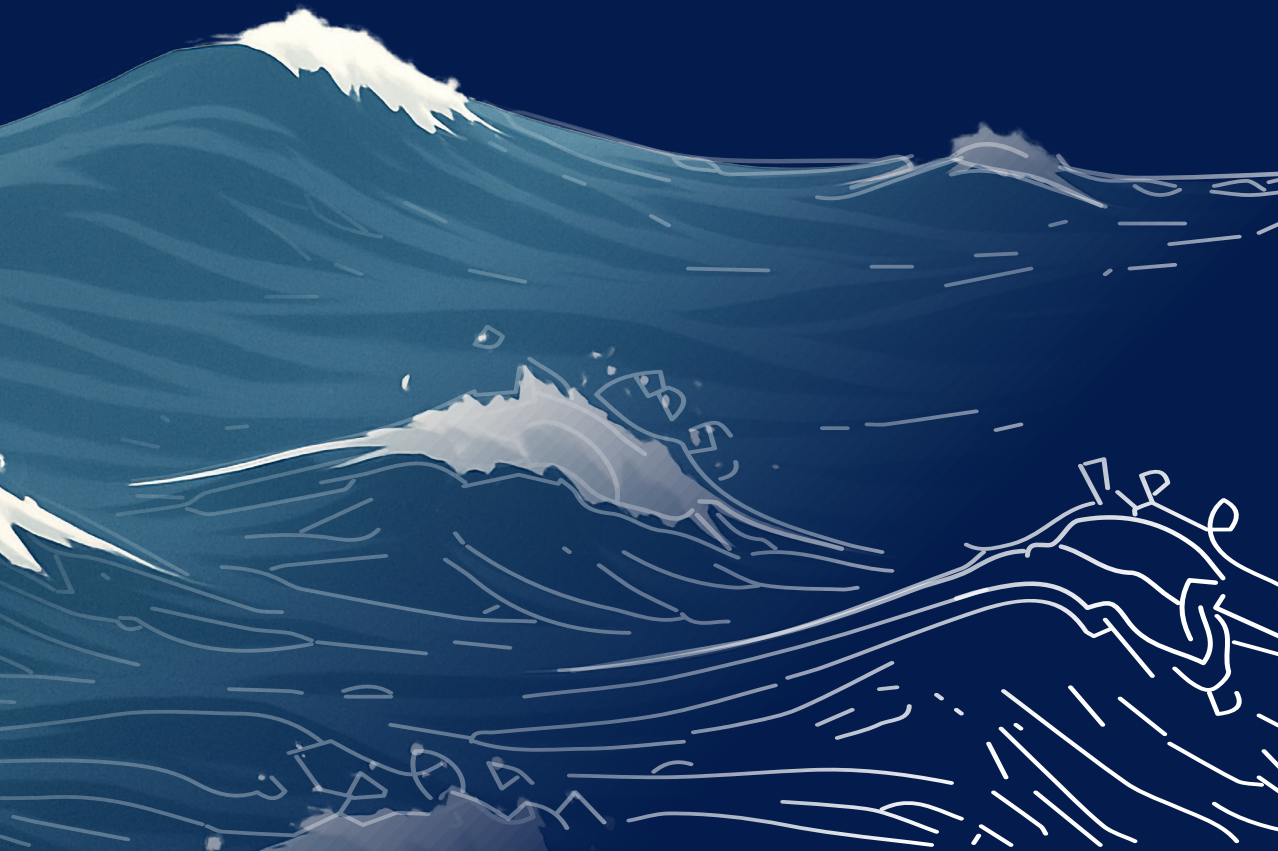
by

Owen O'Driscoll

on

Monday 26th of October  
2026

at 17:30 TU Delft Aula  
Mekelweg 5, Delft



# **FLUXES AND FLOWS**

CHARACTERIZING THE AIR-SEA INTERFACE WITH SPACEBORNE  
RADARS



# **FLUXES AND FLOWS**

**CHARACTERIZING THE AIR-SEA INTERFACE WITH SPACEBORNE  
RADARS**

## **Dissertation**

for the purpose of obtaining the degree of doctor  
at Delft University of Technology  
by the authority of the Rector Magnificus,  
Prof.dr.ir. H. Bijl,  
chair of the Board of Doctorates  
to be defended publicly on  
Monday 26 October 2026 at 17.30

by

**Owen Patrick O'DRISCOLL**

This dissertation has been approved by the (co)promotors

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*Surrounded as we are by such people - so confused, so ignorant of what they're saying and whatever faults they may or may not have, where those faults come from and how to get rid of them - I think we too should make a habit of asking ourselves,  
"Could it be that I am one of them too?"*

Epictetus



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## SUMMARY

The launch of NASA's SEASAT satellite in 1978 ushered in the era of radar oceanography. So treasured were the insights provided by this mission that its untimely demise, only three months after launch, did not preclude a legacy of success. In fact, rumors of sabotage sprang up, claiming that the instrument's remote sensing prowess had jeopardized military assets. Scuttling SEASAT had surely been a matter of national security.

Like plenty of rumors, these, too, were grounded in some truth: SEASAT had shed light on many a mystery, though primarily in the field of physical sciences rather than Cold War conspiracies. Nonetheless, the value of spaceborne oceanography was now clear, and space agencies around the world did not stand idly by. Europe quickly followed suit with its own missions, launching in succession a series of high-resolution imagers, including ERS-1, ERS-2, ENVISAT, and, since 2014, the Sentinel-1 constellation.

Aided by these instruments and many others, the previous decades have been marked by continued scientific advances in the ever-growing field of radar oceanography. Building on that rich heritage, this dissertation aims to advance two distinct (but entwined) subdomains relating to either side of the air-sea interface.

In the first half of this dissertation, Chapters 2 and 3, we investigate the ubiquitous yet often overlooked atmospheric features present in most high-resolution radar images of the ocean. It may seem counterintuitive to study the atmosphere using ocean imagery, but much of the ocean's surface variability is wind-driven, such that the ocean surface acts as a mirror for the wind field aloft. Till recently, the only systematic use for these atmospheric features had been in studies aiming to relate (an)isotropy to wind directions. But the information content is rich, and much more can be done.

In Chapter 2, we show that significant quantities of atmospheric information remain unexploited. And by using a domain-inspired encoding scheme, we transform high-dimensional radar images into a much lower-dimensional latent space, from which we extract substantially more atmospheric information than preexisting analytical methods. Then in Chapter 3 we leverage the ever-increasing catalog of Sentinel-1 observations to go one step further. We illustrate that radar-derived atmospheric variables are complementary to state-of-the-art and reference atmospheric estimates. The challenge here is one of persuasion: how to argue that new estimates can complement state-of-the-art estimates when there are insufficient "ground truth" measurements to reconcile discrepancies between them? We aim to address this difficulty through a series of qualitative and quantitative assessments.

In the second half of the dissertation, Chapters 4 and 5, we switch to the other side of the air-sea interface, to investigate different methods of retrieving surface currents—a long-standing challenge in spaceborne oceanography. First, we investigate surface current retrieval for a proposed satellite modification, DopSCA, in Chapter 4. This system could be uniquely capable of retrieving surface current information, but its unorthodox design makes it susceptible to several additional noise sources. One of these noise

sources, which we refer to as leakage—the undesired interaction between geometric Doppler, azimuthal backscatter gradients, and the antenna pattern—is investigated to assess its mission-compromising potential. Fortunately, this seems to be a comparatively minor issue.

Then, using a very different instrument in Chapter 5, we consider an alternative surface-current retrieval that incorporates polarimetry. Here we rely on the cross-correlation between wave motion, its radar cross section, and polarization to disentangle the convolved mixture of signals received by the satellite. Simulations and limited real observations illustrate that this approach may be a fruitful avenue towards the long-standing challenge of distinguishing between wave- and current motions. Future systems with additional polarimetric capabilities, such as Harmony or Sentinel-1 Next Generation, stand to gain from this approach in particular.

To summarize, this dissertation investigates radar-based retrieval of heat and momentum transport (from atmospheric convection and surface currents, respectively) by exploiting unique observational properties of a variety of radar satellites. We've made progress in both domains: providing the first quantitative and SAR-retrieved air-sea heat-flux estimates, and introducing a new method for surface-current retrieval. But fear not, enough work remains to entertain many radar oceanographers to come ;)

## SAMENVATTING

De lancering van NASA's SEASAT-satelliet in 1978 luidde het tijdperk van radar-oceanografie in. De inzichten die deze missie opleverde waren zo waardevol dat haar voortijdige einde, slechts drie maanden na de lancering, geen afbreuk deed aan haar succesvolle nalatenschap. Sterker nog, geruchten over sabotage verspreidden zich: men beweerde dat de remote sensing mogelijkheden van SEASAT militaire middelen in het gevaar hadden gebracht. De sabotage van SEASAT zou dan ook een kwestie van nationale veiligheid zijn geweest.

Zoals bij veel geruchten, zat ook hier een kern van waarheid in: SEASAT had inderdaad tal van mysteries opgehelderd, zij het voornamelijk binnen de natuurwetenschappen en niet met betrekking to complottheorieën. Desondanks was de waarde van satellietgebaseerde oceanografie nu duidelijk, en ruimtevaartorganisaties wereldwijd bleven niet stilzitten. Europa volgde snel met zijn eigen missies en lanceerde achtereenvolgens een reeks satellieten, waaronder ERS-1, ERS-2, ENVISAT en, sinds 2014, de Sentinel-1-constellatie.

Dankzij deze en vele andere instrumenten werden de afgelopen decennia gekenmerkt door voortdurende wetenschappelijke vooruitgang en ontwikkelingen binnen het vakgebied van de radar-oceanografie. Voortbouwend op deze rijke erfenis beoogt dit proefschrift twee afzonderlijke (maar met elkaar verweven) subdomeinen te bevorderen met betrekking tot beide zijden van de atmosfeer-zee raakvlak.

In de eerste helft van dit proefschrift, hoofdstukken 2 en 3, onderzoeken we de alom aanwezige, maar vaak over het hoofd geziene, atmosferische structuren die zichtbaar zijn in de meeste hoge-resolutie radarbeelden van de oceaan. Het lijkt misschien contra-intuïtief om de atmosfeer te bestuderen aan de hand van oceaanbeelden, maar een groot deel van de variabiliteit van het zeeoppervlak wordt door de wind aangedreven. Hierdoor fungeert het oceaanoppervlak als een spiegel van het bovenliggende windveld. Tot voor kort werden deze atmosferische structuren voornamelijk systematisch gebruikt in studies die (an)isotropie relateren aan windrichtingen. De informatie-inhoud is echter rijk en biedt veel meer mogelijkheden.

In hoofdstuk 2 tonen we aan dat er aanzienlijke hoeveelheden atmosferische informatie onbenut blijven. Door gebruik te maken van een domeingeïnspireerd coderingsschema transformeren we hoog-dimensionale radarbeelden naar een veel lager-dimensionale “latent space”, waaruit we aanzienlijk meer atmosferische informatie weten te extraheren dan met bestaande analytische methoden mogelijk is. In hoofdstuk 3 bouwen we hierop voort door gebruik te maken van de steeds groeiende catalogus aan Sentinel-1-observaties. We laten zien dat uit radar afgeleide atmosferische variabelen complementair zijn aan state-of-the-art en referentie-atmosferische schattingen. De uitdaging ligt hier in overtuigingskracht: hoe toon je aan dat nieuwe schattingen een aanvulling vormen op bestaande methoden wanneer er onvoldoende “ground truth”-metingen beschikbaar zijn om verschillen te verklaren? We proberen deze moeilijkheid

te ondervangen met een reeks kwalitatieve en kwantitatieve evaluaties.

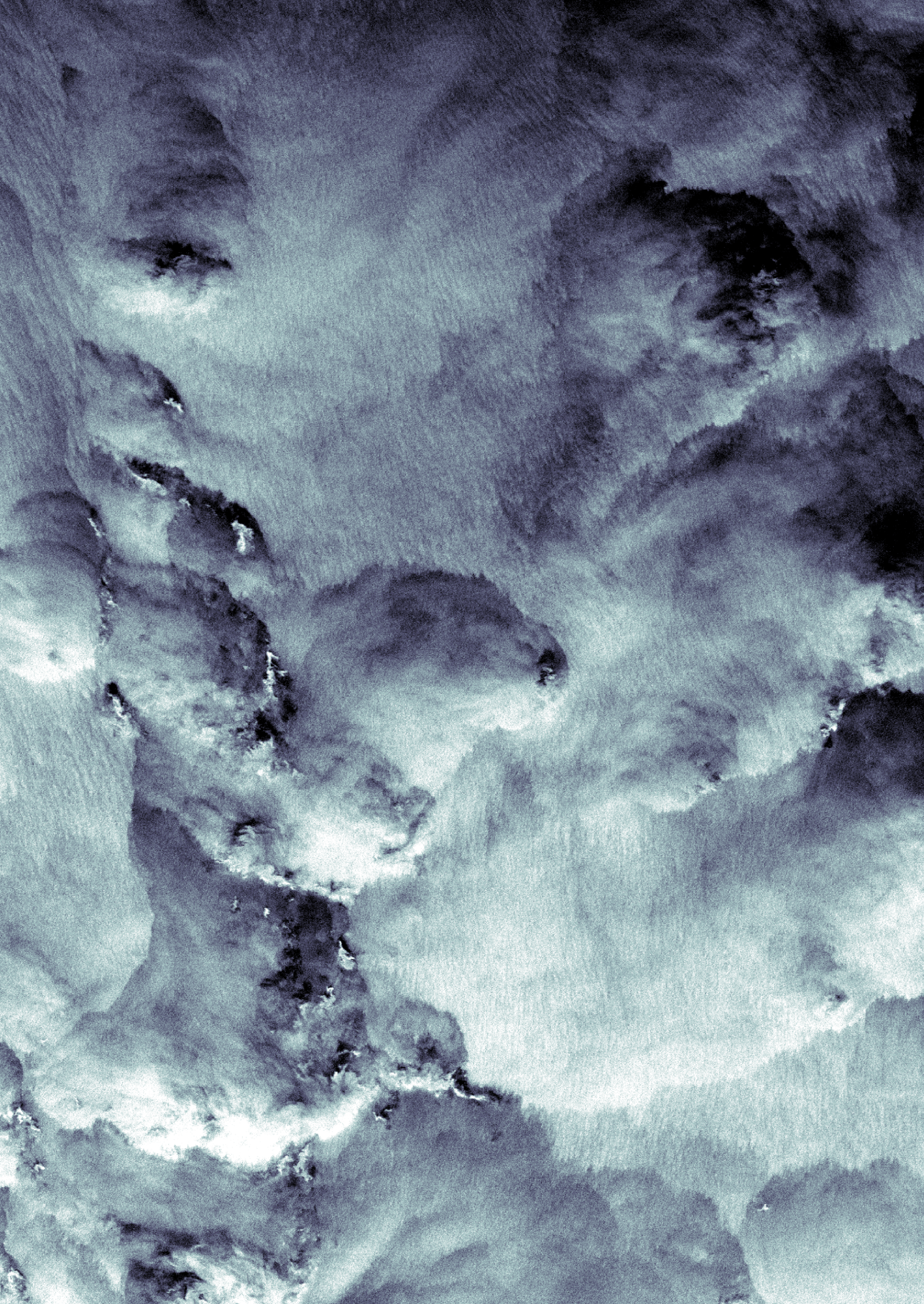
In de tweede helft van het proefschrift, hoofdstukken 4 en 5, richten we ons op de andere kant van de atmosfeer-zee-raakvlak en onderzoeken we verschillende methoden om oceaanstromingen te meten—een langdurige uitdaging in het veld van satellietgebaseerde oceanografie. Eerst bestuderen we in hoofdstuk 4 het afleiden van oceaanstromingen voor een voorgestelde satellietmodificatie, genaamd DopSCA. Dit systeem zou bij uitstek geschikt kunnen zijn om oceaanstromingen te meten, maar het onorthodoxe ontwerp maakt het gevoelig voor extra ruisbronnen. Eén daarvan, aangeduid als “leakage” wordt onderzocht om het potentiële risico voor de missie te beoordelen. Gelukkig blijkt dit een relatief beperkt probleem te zijn.

Vervolgens beschouwen we in hoofdstuk 5, met behulp van een heel ander instrument, een alternatieve methode om oceaanstromingen te meten aan de hand van polarimetrie. Hierbij maken we gebruik van de kruiscorrelatie tussen opervlakte golfbeweging, radar doorsnede en polarisatie om het samengevoegde signaal dat door de satelliet wordt ontvangen te ontleden. Simulaties en beperkte echte observaties laten zien dat deze aanpak een veelbelovende methode kan zijn om golfbewegingen te onderscheiden van oceaanstromingen. Toekomstige systemen met uitgebreidere polarimetrische mogelijkheden, zoals Harmony of Sentinel-1 Next Generation, zouden hier in het bijzonder van kunnen profiteren.

Kort samengevat, dit proefschrift onderzoekt mogelijkheden voor het meten van warmte- en momentumtransport (respectievelijk afkomstig van atmosferische convectie en oceaanstromingen) met behulp van verschillende radarsatellieten. In beide domeinen is vooruitgang geboekt: we presenteren de eerste kwantitatieve en met SAR afgeleide schattingen van lucht-zee warmtestromen en introduceren daarnaast een nieuwe methode voor het bepalen van oceaanstromingen. Maar geen zorgen, er blijft meer dan genoeg werk over om toekomstige radar-oceanografen bezig te houden ;)









# 1

## INTRODUCTION

Over the past few years, I've learned that it is best to present oneself as a radar expert when in the presence of oceanographers or atmospheric scientists, and vice versa when surrounded by electrical engineers. Now I must defend myself to both camps, at the same time. This dissertation is my attempt to carve out a subdomain bridging these fields, where I can comfortably refer to myself as a radar oceanographer (the title of radar meteorologist is already taken). So join me on this quest where, much like the alchemists of old, we aim to transmute an abundant commodity (plentiful radar observations) into one with greater intrinsic value (geophysical insights relating to the ocean and atmosphere).

### 1.1. THE MEASUREMENT VOID

A quick glance at most radar observations will convey the prevalence and diversity of geophysical processes at play in the air-sea-interaction submesoscale  $\mathcal{O}(0.1\text{-}100\text{ km})$ . The cover image on the previous page (approximately 150 km by 250 km) shows meandering wind streaks broken by large, energetic gusts from cold pools, which themselves contain signatures of rain cells. It is this interplay of local, small-scale processes that has repeatedly been identified as a significant driver of air-sea interaction (e.g. Cronin et al., 2019; Edholm et al., 2025; Iyer et al., 2022; Reymondet et al., 2026; Strobach et al., 2022; Su et al., 2018). But contemporary weather and climate models are coarse; all scales of variability contained within our radar image may be represented by a single grid cell. Since such coarse scales are insufficient to explicitly model small-scale processes directly, these are parameterized instead: simplified using several assumptions. But this parameterization process incurs a penalty in representability, such that small-scale phenomena, and in particular their deviations from the mean state, may no longer be represented accurately. Systematic misrepresentation of these small scales may even lead to accumulation errors in the large scales (e.g. Busecke et al., 2025; Moura et al., 2024, 2025, where the diversity in regional flux trends is attributed to unresolved small-scale processes and parameterization choices).

To resolve this predicament, one would need to overhaul existing parameterization schemes or develop much higher-resolution weather and climate models. Of course, high-resolution measurements are needed to constrain such developments.

For observations, there is generally a trade-off between coverage and resolution. Indeed, measurements with the highest spatiotemporal resolution tend to be highly local-

ized, such as moored buoys. These are great for validation, among other purposes, but they may lead to over-reliance on individual measurement platforms/arrays (e.g. Ricciardulli et al., 2025; S. R. Smith et al., 2011), and local point measurements will always be limited in their ability to represent regions beyond their immediate vicinity. Systems with greater coverage are needed.

Spaceborne remote sensing can provide that coverage, which is why these systems provide the best observations for vast swaths of Earth's oceans: there are often no in-situ alternatives. Yet remote sensing methods are limited in the geophysical variables they can retrieve and in the resolution at which they can be obtained. For some variables, such as air-sea heat fluxes and surface currents, there are simply no viable remote-sensing alternatives.

It is true that altimeters can already derive the geostrophic component of surface currents over much of the oceans, but not at the submesoscales of interest. Other systems do promise such high-resolution observations, particularly from high-resolution radars (e.g. Goldstein & Zebker, 1987; Romeiser et al., 2014), but these bring their own limitations and have thus far not been suitable for global use. One exception is the Harmony mission, which will enable high-resolution surface current retrieval in the near future (Lopez-Dekker et al., 2019), but its coverage remains insufficient for high-resolution global usage.

The field of air-sea heat-flux retrieval finds itself in a similar bind, as no singular satellite is capable of retrieving the fluxes in question, let alone at the desired  $\mathcal{O}(10\text{ km})$  scales. The state of the art consists of rerunning bulk formulae in which one input is retrieved from observations, rather than reanalysis (e.g. Asharaf et al., 2026). There have been several attempts at blending different satellite products with models to provide observation-inspired global flux estimates, notably J-OFURO3 (Tomita et al., 2019) and OAFLUX (Yu, 2019), but even these offer limited reliability for climate studies (IPCC, 2023).

Our oceans continue to respond to climate change, and are likely to do so for centuries to come. The full implications for our coupled climate system are not yet clear, in part for want of observational corroboration (IPCC, 2023; Pirani et al., 2024). Yet we find ourselves without eyes to systematically monitor and study essential contributions to the ocean's vertical heat fluxes or current-driven momentum transport. And without eyes, how can we task the brain to adapt and respond accordingly? There is thus a critical observational gap which necessitates not just more observations, but at ever higher resolution too (e.g. Y. Chen et al., 2025; Cronin et al., 2019; IPCC, 2023; Nuijens et al., 2024; Pirani et al., 2024; Wu et al., 2026). I would like to think that the work of Chapters 2-5 brings us a step closer to resolving this predicament.

## 1.2. RADAR OCEANOGRAPHY

Oceans are tricky things to measure. Imagine trying to describe the ocean's surface using the ephemeral impressions made on the eye: sometimes pristine blue pierced by white breaking waves, other times murky brown with suspended mats of biological matter. During overcast weather, it will be dark, while a smooth surface at sunset might cause blinding glints. But what does this kaleidoscope of properties mean? And can we even relate "blue-ness" or "sun-glinty-ness" to consistent geophysical phenomena? We will

need a more convenient set of properties to attempt science.

This is where radars come in. In the simplest sense, radars are like bats: they emit a signal which interacts with the world around, so that the returning echo carries information on a limited set of quantifiable properties. For instance, the delay between signal transmission and reception is indicative of target distance, repeated and coherent distance measurements (phase) through time provides motion (Doppler), the strength of the returning echo (magnitude) captures information relating to the size or dielectric properties of the target, while a rotation of the reflected echo's electromagnetic plane (polarization) informs us of the target's geometry.

These succinct parameters provide a systematic framework with which to describe something as complex as the ocean surface. And they do so for a fine range of wavelengths (usually in the centimeter-scale) rather than the broad purple to red optical range we observe visually. Thus, to interpret these disparate radar observables, we need only see the world through the lens of the centimeter-scale. In a sense, this greatly simplifies the nature of radar observation as compared to optical systems. And there are more benefits still. To monitor as much of the Earth's oceans as possible, you'll want to deploy your remote-sensing instrument on a satellite. This introduces all sorts of hurdles for optical systems, since Earth tends to be covered by clouds, masking vast swaths of the ocean. But unlike optical systems, common radar systems, such as those operating at C-band, transmit centimeter-scale,  $\lambda = \sim 0.055$  m, "radio waves" which are so large that they pass the cloud's tiny water droplets (almost) unaffected—imagine trying to catch air with a tennis racket.

Having established that radars effectively capture ocean-surface descriptors, what phenomena can we study using these descriptors? Here lies the objective of this dissertation: relating disparate radar observables to various geophysical phenomena. The chain of relations is outlined in Figure 1.1. We start with scattering processing at the centimeter-scale. These processes are regulated by larger oceanographic and atmospheric phenomena, leaving distinctive imprints in high-resolution radar observations. In this manner, radars can resolve much finer air-sea processes than those commonly resolved in model products, while erroneous parameterization of these processes may introduce large-scale aggregation biases.

The essential building blocks for our investigations have been laid down over the previous decades, relating, for instance, wave speed to Doppler, ocean surface roughness to backscatter, and scattering sources to polarization. In the next chapters, we will investigate what other air-sea properties can be deduced. But first, let us cover some background.

### 1.3. WIND, WAVES, AND CURRENTS

Aside from the electromagnetic waves that constitute the radar's probing tools, there are several distinct ocean waves relevant to this story, from centimeter-scale capillary waves to kilometer-long swell waves.

Capillary waves are the smallest ocean waves that we will consider, with wavelengths on the order of 1 cm or smaller (Holthuijsen, 2010; Ulaby & Long, 2014). These waves spring up quickly as the wind picks up, and they vanish once the wind dies down. Take a look at any pond or canal in the presence of wind gusts to observe this visual spectacle.

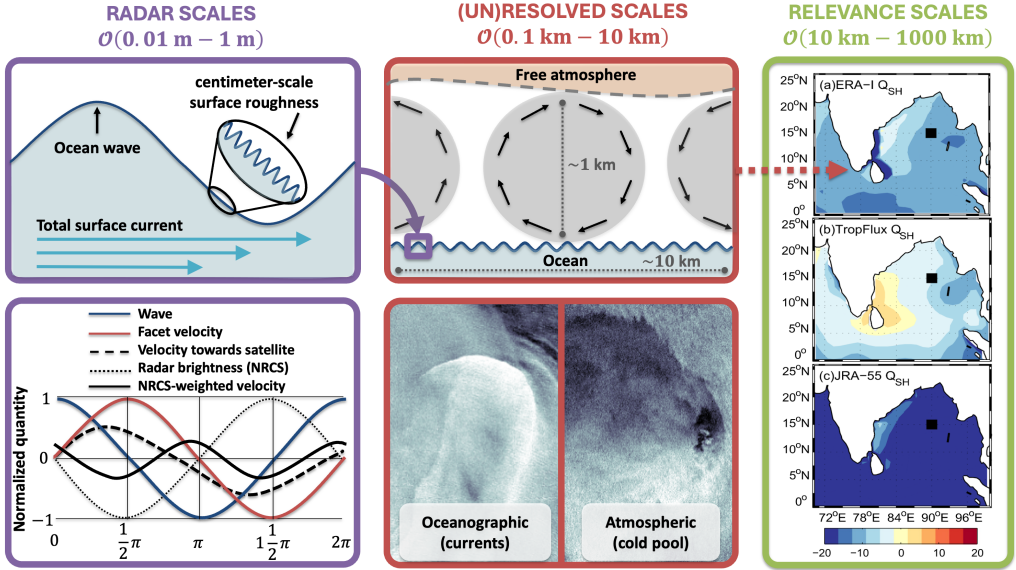


Figure 1.1: A journey across scales. Top left) the ocean surface contains roughness elements that interact with and reflect radio waves. The integrated reflections over a given area—resolution cell—are detected by the radar. Total surface currents represent the net mean motion of the considered water parcel, which can vary with depth. Lower left) radar brightness and wave velocity for a simplified wave, adapted from Chapron, 2005. The correlation between radar brightness and satellite-projected velocity results in a convoluted perceived velocity signal. Top center) the atmospheric boundary layer sits between the ocean surface and the free atmosphere. High-resolution radars can resolve atmospheric and oceanographic processes that impart characteristic roughness patterns onto the ocean surface. These scales are typically unresolved in weather/climate models, despite growing evidence of their outsized contribution to net air-sea exchanges. Lower center) radar brightness cutouts from the page-wide inter-chapter images. Air-sea processes locally enhance/suppress surface roughness, affecting the observed radar brightness. This results in sharp delineations of a current front on the left and the asymmetric brightness response of a cold pool on the right. Right) multi-year mean sensible heat fluxes over the monsoon season derived from three different heat-flux products (obtained from Sanchez-Franks et al., 2018). These models are too coarse to resolve critical  $\mathcal{O}(0.1 \text{ km}-10 \text{ km})$  scales, thus having to resort to different parameterization schemes. The model outputs differ significantly, even disagreeing on the sign of the flux. In-situ validation is limited to a single buoy represented by the black square, which not only complicates the characterization of model performance but also indicates the limited availability of measurements for developing, constraining, and evaluating model outputs. Assimilation of new spaceborne air-sea parameters may improve future model performance, perhaps alleviating similar large-scale biases.

Moving up in size, we reach gravity waves, the smallest of which are just a bit larger than capillary waves, but they respond as rapidly to the winds. Gravity waves are distinct from capillary waves in that their restoring force is no longer dominated by surface tension—as is the case for capillary waves (Holthuijsen, 2010)—and is instead governed by gravity. From a remote sensing perspective, it is important that capillary/gravity waves are similar in size to the radar’s centimeter-scale electromagnetic waves, enabling the latter to interact with and resonate with the former. Essentially, the radars considered in this dissertation “see” these small centimeter-scale waves superimposed on larger waves, as in the top left panel in Figure 1.1. These larger waves or other effects are primarily relevant in that they can modulate the small waves. The breaking of large,

meter-scale waves, for instance, will simply spawn many little centimeter-scale waves, whilst oil slicks will suppress them instead.

When winds are persistent, gravity waves continue to grow into meter-scale wavelengths and beyond. Now the winds can disappear, but the waves will persist, at least for some time. The maximum wavelength of these waves depends on the duration and strength of the winds to which they were exposed. It is not uncommon for waves to reach wavelengths in the order of several hundred meters, and under extreme conditions, they can even exceed a kilometer. When systems of such waves propagate across oceans, they separate along wavelengths into trains with faster/slower phase speeds. Thus, sufficiently far from the wave's origin, and once the faster and slower waves have separated, one can observe neatly periodic waves called swell waves. If you surf, these waves are your friends.

Currents complicate the whole story by bending and refracting surface waves. This modulates the centimeter-scale waves and can even cause wave breaking, both of which affect the reflectivity observed by our radars (V. Kudryavtsev et al., 2005). Making things more complicated is the fact that surface currents vary with time, depth, and horizontal location; currents at 100 m depth might be oriented opposite currents at 1 m depth, which could be perpendicular to the current at 1 cm depth. Things become still more complicated when we consider that the ocean surface is neither flat nor stationary, with vertical wave undulations interfering with our neat conceptual model of homogeneousness and lateral translations. It is often pragmatic to discard some of these complexities and refer to a “total surface current” (TSC), which is some averaged horizontal translation accounting for all current components close to the surface (i.e., geostrophic currents, wind-driven currents and Stokes drift, Gille et al., 2025).

## 1.4. ATMOSPHERIC STABILITY AND HEAT FLUXES

On average, the oceans are slightly warmer than the atmosphere above. In response to this thermal disequilibrium, the oceans warm up the lowest layer of the atmosphere through conduction. This is called sensible heat transfer. The warming air parcel expands, decreasing its density but increasing its capacity to hold moisture. A decreased density makes this air parcel lighter than the cold air above it. Buoyant forces take control and propel the warm parcel upwards, allowing colder, heavier air to take its place. While rising, this buoyant parcel of air starts to cool, till at some point it has cooled so much that it can't hold on to the moisture it had picked up earlier. Moisture begins to condense into tiny suspended water droplets, sometimes forming visible clouds. Condensation releases large amounts of energy, known as latent heat, which provides a second impetus, propelling the air parcel further upwards. Latent heat transfer is generally an order of magnitude greater than sensible heat transfer (Stull, 1988). But now our air parcel has exhausted its main stores of energy, and it shall rise no further (unless cloud dynamics take over or the boundary layer has been pierced, Stull, 1988). In the meantime, the air at the ocean surface has warmed again, and its ascent forces the depleted air parcel to descend. The convective cycle, such as illustrated in the center of Figure 1.1, continues until an equilibrium state is reached.

That part of the atmosphere which is directly affected by the cycle of heating and cooling is usually referred to as the atmospheric boundary layer (Stull, 1988), with the

free atmosphere above. This boundary layer is often no more than a kilometer in height—the choice of nomenclature can be quite insightful here, as one’s background usually determines whether the boundary layer is described as having a height or a depth—and, over the oceans, tends to be in a state of disequilibrium.

In addition to vertical and kilometer-scale buoyancy-driven transport, we may also find horizontal and synoptic-scale  $\mathcal{O}(1000\text{ km})$  pressure gradients. These gradients give rise to large-scale horizontal wind patterns, such that local buoyancy-driven turbulence (in response to a vertical disequilibrium) is superimposed on large-scale shear-driven turbulence (resulting from a horizontal disequilibrium). Different metrics exist to quantify the balance between the horizontal and vertical components. One used frequently in this dissertation is the Obukhov length (Monin & Obukhov, 1954), but others exist as well.

More important than the naming convention of this balance is the fact that different combinations of vertical/horizontal turbulence result in different atmospheric structures inhabiting the boundary layer: pure vertical convection tends to structure along horizontally isotropic Rayleigh-Bénard type convection, illustrated in Figure 1.1 (like boiling water in a pan), to maximize vertical transport efficiency, whereas horizontal shear-driven convection tends to follow horizontally linear and anisotropic structures instead. Since these structures form within the boundary layer, they are constrained by its size. Therefore, the kilometer-scale organization of the atmospheric wind field encodes substantial information about the atmospheric state.

## 1.5. THE USUAL SUSPECTS (OR TOOLS OF THE TRADE)

Certain instruments and concepts are repeatedly mentioned throughout the chapters of this dissertation. I’d like to briefly describe several recurring ones in one place.

### 1.5.1. SCATTEROMETERS

Scatterometers are the workhorses of spaceborne radars. These satellite platforms generally carry a radar with multiple transmitters/receivers, which, when pointed in different directions, provide wide spatial coverage (global coverage in days) at a relatively low spatial resolution,  $\mathcal{O}(10\text{ km})$ . Different flavors of scatterometers exist (e.g., push-broom/pencil-beam, C/Ku/Ka-band), but these are irrelevant for our story. The *raison d’être* of scatterometers is the retrieval of global ocean vector wind fields. This is a task at which they excel due to their multiple viewing geometries, broad spatial coverage, and high radiometric fidelity.

Scatterometers primarily hold an indirect relevance to this dissertation (with the exception of Chapter 4, where we investigate the performance of a Doppler-targeting scatterometer design). But it is within the context of the scatterometer’s well-established conventional capabilities that the objectives of this dissertation should be understood; we are exploring new applications of high-resolution radars to study air-sea interactions for which the default spaceborne tools—scatterometers—seem less suitable.

### 1.5.2. SYNTHETIC APERTURE RADAR

Synthetic Aperture Radars (SAR) are the cool siblings of scatterometers. They generally carry a single, more complex radar, leading to reduced global coverage (which can take a week or more), but with much richer localized observations. This allows SARs to be used for a diverse range of remote sensing tasks.

It would be easy to go on raving about the unique properties, abilities, or workings of SAR, but for Chapters 2 till 5 it is primarily relevant that SARs can image the oceans at relatively high spatial resolutions,  $\mathcal{O}(0.1 \text{ km})$ . For Chapter 5, it is additionally relevant that SARs can be used to infer surface velocities.

### 1.5.3. REANALYSIS

In-situ measurements of atmospheric or oceanographic quantities are generally considered “ground truth”. Unfortunately, they are both complex and expensive to acquire. To make up for the resulting dearth of observations, different models have been designed to combine local measurements with some theoretical framework to fill in measurement voids (of which there are many). These are so-called reanalysis products, because they combine observations with models to re-assess the most likely past atmospheric states. In that sense, they differ from forecasting models, which predict some future state. The most prevalent reanalysis product at the moment is probably the European Centre for Medium-Range Weather Forecasting (ECMWF) fifth generation reanalysis: ERA5. Its popularity is attested by the whopping  $\sim 27 \text{ k}$  citations listed on Google Scholar for the introductory paper (Hersbach et al., 2020). Nonetheless, ERA5 should not be seen as a substitute for some absolute truth, and its effective resolution is rather coarse (closer to  $\mathcal{O}(100 \text{ km})$  based on its spectral characteristics), compared to the air-sea interactions sub-mesoscales of interest,  $\mathcal{O}(1\text{-}100 \text{ km})$ . Thus, it can provide a decent constraint on large-scale phenomena, but it does not explicitly resolve all the observed scales. Furthermore, large differences can occur between different reanalysis products, see the right panel of Figure 1.1, illustrating the need for additional observational corroboration

Reanalysis products such as ERA5 pop up in all chapters of this dissertation, but they are particularly relevant for Chapters 2 & 3, where they provide the main source of reference data.

### 1.5.4. GEOPHYSICAL MODEL FUNCTIONS

Stronger winds increase ocean surface roughness, or stress, which in turn results in more radar backscatter. Deriving an analytical expression between backscatter and wind speed (or other properties) is rather tedious. Instead, empirical relations are used to describe observed quantities as functions of relevant parameters (e.g., observational properties, wind parameters, sea-state descriptors, etc.). These are so-called Geophysical Model Functions (GMFs). In this dissertation, we mainly use wind-retrieval GMFs to estimate the wind magnitude at 10 m above the surface. The most popular GMFs for C-band observation platforms are probably those from the CMOD family. But other GMFs exist as well, such as those used to estimate wind-induced wave Doppler (e.g., CDOP, also for C-band, from Mouche et al., 2012).

Often we can't be sure whether wind or another phenomenon led to changes in observed roughness; for the same 10 m mean horizontal wind speed, an unstable atmo-



sphere causes more turbulence and surface roughness than a neutrally stratified atmosphere. With this in mind, retrieval models have been designed to predict a so-called stress-equivalent wind, i.e., a hypothetical wind resulting from assumed stress conditions. Then, if one knows the true stress contributors, these can be combined with the stress-equivalent wind to estimate the true wind.

Importantly, common wind-retrieval GMFs do not account for all sources of non-wind stress. For instance, CMOD5.N explicitly accounts for atmospheric stability by providing an equivalent neutral wind (i.e., with known stability conditions, the equivalent neutral winds can be converted to a true wind speed), but it does not account for air density fluctuations, local sea-state variations, and surface currents. Yet all of these affect the wind's ability to exert stress on the ocean surface (de Kloe et al., 2017; Hersbach, 2010). Thus, GMF retrievals, such as those from CMOD5.N, should be understood to represent the average stress-equivalent neutral winds sampled from a distribution of potential stress contributions observed during the model's fitting stage. This verbose, caveated description and the “10 m stress-equivalent-neutral” prefix are often dropped in this dissertation when discussing GMF retrieval products.

GMFs are relevant for all chapters of this dissertation. In Chapters 2 & 3 they are used to negate the incidence-angle dependence of backscatter observations, in Chapter 4 they are used to translate radar observables from one viewing geometry to another, and in Chapter 5 we essentially develop our own GMF for wind-related Doppler, rather than wind (though the principles remain the same).

## 1.6. EXISTING RESEARCH GAPS

This dissertation could be split into two, though two sides of the same coin (if the coin represents the air-sea interface). The first half, with Chapters 2 & 3, focuses on phenomena occurring above the interface—the lower atmosphere—and how it can indirectly be studied using radar observations of the ocean. Then, in the second half, Chapters 4 & 5, the focus shifts to the other side of the air-sea interface, and how radars can be used to measure surface currents.

### 1.6.1. FLUXES: WHAT TO DO WITH ALL THIS ATMOSPHERE?

Take a look at any high-resolution radar image of the ocean, and you'll likely find the atmosphere staring back at you; winds imprint characteristic roughness patterns on the ocean surface, mirroring atmospheric structures, which enable roughness-measuring radars to indirectly trace various atmospheric processes, see Figure 1.1. But what to do with all this beautiful and high-resolution atmospheric information? Until quite recently, the response to this question would be: just throw it all away. So it came to pass that only the coarsest scales of atmospheric information would be considered worthy of investigation (looking at you, scatterometers), and even that wasn't without a struggle, as Brown, 2000 recounts. Attitudes began to change around the turn of the century, with efforts to extract at least some of the rich atmospheric information. One of these, focusing on atmospheric-stability estimation from a singular SAR scene (Young et al., 2000), will prove central to this dissertation. But these efforts were ahead of their time and, due to practical restrictions, rarely strayed beyond individual case studies. It would be another

two decades before a systematic inventorization, powered by new algorithms, evidenced the prevalence of all these atmospheric signals (C. Wang, Tandeo, et al., 2019).

It is just after this point in time that I began work on this dissertation. From the start, the research objective was limited in scope to a validity assessment of previous efforts by Young et al., 2000, to infer atmospheric conditions from SAR spectra, but then extended to a broader range of conditions than the original singular case. Hence, the first research question reads:

**Question 1** *Can radar-observed surface textures quantifiably inform us of the atmospheric stability conditions at the surface?*

This question is tackled in Chapter 2, for which the conclusion can succinctly be put as: no, but also yes. Although we were unsuccessful in replicating the atmospheric stability retrieval using the proposed analytical methodology, empirical methods offered an alternative way forward.

The beauty of empirical methods lies in their ability to leapfrog lapses in current knowledge, whereas analytical approaches are susceptible to getting bogged down in details (e.g. a review of 25 years of studies to determine whether the von Kármán *constant* used in atmospheric stability retrieval should be fixed at 0.35, 0.41, or maybe 0.65 after all, Högström, 1996). Meanwhile, if an empirical approach bears fruit, you can return with new insights and refine your analytical methodology. And, if it doesn't work, then at least you didn't worry needlessly about tuning details.

This comparison is a little unfair since empirical methods introduce their own headaches. For one, they require vast quantities of “ground truth” data to learn any empirical relation. But global measurements on air-sea interactions are sorely lacking (which is one of the motivators for space-borne retrieval of these parameters!). Therefore, we've had to develop our empirical methodology using one of the few available sources of global reference data: the ERA5 reanalysis product.

Given that we are limited to this single reference (which itself can be flawed), this raises the obvious question: how can we determine whether a radar-derived product trained on ERA5 is better or worse than ERA5? This challenge is tackled in Chapter 3, where we assess complementarity between radar-derived fluxes and existing reference products. The central question reads:

**Question 2** *Are SAR-derived air-sea interaction variables complementary to state-of-the-art reference sources?*

### 1.6.2. FLOWS: WAVE MOTION AND SURFACE CURRENTS

Had Indiana Jones been a radar oceanographer, his Holy Grail would have been the retrieval of accurate surface currents. Radars seem like the ideal tool for this task, owing to their ability to measure precise velocities. And indeed, almost forty years ago, this problem seemed solved (Goldstein & Zebker, 1987). Yet here we are, many years later, still attempting the same feat.

Up till now, remote sensing systems have enabled us to study surface motions on either very large scales (e.g., altimeters'  $\mathcal{O}(100\text{ km})$  scales), or highly localized on small scales (e.g., SAR over a river or tidal plane). I specifically use the word “motion” because

no system directly yields what we would consider a surface current. Altimeters rely on a geostrophic balance, which assumes that pressure gradients are in balance with the Earth's Coriolis force. This assumption is generally valid far from the equator and for very large scales,  $> \mathcal{O}(100 \text{ km})$ , but it starts to fall apart for smaller scales or near the equator (Taylor & Thompson, 2023). And although alternative retrievals using Doppler-targeting radars seem promising at first, as in Goldstein and Zebker, 1987, they are sensitive to a host of other unwanted surface motions. In fact, it has long been known that the correlation between the varying orbital velocity of waves and their relative radar brightness introduces a so-called “wave Doppler” (Chapron, 2005). Thus, even without any net surface motion, wave Doppler can introduce an apparent net Doppler signal that is an order of magnitude greater than the surface currents of interest.

This wave Doppler is distinct from Stokes drift (the net horizontal motion resulting from passing waves), which is similarly caused by waves; wave Doppler is dependent on the observation geometry and could be viewed as a mathematical aggregation bias, whereas Stokes drift is measurement-independent and represents a *real* net translation. Since both processes are intrinsically linked to waves, they are hard to differentiate from a measurement perspective.

Chapters 4 & 5 focus on disparate radar-based surface-current retrieval schemes that explicitly account for this wave Doppler. Chapter 4 focuses on DopSCA: a proposed expansion of capabilities for the next generation of the European scatterometer program. Before getting into the details of DopSCA, it is important to recall that scatterometers are designed with wind retrieval over the oceans as their primary objective. Hence, scatterometers provide some of the most timely and accurate wind estimates. The correlation between wind speed and wind-driven wave Doppler is relatively well established (e.g. Mouche et al., 2012), such that scatterometers capable of retrieving Doppler in addition to wind vectors would be well placed to remove the unwanted wave-Doppler component. But most scatterometers ignore surface velocities and instead allocate their resources to optimal wind retrieval.

Here DopSCA differs from the pack. The underlying idea of DopSCA is quite simple: send out two radar pulses in quick succession such that the coherent phase change between pulses captures the surface displacement over time, i.e., a motion. Thus, DopSCA can obtain both surface motions and winds! Unfortunately, its motion-monitoring capabilities could generously be described as non-ideal. For this reason, several analyses have been conducted to determine the expected level of performance. In Chapter 4 we focus on one uncertainty source in particular, which we coin “leakage”, since it relates to the leakage of platform motion into the perceived surface motion. Other names have been used to describe the same phenomena, such as non-uniform beam filling, but these describe the cause rather than the effect. It is perhaps relevant to note that leakage stems from the fact that satellites like DopSCA whiz around our planet at kilometers per second, which is orders of magnitude faster than even the strongest surface currents. Confounding these two signals, even just a little, will percolate as huge errors in the surface-current estimation. Therefore, the central question asked in Chapter 4 reads:

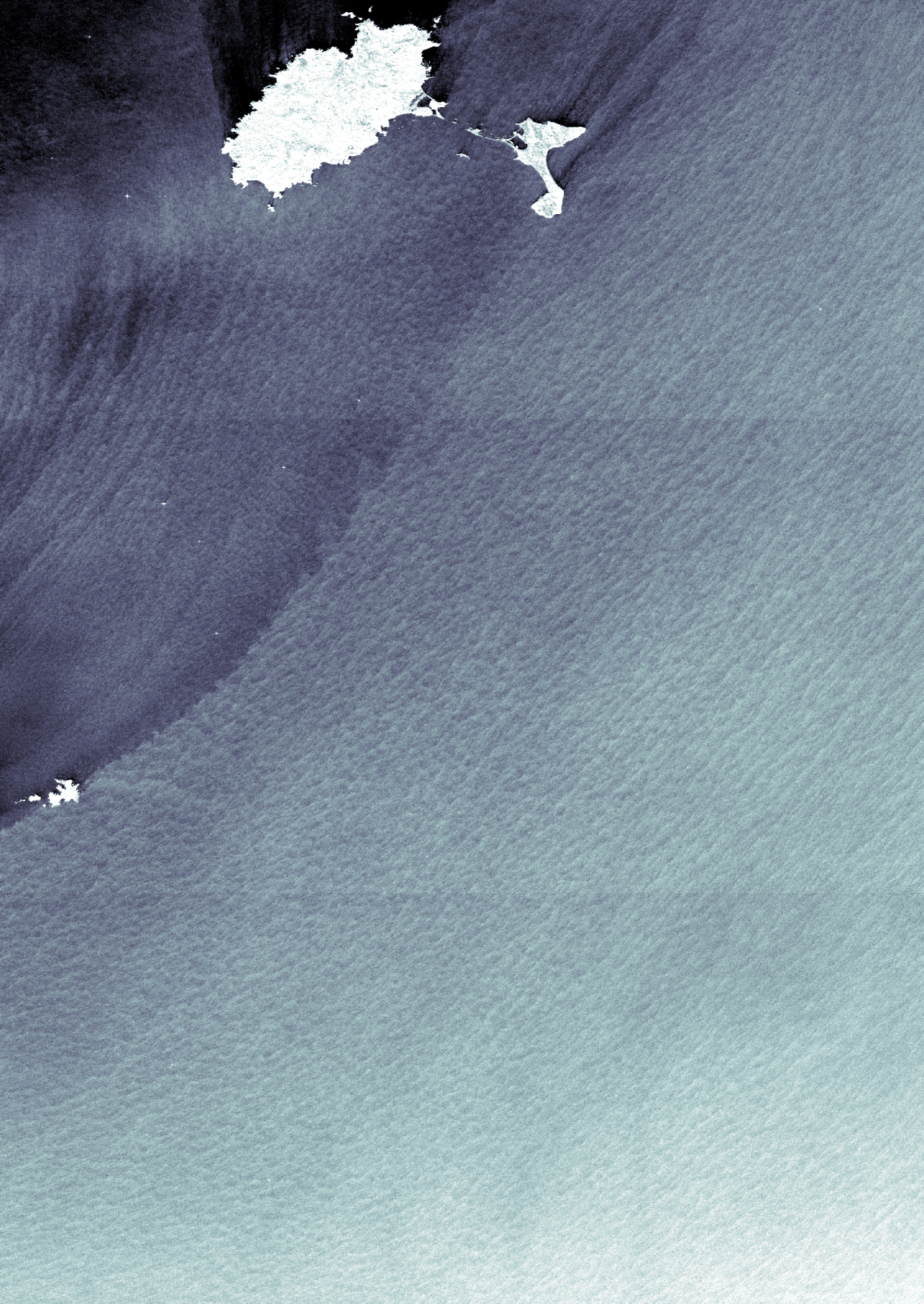
**Question 3** *Does leakage of geometrical Doppler into the perceived geophysical Doppler jeopardize surface-motion retrieval of Doppler scatterometers?*

The aforementioned DopSCA system would rely on knowledge of the wind field to remove the undesired wind-driven wave-Doppler contribution. But existing theoretical frameworks, such as those by Hansen et al., 2012; V. Kudryavtsev et al., 2005, suggest an alternative separation strategy could utilize radar polarimetry instead. In Chapter 5, we assess whether a polarimetric decomposition of unique polarized observables could indeed achieve wave-Doppler separation without needing ancillary wind or wave information. The proposed technique is not unlike that used in a simple pair of sunglasses, where polarimetry removes blinding reflections from a windshield or water body. The last research question reads:

**Question 4** *To what extent can wind-driven wave Doppler be separated from surface currents using polarized radar observables?*

We have now completed our trinity of radar observables, harnessing the power of backscatter intensity in Chapters 2 & 3, (simulated) Doppler in Chapter 4, and Doppler and polarimetry in Chapter 5. What can we conclude from this exercise? Firstly, that radars are uniquely sensitive, through various mechanisms, to the air-sea processes of interest. Secondly, more information on high-resolution air-sea processes can be retrieved from radar observations than previously shown. Lastly, this information sheds light on spatiotemporal scales that are commonly unresolved in model/reanalysis products, paving the way for radar-based observations to inform and validate new generations of weather and climate models through process studies or direct assimilation.







# 2

## OBUKHOV LENGTH ESTIMATION FROM SPACEBORNE RADARS

*All beginnings are marked by error, as fire is by smoke*

Krishna

*Two air-sea interaction quantification methods are employed on synthetic aperture radar (SAR) scenes containing atmospheric-turbulence signatures. Quantification performance is assessed on Obukhov length,  $L$ , an atmospheric surface-layer stability metric. The first method correlates spectral energy at specific turbulence-spectrum wavelengths directly to  $L$ . Improved results are obtained from the second method, which relies on a machine-learning algorithm trained on a wider array of SAR-derived parameters. When applied to scenes containing convective signatures, the second method is able to predict approximately 80% of observed variance with respect to validation. Estimated wind speed provides the bulk of predictive power while parameters related to the kilometer-scale distribution of spectral energy contribute to a significant reduction in prediction errors, enabling the methodology to be applied on a scene-by-scene basis. Differences between these physically-based estimates and parameterized numerical models may guide the latter's improvement.*

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This chapter is adapted with minor edits from O'Driscoll, O., Mouche, A., Chapron, B., Kleinherenbrink, M., & López-Dekker, P. (2023). *Obukhov length estimation from spaceborne radars*. [Geophysical Research Letters](#), 50(15), e2023GL104228.

## 2.1. INTRODUCTION

Oceans regulate our climate system, with ocean warming accounting for over 90% of the Earth's energy inventory increase between 1971 and 2010 (IPCC, 2014). Fluxes across the air-sea interface are driven by kilometer-scale coupled processes. Temperature variations and gradients at the interface can change near-surface stratification properties. Resulting air-sea fluxes of momentum, heat, and water vapor are also affected. On the atmospheric side of this interface, these near-surface stratification properties are generally traced by the occurrence of organized, large, coherent structures.

Indeed, for decades it has been known that wind fields contain atmospheric stability information within their kilometer-scale organization (e.g. Figure 12 Grossman, 1982). Vertical temperature and wind gradients lead to microscale convection,  $\mathcal{O}(10^2 - 10^3 \text{ m})$ , whereas large-scale horizontal gradients result in mesoscale convection,  $\mathcal{O}(10^3 - 10^5 \text{ m})$ , (Fiedler & Panofsky, 1970; Lilly, 1989). Today, global climate models parameterize the kilometer-scale convection. Future models with the capacity to fully capture all scales of convection up to a climatological level are still decades away (e.g. National Academies of Sciences, 2019; Rio et al., 2019). To aid the representation of kilometer-scale marine atmospheric boundary layer (MABL) properties—necessary to project the impact of changing coupled air-sea interactions on a climatological scale (Christensen & Zanna, 2022; Cronin et al., 2019)—more observational quantitative estimates are necessary. Yet, over the oceans, direct insight into the small-scale boundary-layer processes remains rather difficult. Field campaigns (e.g. Bony et al., 2017) are conducted locally with high costs, and optical satellite images are often limited due to low-resolution and high cloud coverage. Synthetic aperture radar (SAR) satellite observations have been proposed as a solution to resolve this data gap (Sikora & Ufermann, 2004). SAR measurements can indeed capture and quantify sea-surface roughness changes induced by the MABL-stratification properties (Alpers & Brümmer, 1994; Sikora et al., 1995; Vandemark et al., 2001). The visibility of MABL-related coherent structures on SAR images is quite systematic as perturbations of surface winds at kilometer-scales, which modulate the centimeter-scale ocean roughness, leave measurable imprints (C. Wang, Tandeo, et al., 2019; C. Wang et al., 2018, 2020).

At medium scales,  $\mathcal{O}(10 \text{ km})$ , first-order wind-field statistics can quantify momentum fluxes, but are generally insufficient at distinguishing between atmospheric regimes. This is illustrated by the upper two SAR-derived wind fields presented in Figure 2.1. Despite similar median wind characteristics, corresponding wind-field textures suggest different atmospheric surface-layer stability regimes. This stability is quantified following surface-layer similarity theory from Monin and Obukhov, 1954 in

$$L = - \frac{\overline{T_v} u_*^3}{\kappa g w' T_v'}, \quad (2.1)$$

where friction velocity  $u_*^3$  captures the wind-stress related shear production of turbulence and  $\overline{w' T_v'}$  the heat-flux related convective production (Stull, 1988).  $T_v$  is the virtual temperature,  $\kappa$  the von Kármán constant and  $g$  the gravitational acceleration. The resulting Obukhov length  $L$  could therefore be seen as the balance between two competing sources of turbulence. For greater wind speeds, the shear component generally



dominates, forming roll-like wind-field structures. At low wind speeds the convective component dominates, and cell-like structures are formed. Therefore cell- and roll-like structures span different, though partially overlapping, parts of the wind-speed range. Obukhov length is proportional to the atmospheric stability parameter  $\zeta$  following

$$\zeta = \frac{z}{L} \quad (2.2)$$

with  $z$  being the measurement height. A negative  $\zeta$ -sign represents unstable conditions. This study works with a constant measurement height of 10 m such that the inverse of  $L$  gives consistent insight into atmospheric stability.

Co-located reanalysis data from the European Centre for Medium-Range Weather Forecasts' (ECMWF) ERA5 confirms that  $L$  corresponding to the second wind field, whose cell-like texture contrasts the streaky patterns of the former (ignoring the swell), indicates greater instability. SAR measurements are thus apparently capable of capturing high-resolution,  $\mathcal{O}(10^1 - 10^3 \text{ m})$ , surface wind-field perturbations, which contain information on the local stability conditions.

Young et al., 2000 first proposed to estimate atmospheric surface-layer stability from SAR imagery by relying on work from Kaimal et al., 1972, 1976, and assuming that the wind-field's spectral amplitude within the microscale inertial subrange is related to atmospheric turbulence. Though this analysis yielded promising results on a handful of case studies (e.g. Sikora & Thompson, 2002; Sikora et al., 2000), when applied on a greater collection of SAR scenes its flaws become apparent. The lower graph in Figure 2.1 indicates that the wind-field spectral amplitude obtained from SAR scenes (y-axis) does not uniquely correspond to an atmospheric stability (x-axis) for convective scenes observed with similar wind speeds and viewing geometries (i.e. similar backscatter amplitudes); spectral amplitudes contain too little information to discriminate between atmospheric stability properties. Furthermore, Young's approach requires a clear spectral peak and inertial subrange within the microscale, a range often obscured in SAR-derived spectra due to the presence of long-wavelength swell (an inevitable consequence of global analyses) or imaging artifacts. Additionally, the selection of constants in Young's approach implicitly assumes a specific (currentless) sea state and atmosphere (e.g.  $a = 0.011$  and  $\Psi = 0.6$  in Equations 3 and 11 of Young et al., 2000 respectively). A clear microscale and adherence to specific sea- and/or atmospheric states cannot be guaranteed for global analyses.

To overcome these uncertainties, a greater quantity of kilometer-scale wind-field information is thus likely necessary. In this study, several additional parameters are derived to improve the characterization of the wind-field's distributed variance, in addition to first-order parameters (such as median wind speed) and parameters originally derived in Young's analytical methodology. Machine Learning (ML) is then employed to connect the additional wind-field information to  $L$ . The addition of ML is intended to make up for the lack of an analytical framework through which to combine all derived parameters, to compensate for incorrect assumptions (such as those related to the sea state and atmosphere), to squeeze out extra information on the atmosphere which remained untapped in the purely analytical method and to facilitate the analysis of vast quantities of observations.

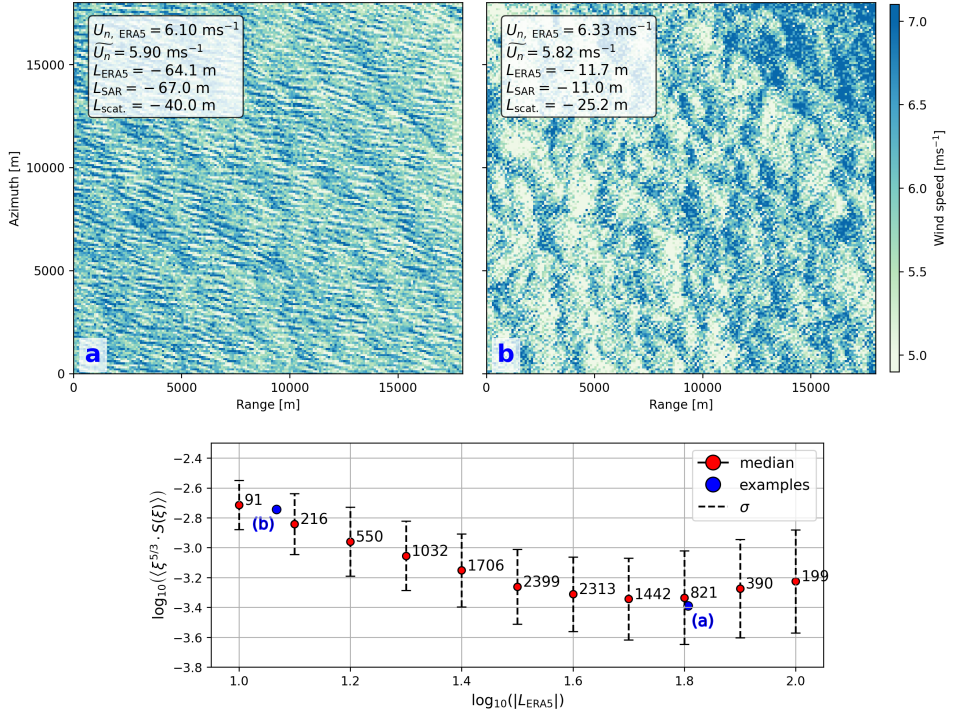


Figure 2.1: Two 10 m stress-equivalent neutral wind fields (upper panels) calculated from Sentinel-1B, date: 06-04-2020, absolute orbit: 021017, vignette: 70, product unique ID: BD8A (left) and Sentinel-1A, date: 09-03-2021, absolute orbit: 036917, vignette: 128, product unique ID: 5608 (right), using the CMOD5.N geophysical model function (Hersbach, 2010). (Lower panel) Atmospheric instability from ERA5 (only unstable conditions considered) versus mean normalized spectral amplitude within the estimated inertial subrange for a specified number of SAR scenes classified as wind streaks or micro convective cells obtained from the same incidence angle (WV2) and similar wind speeds ( $U_{n, \text{ERA5}}: [5.5, 6.5] \text{ ms}^{-1}$ ). Location on the graph highlighted for the upper left (a) and upper right (b) wind fields.

Since the launch of ESA's Sentinel-1 missions in 2014 (Sentinel-1A) and 2016 (Sentinel-1B), millions of SAR observations over the oceans have been acquired, capturing a wide variety of air-sea environmental conditions. Noteworthy is the SAR-image classification work by C. Wang, Tandeo, et al., 2019 which provides a means of selecting a subset of convective SAR observations. The aim of this paper is thus to quantify  $L$  for convective SAR scenes in a regression sense, rather than in terms of classification (e.g. the ternary stability classification of Stopa et al., 2022). The analysis is first performed on 124,682 SAR scenes, classified as containing convective wind streaks (referred to as rolls throughout this study) to determine to what extent it is possible to further discern between  $L$ 's within one of Wang et al.'s convective classes. Afterwards, the scope is extended by including a similar number of micro convective cells (referred to as cells) to determine the applicability of the approach on a broader range of convective conditions and to assess the importance of kilometer-scale SAR-detected features. Validation is performed by a comparison and regression towards co-located retrievals from ERA5. In Appendix A.1

the suitability of ERA5 for validation is assessed through a comparison with a smaller secondary data set comprised of moored buoys.

## 2.2. DESCRIPTION OF DATA

### 2.2.1. OBSERVATIONS

C-band Synthetic aperture radars (SAR) onboard the Sentinel-1 constellation are sensitive to surface roughness variations on the centimeter scale and thereby insensitive to most phenomena occurring in the atmosphere. SARs are thus incapable of measuring atmospheric turbulence directly. Instead, SAR quantitatively traces short-scale turbulence-induced roughness patterns on the ocean surface and indirectly approximates the projection of the atmospheric turbulence spectrum. Naturally, roughness patterns may be contaminated by other phenomena that affect the ocean surface, such as swell, biological films, rain, etc.

Sentinel-1's C-band radars operate at various exclusive modes with different polarizations. This study uses WaVe mode (WV) observations with a resolution of 5 by 5 m. Measurement and processing artifacts such as smearing, azimuthal cut-off and velocity bunching (e.g. Brüning et al., 1990; Kerbaol et al., 1998; Rizaev et al., 2022) reduce the effective resolution by orders of magnitude. The WV scenes are then resampled to 100 m resolution. All analyzed images are obtained with the radar transmitting and receiving in VV polarization. A total of 249,496 pre-classified WV scenes are selected within the years 2020-2021, which, according to the convolutional neural network from C. Wang, Tandeo, et al., 2019, contain 124,682 rolls and 124,814 cells. The observations are evenly distributed over both years and Sentinel-1 sensor platforms. The estimation of 100 m resolution wind fields from SAR observations and a geophysical model function (GMF) is provided in Appendix A.1. Filtering of observations is described in Appendix A.2, which aims at reducing noise by removing misclassification and images with poor convective signatures.

### 2.2.2. VALIDATION

This study uses two validation sources: gridded global reanalysis from ERA5 and point-wise observations from various buoys. Acquisition details for both are described in Appendix A.1. ERA5 is used in direct comparison with our estimates. Buoy observations are used as a check on ERA5's validity.

Global hourly validation data on single levels at  $1^\circ \times 1^\circ$  resolution is downloaded from ECMWF's ERA5 reanalysis data set (Hersbach et al., 2020). Each scene is co-located with the nearest ERA5 grid cell. The ERA5 parameters, along with the latitude and respective measurement heights, are fed into the COARE-like algorithm COARE3.5, available at Ifremer, 2015 and based on COARE3 from Fairall et al., 2003, yielding a value of Obukhov length based on ERA5 data only ( $L_{\text{ERA5}}$ ).

The validity of using ERA5 data for validation is assessed in Appendix A.2. For a small sample of triple co-locations (ERA5, SAR, buoys), buoy and ERA5-retrieved validation were found to be approximately equally representative of the atmosphere as extracted from SAR imagery. A separate analysis between triple co-located buoys and ERA5 suggests a minimum of 75.9% of the latter's signal is physically based (up to +80% on a larger

data set of buoy-ERA5 co-locations). Assuming that the obtained results are representative of ERA5's capabilities beyond direct buoy-ERA5 co-locations, this result justifies using ERA5 for validation. Note that the assimilation of buoy observations into ERA5 could artificially inflate the obtained buoy-ERA5 comparison.

## 2.3. METHODOLOGY

### 2.3.1. SAR SPECTRAL-DERIVED PARAMETERS

High-resolution SAR enables the calculation of high-resolution wind-field spectra. This study utilizes information derived from both the one- and two-dimensional wind-field spectra. Our one-dimensional spectra are similar to Figure 2 in Young et al., 2000, with the important distinction that ours are constructed through polar integration. A polar integration of the two-dimensional spectrum is more robust than the equivalent obtained from a one-dimensional cross section. It prevents high-wavenumber noise (such as from swell) projecting itself onto the relevant, larger scales (see Appendix A.2). Furthermore, polar integrations negate the need to rotate and clip images along a particular axis. However, as a trade-off this method adds extra sensitivity to noise occurring at the wavelengths of interest, regardless of orientation. Parameters derived from the two-dimensional spectra are related to spectral-energy contours and orientation. These give insight into the spread and directionality of the spectrum. Details on the derived parameters can be found in Appendix A.2, with an example shown in Appendix A.3.

### 2.3.2. ANALYSIS FRAMEWORKS

#### ANALYTICAL APPROACH

The analytical approach follows the methodology of Young et al., 2000, which assumes a correlation between the sea-surface roughness patterns detected by SAR and the atmosphere above. Specifically, the magnitude of backscatter relates to the wind-induced shear component whereas the backscatter variations are related to the turbulent eddies of the convective component. Having computed a 10 m stress-equivalent neutral wind field, hereafter simply referred to as “wind field” or “wind”, and its one-dimensional spectrum, corresponding shear and convective components are calculated following Young et al., 2000 in Appendix A.2. Eight physically related parameters are computed during this stage, including the analytical estimate of Obukhov length,  $\hat{L}$ .

#### MACHINE-LEARNING ASSISTED APPROACH

Machine Learning (ML) is employed in an effort to overcome inadequacies in, and deviations from, the analytical approach. Parameters from the analytical approach are fed into a ML regression algorithm along with additional zero-dimensional parameters retrieved from the one- and two-dimensional spectrum and the SAR viewing geometry, yielding a second estimate of the Obukhov length,  $\hat{L}_{ML}$ . ML is expected to improve upon the initial estimate by learning when to account for systematic biases and errors. Several distinct ML algorithms are trained in this study. Their general design and training process remain the same. Differences between ML algorithms relate only to the data on which they are trained, unless specified otherwise. The data preparation prior to ML, such as filtering, splitting into train/test subsets, and a description of the regression it-

self, are presented in Appendix A.2.

## 2.4. RESULTS

### 2.4.1. SAR OBSERVED MABL ROLLS

Analytical and ML results,  $\hat{L}$  and  $\hat{L}_{ML}$ , are presented in the top panel of Figure 2.2 respectively. Between  $10 \text{ m} \leq |L_{ERA5}| \leq 100 \text{ m}$  the median trendline of  $\log_{10}(\hat{L})$  appears to follow the slope of ERA5 validation, though with a bias and significant noise. Beyond  $|L_{ERA5}| = 100 \text{ m}$ , the analytical methodology appears incapable of differentiating between stability states. The ML-assisted approach increases both the precision and accuracy of estimates. Additionally, where estimates from the analytical approach plateau, the ML-assisted approach remains capable of discerning between stability states. The ML-assisted method suffers from underestimation for  $|L_{ERA5}| \geq 100 \text{ m}$  and overestimation for  $|L_{ERA5}| \leq 100 \text{ m}$ . This is likely an artifact of the non-uniformly distributed data as visible in the histograms of Figure 2.2.

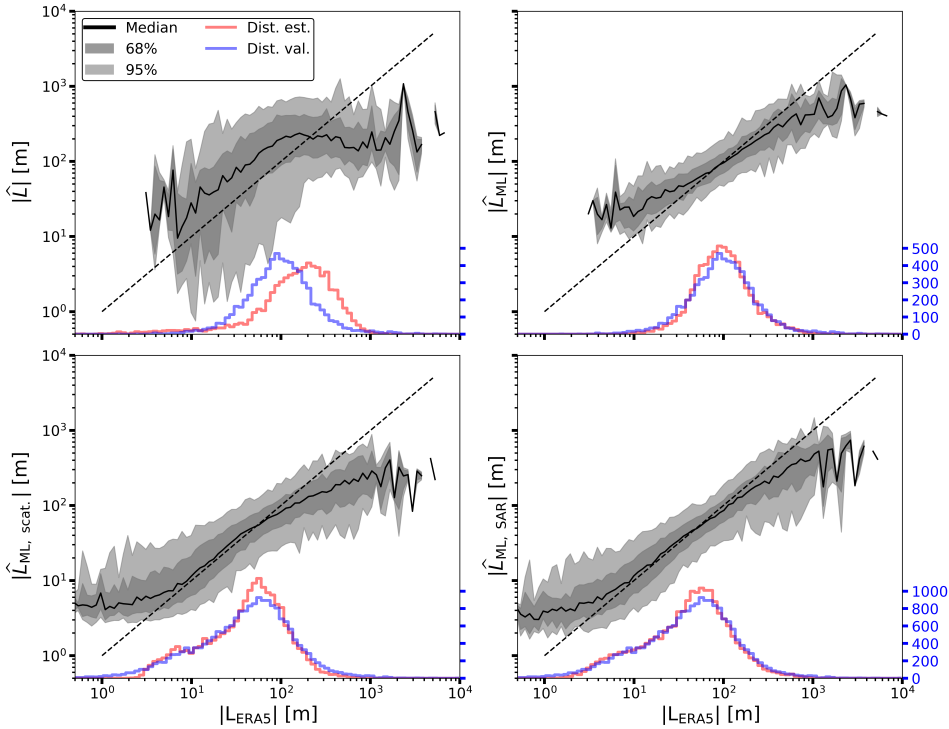


Figure 2.2: Validation versus. Top left) analytical  $L$  estimates on rolls. Top right) ML-assisted  $L$  estimates on rolls. Bottom left) ML-assisted  $L$  estimates on rolls and cells from a synthetic scatterometer. Bottom right) ML-assisted  $L$  estimates on rolls and cells. Histograms of estimation and validation values of  $L$  included

Quantitative assessments are performed using the coefficient of determination ( $R^2$ ) and median absolute error (MAE) on logarithmic  $|L|$ -values. The former gives insight

into the average—and therefore outlier-sensitive—performance. The more robust MAE yields insight into the systematic performance.  $R^2$  values can be interpreted as the fraction of explained variance. An antilog of MAE yields the median relative error (MRE) on a non-logarithmic scale. Means and standard deviations are obtained through a five-fold cross-validation.

Analytical results in the upper left panel of Figure 2.2 do not linearly follow validation data, yielding a negative  $R^2$ . When assisted by ML the  $R^2$  metric increases to 0.673 (see Table 2.1); the ML algorithm can account for over two-thirds of the observed variance. Antilogs of MAE's 0.341 and 0.113 yield MRE's of 119% and 30% for  $\hat{L}$  and  $\hat{L}_{ML}$  respectively; the MRE error decreases by a factor four when assisted by ML, resulting in half of the ML-assisted estimates experiencing a relative error in  $L$ -estimation of less than 30%. Performance varies little across the relevant scales of turbulence, as detailed in Appendix A.3, such that the methodology can be used for both microscale and mesoscale turbulence. A spatiotemporal analysis of results is provided in Appendix A.3, from which can be deduced that  $\hat{L}_{ML}$  estimates are qualitatively similar to  $L_{ERA5}$  (unlike  $\hat{L}$ ) and that coherent correlated errors between the two suggest regional phenomena, such as currents, may induce errors.

Table 2.1: Estimation performance as a function of parameters included in ML algorithms. First, the ML algorithm is trained on a single parameter,  $\tilde{U}_n$ . Next, parameters  $\phi$  and  $\delta$  are included, for a total of three parameters. Then the analysis is performed on  $\tilde{U}_n$  in addition to eight parameters uniquely calculated in the analytical approach (e.g.  $\log_{10}(|\hat{L}|)$ ,  $u^*$ ,  $z_0$ ,  $C_{dn}$ ,  $\sigma_u$ ,  $B$ ,  $w_*$  and  $\chi$ ) for a total of nine parameters. Afterward, all spectral-derived parameters (with the exception of the previous eight) are considered in addition to  $\tilde{U}_n$ ,  $\phi$ , and  $\delta$  for a total of 35 parameters. Lastly, the ML algorithm is trained on all 43 parameters. The R&C results are obtained from an ML algorithm trained on a larger data set comprising both rolls and cells.

| # params             |       | 1                 | 3                 | 9                 | 35                | 43                |
|----------------------|-------|-------------------|-------------------|-------------------|-------------------|-------------------|
| $\hat{L}_{ML}$       | $R^2$ | $0.476 \pm 0.019$ | $0.544 \pm 0.011$ | $0.529 \pm 0.023$ | $0.651 \pm 0.013$ | $0.673 \pm 0.015$ |
|                      | MAE   | $0.158 \pm 0.004$ | $0.144 \pm 0.003$ | $0.149 \pm 0.003$ | $0.117 \pm 0.002$ | $0.113 \pm 0.001$ |
| $\hat{L}_{ML, R\&C}$ | $R^2$ | -                 | $0.709 \pm 0.004$ | -                 | -                 | $0.796 \pm 0.005$ |
|                      | MAE   | -                 | $0.161 \pm 0.004$ | -                 | -                 | $0.125 \pm 0.003$ |

Additional ML algorithms are trained on a subset of available parameters to assess their respective prediction importance (see Table 2.1). When trained on a single parameter, estimated median stress-equivalent neutral wind speed  $\tilde{U}_n$ , the ML algorithm already outperforms the results from the analytical approach and is able to explain 47.6% of the observed  $L_{ERA5}$  variance. Including two parameters related to the viewing geometry (radar incidence angle  $\phi$  and spectral energy direction in range  $\delta$ ), for a total of three parameters, increases the explainable variance by nearly 7%-points to 54.4%; the predictive power extracted from three parameters accounts for over 80% of the total predicted variance. The predictive power contained within  $\tilde{U}_n$  logically follows from Equation 2.1, wherein wind speed directly affects the wind-shear component  $u^*$  and is correlated to  $\overline{w'T'_v}$ . However, neither viewing-geometry parameter is considered in the analytical framework, nor should the atmospheric state depend on them. Yet  $\phi$  and  $\delta$  experience a Pearson's correlation coefficient of 0.27 and 0.31 with  $\log_{10}(|L_{ERA5}|)$  respectively. This indicates a sampling bias introduced by the classification algorithm of C. Wang, Tandeo, et al., 2019 with specific atmospheric conditions being more frequently detected during specific viewing geometries, e.g. low values for  $|L_{ERA5}|$  are disproportionately sampled



at smaller incidence angles (WV1) with wind directions propagating in the along-range direction. Vice versa for greater  $|L_{\text{ERA5}}|$  values. A more detailed analysis on the influence of  $\delta$  on estimation performance is included in Appendix A.3, whose results suggest a decrease in atmospheric information captured in SAR imagery as a function of  $\delta$ .

Combining  $\tilde{U}_n$  with eight parameters derived uniquely in the analytical approach (for a total of nine) yields poorer performance than the model trained on three parameters; parameters retrieved from the analytical approach appear to contain little predictive power beyond that already contained in the wind-speed estimate. The ML algorithm trained on all parameters but those retrieved from the analytical approach, for a total of 35 parameters, explain 65.1% of variance. Lastly, when including the eight previously omitted parameters, for a total of 43 parameters, 67.3% of variance is explained. Therefore, the parameters from the analytical approach appear to uniquely contribute 2.2%-points. This minor improvement is still within the  $2\sigma$  bounds of the previous performance, indicating the marginal value of additional parameters for the considered ML model. A more detailed variance budget is provided in Appendix A.3, which also includes the validation data components.

#### 2.4.2. SAR OBSERVED MABL ROLLS AND CELLS

We perform new analyses on scenes classified as cells in addition to rolls to extend the model for a broader range of convective conditions and to determine whether wind speed remains the dominant predictor across classes. A new ML algorithm is trained on composite data containing the original rolls and approximately twice as many cells (R&C). Data-set details are provided in Appendix A.2.

Estimation results of the new ML algorithm,  $\hat{L}_{\text{ML, R\&C}}$ , are shown in the bottom right panel of Figure 2.2. Qualitatively, the  $\hat{L}_{\text{ML, R\&C}}$  estimates appear as an extension towards greater instabilities from  $\hat{L}_{\text{ML}}$ . The greater spread in the distribution of  $L_{\text{ERA5}}$  corresponding to  $\hat{L}_{\text{ML, R\&C}}$  allows the new ML algorithm to remain unbiased for a greater range between approximately  $10 \leq |L_{\text{ERA5}}| \leq 100$  m. An apparent asymptote at  $|L_{\text{ERA5}}| \leq 10$  m prevents correct estimation for very unstable scenes. This may be the result of fewer observations nearing said asymptote, or due to the fleeting nature of very unstable atmospheric conditions causing greater decorrelation between observation and validation. The  $R^2$  metric for  $\hat{L}_{\text{ML, R\&C}}$  shoots up to 0.795 as compared to 0.673 from  $\hat{L}_{\text{ML}}$ , indicating that  $L$ -estimation can successfully be applied on a broad range of stabilities. The near three-fold increase in observations is likely to account for part of the apparent improvement, as is the increased spread of  $L_{\text{ERA5}}$ : the  $R^2$  metric weights errors inversely proportional to the variance of the validation data, which is greater when considering both cells and rolls. Meanwhile the MAE metric of  $\hat{L}_{\text{ML, R\&C}}$  increases slightly to 0.125 as compared to 0.113 from  $\hat{L}_{\text{ML}}$ ; despite significantly increasing the range of estimation possibilities, the median error only marginally increases.

## 2.5. DISCUSSION

Roll-analysis results indicate that two-thirds of the predictive power is extracted from the GMF-retrieved median wind speed. A second analysis on both rolls and cells indicates an even greater relative importance of wind speed on stability estimations. These

observations may give the impression of high-resolution information being redundant. The additional value of high-resolution SAR observations is perhaps best illustrated by an example. The two SAR scenes in Figures 2.1 occurred during similar wind speeds and are part of the test fraction of data. They are classified as containing rolls and cells respectively, with ERA5 confirming that the right-hand figure occurred in a more unstable regime. Predictions from the ML algorithm trained on parameters derivable through SAR ( $\hat{L}_{\text{ML, R\&C}}$  trained on all available 43 parameters),  $L_{\text{SAR}}$ , are significantly closer to validation than  $L_{\text{scat}}$  ( $\hat{L}_{\text{ML, R\&C}}$  trained only on parameters obtainable from hypothetical scatterometers, i.e.  $\widetilde{U}_n$ ,  $\phi$  and  $\delta$ ). Since  $\widetilde{U}_n$ 's are similar and both observations were made at the same incidence angle, the only remaining degree of freedom is  $\delta$ , whose prediction contribution springs from observational biases. Therefore, the contribution of parameters obtainable with high-resolution SAR appears to mainly lie in error reduction rather than first-order approximations. This finding also holds on a statistical level, as is evident from the results in Table 2.1, demonstrating that high-resolution related parameters result in a relatively greater decrease in MAE than the relative increase in  $R^2$ .

Globally  $L_{\text{SAR}}$  consistently outperforms  $L_{\text{scat}}$  in our preliminary investigation. Therefore, by mapping the difference between the two, we can identify where the ML algorithm benefits from high-resolution information (see Figure 2.3). Regionally coherent structures, such as off the North American East Coast, suggest local importance of high-resolution information. In the past, this region was the subject of studies investigating current signatures of the Gulf Stream in SAR imagery (e.g. Beal et al., 1997; Marmorino et al., 1997). The Gulf Stream's warm currents transport heat from the tropics up to the mid-latitudes, where the resulting enhanced air-sea temperature gradient provides ample opportunity for atmospheric convection. Even more so, when the prevailing westerlies transport cold continental air over the warmer western boundary current. The negative sign of the structure indicates  $|L_{\text{scat}}|$  underestimates the atmospheric instability with respect to  $|L_{\text{SAR}}|$  (and  $|L_{\text{ERA5}}|$ ); without kilometer-scale texture information  $L_{\text{scat}}$  is incapable of estimating atmospheric instability beyond a first-order approximation. Consequently, we deduce from this regional example, the comparison discussed in Figure 2.1 and the summary statistics in Table 2.1 that kilometer-scale texture information is needed to uniquely distinguish between instabilities. Furthermore, kilometer-scale information is prerequisite on account of having to identify convective SAR scenes.

Naturally, results would change as a function of data distribution. If our data set had contained excessive observations over the Gulf Stream, estimation for this region would improve (regardless of parameters included) at the expense of all other regions. Similarly, estimation will be poor for any new observation with previously unsampled convective signatures. The presented performance should therefore be seen as secondary to the facts that  $L$  can quantitatively be extracted from SAR scenes and that robust extraction necessitates high-resolution information. Without this information and following Equation 2.1,  $L$ -estimates would provide poor constraints on momentum and heat fluxes—in particular for infrequently sampled regions with unique convection-driving mechanisms—across the air-sea interface. This could subsequently affect derived regional weather forecasts and, potentially, cascade into erroneous climatological predictions.

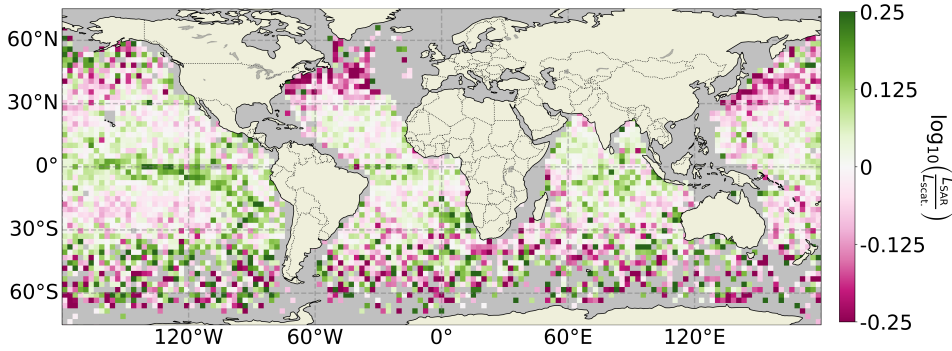


Figure 2.3: Difference between  $L_{\text{SAR}}$  and  $L_{\text{cat}}$  on  $2.5^\circ \times 2.5^\circ$  for the 20% test fraction of the composite data set.

## 2.6. CONCLUSION AND PERSPECTIVE

Results confirm the possibility of inferring stability conditions at the air-sea interface from SAR imagery. The analytical method proposed by Young et al., 2000 has limited applicability but provides useful guidance and parameters with which to filter non-convective observations. Our method, based on an ML algorithm trained on zero-dimensional parameters, demonstrates a leap forward in performance. The MAE largely drops while  $R^2$  increases, suggesting that 67.3% of the validation variance can be explained for rolls, and up to 79.6% when considering rolls and cells. Accordingly, atmospheric information can be extracted from relatively simple parameters to discriminate between an already narrow range of atmospheric states.

Much of the prediction power could be achieved with scatterometer measurements due to the importance of wind speed in making a first-order approximation. Though texture-related parameters derived from high-resolution SAR scenes enable a significant reduction in errors. In fact, without information on kilometer-scale features, the ML algorithm is incapable of providing more than a first-order approximation.

Future high-resolution Earth observation missions, such as EE10 Harmony (Lopez-Dekker et al., 2019), could improve results by providing multiple observations obtained from additional viewing angles. With the added degrees of freedom, it may be possible to identify, learn, and infer what atmospheric information might otherwise be lost as a function of viewing geometry. In turn, this would allow for the creation of a global convective-scenes dataset unbiased by viewing geometry.

The presented results illustrate the prediction potential when trained exclusively on a parameterized model. A new generation of co-located validation data is needed to go beyond the current ML predictions, to make estimates independent of and surpassing ERA5. However, the present predictions can already be employed to improve parameterization despite being trained towards a parameterized model. Discrepancies between our estimates and ERA5 may highlight where the latter falls short (e.g., poorly parameterized regions/phenomena). Future work could include localized ground truth measurements, regional models, and ancillary information in the training data to locally enhance predictions. An ML model trained on such enhanced databases could, in turn, provide

new constraints on parameterized models by providing vast quantities of estimates covering complex phenomena. After all, Sentinel-1 satellites promise decades of data and continuity.

Additionally, enhanced wind-field inversion schemes would evidently benefit from including high-resolution texture information to retrieve non-neutral wind-fields and stability information (as opposed to the scatterometer-based statistical inversion schemes in the CMOD family). If incorporated in a deterministic manner, an improved understanding of the connection between textures and stability conditions would be required. This connection may be inferred from the ML algorithm by deliberate manipulation of the test dataset (and study of its propagated effect), by dissecting the ML algorithm itself (akin to studying the intermediate layers of a neural network) or through joint analysis of wide-swath predictions with corresponding large eddy simulations (LES). Furthermore, the ML algorithm could be applied and/or trained on LES-retrieved wind fields to aid in constraining new inversion schemes developed on LES-derived backscatter fields.

Lastly, our methodology could serve as an example to future studies on leveraging preexisting databases of satellite observations in combination with ML for preliminary feasibility assessment. Future studies can go beyond Obukhov length and employ the same methodology on other/additional data sets to estimate parameters related to the Richardson number, ocean currents and heat fluxes.

## 2.7. OPEN RESEARCH

This study relied on buoy measurements, ERA5 reanalysis and Sentinel-1 acquisitions. Processed data are available at [doi.org/10.5281/zenodo.7801577](https://doi.org/10.5281/zenodo.7801577). A GitHub repository with example notebooks is provided at [github.com/owenodriscoll/supplement\\_paper](https://github.com/owenodriscoll/supplement_paper) and [doi.org/10.5281/zenodo.8064027](https://doi.org/10.5281/zenodo.8064027).

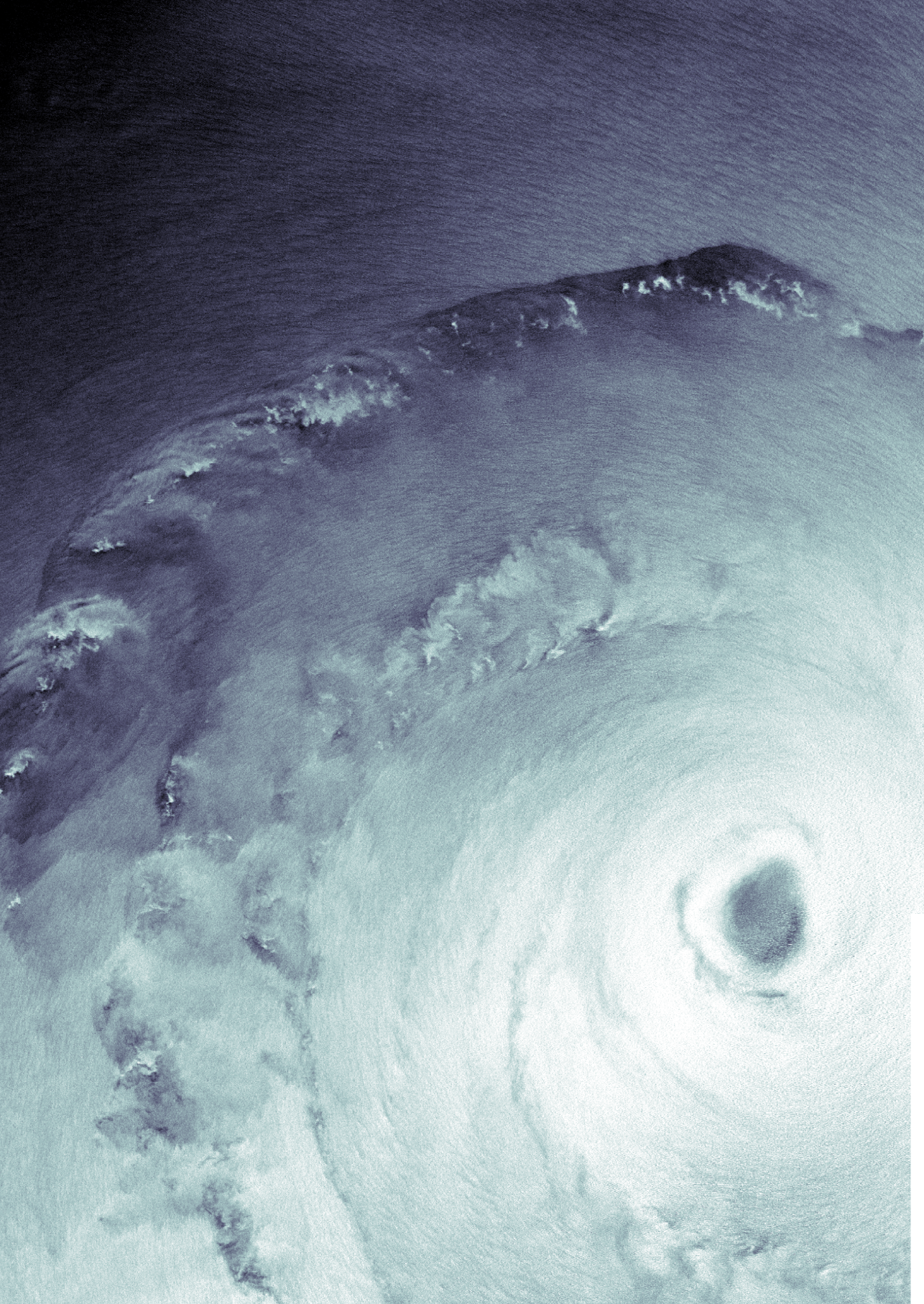
Raw data for the WHOTS and Stratus buoys are available at WHOI, 2022. Additional buoys off the North American coast are made available by NOAA at NDBC, 2022, with data from the PAPA network available at NOAA, 2022b. Data from the Triton, RAMA and PIRATA buoy networks are made available by Ifremer at [tds0.ifremer.fr/thredds/catalog/CORIOLIS-OCEANSITES-GDAC-OBS/DATA/catalog.html](https://tds0.ifremer.fr/thredds/catalog/CORIOLIS-OCEANSITES-GDAC-OBS/DATA/catalog.html). ERA5 data (Hersbach et al., 2020) is made available by the Copernicus Climate Change Service. The Sentinel-1 SAR images are hosted by Ifremer, whose data set contains Copernicus Sentinel data, 2022. Freely accessible Sentinel-1 data are available at ESA's Sentinel Open Access Hub .

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# 3

## ORGANIZED OCEAN SURFACE ROUGHNESS TEXTURES UNIQUELY TRACE AIR-SEA HEAT FLUXES

*Quantity has a quality all its own.*

Georgian proverb

*To fully characterize the air-sea heat-flux exchange using conventional bulk-flux methods, a host of disparate geophysical parameters needs to be measured simultaneously. Only a few dedicated and localized in-situ systems can fulfill this task, making retrieval of air-sea heat fluxes both rare and difficult.*

*Here we show that very high-resolution ocean roughness observations offer an alternative flux-retrieval path. In particular, spaceborne Synthetic Aperture Radar (SAR) measurements often capture a proxy of the atmospheric turbulence spectrum imprinted onto the ocean surface, which strongly correlates to air-sea fluxes. By exploiting this correlation, we can directly link the SAR-observed spatial structures to heat fluxes or their state variables.*

*The proposed retrieval, which we call FluxSAR, enables the first observation-based view of multi-year global ocean and inland sea heat-flux variability. By focusing on disparate case studies, we illustrate the unique advantages of the FluxSAR retrieval, which include tracing observation-based long-term fluxes, filling existing data gaps, aligning phase offsets between forecasts and observations, and supporting investigations into mesoscale flux co-variability.*

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This chapter was submitted in 2026 as O'Driscoll, O., López-Dekker, P., Chapron, B., Mouche, A., Chapman, C., & López-Dekker, P. *Organized Ocean Surface Roughness Textures Uniquely Trace Air-Sea Heat Fluxes* to Communications Earth & Environment.

### 3.1. INTRODUCTION

One quickly discovers the dire state of oceanographic heat-flux monitoring when searching for a global network of validation measurements: there are none. Yet heat fluxes are an essential climate variable, with the transport of heat across the air-sea interface affecting an immense range of phenomena from local cloud formation to global warming (Cronin et al., 2019; Nuijens et al., 2024; Pirani et al., 2024).

The gold standard for heat-flux observations uses the so-called eddy-covariance method, measuring the time-integrated small-scale temporal (co-)variability of specific turbulent quantities that directly relate to fluxes (Aubinet et al., 2012; Large & Pond, 1982). Several moored ocean buoys are equipped with eddy-covariance sensors, but, owing to their cost and sensitivity, they are few and far between (Centurioni et al., 2019).

To circumvent the need for covariance measurements, bulk parameterization algorithms are used; fluxes are estimated from time-averaged measurements of sea surface temperature, air temperature, surface winds, and humidity (Fairall et al., 1996, 2003). But regardless of method, most ocean basins lack systematic observations (see for instance Figure 1 in the extensive review by Bentamy et al., 2017, indicating a complete absence of moored buoys south of 20°S). Measurement expansions have been suggested, envisioning entire new buoy networks (e.g. Cronin et al., 2019) or even a fleet of uncrewed measurement systems (e.g. Patterson et al., 2025), but these too would be ill-suited to capture global variability on scales smaller than  $\mathcal{O}(1000 \text{ km})$  (Gille et al., 2025).

Conventional remote sensing methods also rely on the parameterized bulk-flux algorithms, but the prerequisite state variables are exceedingly difficult to measure from space, and particularly at  $\mathcal{O}(1\text{-}10 \text{ km})$  scales; coarser resolutions will compound representation errors, possibly leading to large net errors (e.g. Iyer et al., 2022). Indeed, no dedicated spaceborne instrument can observe all needed quantities simultaneously. The resulting inability to directly obtain heat fluxes from space has repeatedly been identified as a critical gap in Earth-observation capabilities (Cronin et al., 2019; Gentemann et al., 2020; Nuijens et al., 2024).

To bridge the model-observation divide, different hybrid products strive to optimally combine an insufficiency in observations with available models and reanalysis data (e.g. Tomita et al., 2019; Yu & Weller, 2007), spawning plenty comparisons (Bentamy et al., 2017; Hermes et al., 2019). But naturally, these remain dependent on the availability of—currently lacking—observations. With no conventional solutions on the horizon, either from new remote sensing systems or Herculean efforts in additional buoy deployments, we need to look elsewhere to resolve this observational gap.

In this work, we propose an alternative heat-flux retrieval methodology; one that exploits the ubiquitous atmospheric information captured in high-resolution,  $\mathcal{O}(0.1 \text{ km})$ , synthetic aperture radar (SAR) observations of the ocean surface. These radar systems operate in the centimeter range of the electromagnetic spectrum (Torres et al., 2012), and, therefore, are uniquely sensitive to centimeter-scale wind-driven ocean surface roughness while being impervious to clouds (at centimeter wavelengths, clouds are mostly transparent). The wind-imprinted roughness patterns enable SAR to identify organized atmospheric-turbulence structures across a wide range of scales  $\mathcal{O}(0.1\text{-}100 \text{ km})$ , which overlaps with the  $\mathcal{O}(1\text{-}10 \text{ km})$  domain resulting from 10-minute to hourly time integrations used in eddy-covariance and bulk-flux methods (Aubinet et al., 2012; Fairall et al.,

1996). As a result, SAR observations generally provide a unique spatial surrogate for the temporal statistics captured by conventional flux-estimation methods.

Building on past efforts (Alpers & Brümmer, 1994; O'Driscoll et al., 2023; Sikora & Ufermann, 2004; Stopa et al., 2022, 2024; Vandemark et al., 2001; C. Wang, Tandeo, et al., 2019; C. Wang et al., 2020, 2025; Young et al., 2000), we leverage the large and ever-increasing catalog of SAR observations to learn the statistical relation between local SAR-observed  $\mathcal{O}(0.1\text{--}10\text{ km})$  roughness variations and coincident air-sea heat fluxes. This approach starts by collecting a database of Sentinel-1 SAR images (Torres et al., 2012), and sourcing co-located reference data, in this case the globally available fifth generation reanalysis product from the European Centre for Medium-Range Weather Forecasts (ECMWF): ERA5 (Hersbach et al., 2020). The reference data enables the construction of an empirical model that captures the average relation between SAR-detected surface roughness variability and the corresponding atmospheric state. In this sense, the high-resolution SAR-derived fluxes are constrained to match the large-scale reference fluxes. The choice for an empirical (rather than analytical) methodology helps negate the as-of-yet unresolved complexities relating to the high-resolution mapping (projection) of SAR scenes to fine-scale,  $\mathcal{O}(0.1\text{ km})$ , wind fields. Different empirical models are created to target sensible and latent heat fluxes. Each of these models uses an additional calibrated uncertainty estimator to filter scenes with possible textural contaminants. One could also target the constituent components of these heat fluxes, provided the atmospheric structure uniquely traces their variability.

The developed empirical model provides the first multi-year and observation-based heat-flux retrieval on a global scale. The sole reliance on SAR untethers us from both the confined in-situ measurements as well as the restrictive necessity for synergistic measurements (needed in bulk parameterization schemes), and it simultaneously enables the exploitation of decades worth of existing ocean-covering high-resolution radar observations: no new sensors or instruments are required and, courtesy of the European Copernicus space program, continuity is secured (Geudtner et al., 2021). In the subsequent sections, we detail our methodology and demonstrate the unique benefits of radar-based heat-flux retrieval, called FluxSAR, across multiple spatiotemporal scales and observation modes.

## 3.2. DATA & METHODS

The following subsections detail the preparation of radar and reference data, as well as the retrieval model connecting the two. A high-level overview of the different FluxSAR processing stages is included in Figure B.7.

### 3.2.1. RADAR DATA PREPARATION

The FluxSAR methodology is applied on Sentinel-1's WaVe (WV) mode observations acquired between 70°N-70°S starting May 12th, 2020, till the end of 2025, for which stably calibrated data are available (Peureux Charles et al., 2020), yielding nearly four million independent 20×20 km WV vignettes (see Figure B.1 for an illustrative track of multiple WV observations).

The Interferometric Wide (IW) swath mode time series utilized in this study extends

back to 2014 and comprises the Mediterranean, the North Sea, and select tracks along the North American coasts. And, though fewer in number at several hundred thousand scenes, each IW scene covers a far greater extent than its WV counterpart, such that all the IW scenes contain in excess of a hundred million  $20 \times 20$  km tiles. The WV and IW modes differ in several aspects, but for this study, only their varying spatial extent and distinct regional coverage are of relevance.

Each radar scene (i.e., individual WV vignettes or the larger IW scenes) is processed with Ifremer's XSAR processing package (Olivier Archer et al., 2025) to a 100 m grid spacing. A coarser grid spacing would start to compromise the ability to retrieve necessary spectral features. For IW scenes, the far- and near-range tiles are removed due to persistent edge artifacts. Feature extraction on scenes begins by converting the backscatter fields to hypothetical stress-equivalent neutral wind fields for several fictitious wind directions, using the CMOD5.N algorithm (Hersbach, 2010). Then, using signal processing package `xrft` (Uchida et al., 2023), second-order statistics (features) are derived from the fictitious wind fields for each of the  $20 \times 20$  km vignettes/tiles. These hand-picked features aim to trace transient atmospheric regimes through their manifestation in second-order statistics at  $\mathcal{O}(0.1\text{--}1\text{ km})$  scales, akin to Beaufort's choice to rely on sailing properties as an instrument to structurally identify wind magnitudes (as detailed in Fitzroy & King, 1839). The choice for second-order statistics relates to the known physical relationship between convective structures—conventionally summarized using second-order statistics such as power spectra—and atmospheric conditions. And unlike in O'Driscoll et al., 2023, no auxiliary atmospheric information, such as wind direction, is needed; the second-order statistics are derived solely from the SAR images and are free of reanalysis contamination. The spectral statistics are then aggregated across the different fictitious wind directions, yielding a mean and standard deviation (indicative of directional sensitivity) for each  $20 \times 20$  km vignette/tile. These are fed to the retrieval algorithm.

### 3.2.2. REFERENCE DATA PREPARATION

The main source of reference, ERA5, provides hourly average latent and sensible heat fluxes on a global  $0.25^\circ$  grid (Hersbach et al., 2020). To make these variables more representative of in-situ conditions, the minimal required ERA5 state variables (i.e. wind speed, surface pressure, temperatures, humidity, rain rate and radiative fluxes), which represent a snapshot value (with the exception of rain rate and radiative fluxes), are fed into the COARE3.6 bulk parameterization scheme (a modified COARE3.5 based on Edson et al., 2013), yielding new estimates of latent and sensible heat fluxes. These estimates enhance retrieval performance on independent buoy co-locations, confirming that they convey more instantaneous geophysical information. Throughout the text, these are referred to as ERA5's heat fluxes.

Buoy data from active and historical RAMA/TOA-TRITON/PIRATA sites is used as a secondary validation source. NOAA makes several assumptions in preparing buoy products to increase the total number of flux observations. These include using absolute winds (since surface currents are rarely available) and climatological long-wave estimates, rather than observations. Uncertainty added in this manner amounts to  $\mathcal{O}(1.0\text{ Wm}^{-2})$  and  $\mathcal{O}(0.1\text{ Wm}^{-2})$  for latent and sensible heat fluxes respectively.

Having created a collection of SAR vignettes/tiles, each with their second-order statis-

tics and corresponding target atmospheric state, we next train an empirical retrieval model.

### 3.2.3. RETRIEVAL MODEL

The retrieval model builds on the regression framework of O'Driscoll et al., 2023; a combination of linear and boosted models is stacked to yield a single inference. In this work, we enhance the diversity of the disparate models by adding a conventional K-nearest neighbor regressor (though only for the WV analyses, since it overloads on the more plentiful IW tiles) in addition to several *weak* regressors of each architecture type. These weak models contain unoptimized hyperparameters; they may excel under a subset of conditions but perform worse overall. Combining different model architectures with varying degrees of hyperparameter optimization increases the total diversity of learnable parameters.

For both WV and IW, a unique latent- and sensible-heat-flux retrieval model is trained on a continuous year of training data. This ensures an additional degree of independence with respect to the test data, represented by the remaining time frame. IW and WV are not interchangeable since their incidence angles only partially overlap. The models for WV are trained exclusively on vignettes classified as containing either Atmospheric Fronts, Pure Ocean Swell, Wind Streaks, or Micro Convective Cells (C. Wang, Tandeo, et al., 2019). This reduces the number of observations from approximately 4 to 2.5 million. No classification is available for the IW tiles.

Conformalized quantile regression is added on top of the original model predictions to provide calibrated uncertainty estimates for each inference. A fraction of data not seen during training nor testing, constituting a couple of hundred thousand vignettes/tiles, is used to calibrate this uncertainty estimator. The resulting 95% uncertainty interval for each estimate can then be compared with the uncertainty intervals of other estimates of similar magnitude (through fine binning) to select a subset of observations with the highest relative certainty. By applying such relative filtering, we can select a subset of estimates with greater relative confidence without altering the inference distribution. Unless stated otherwise, this uncertainty filtering is applied to both IW and WV to select the 50% of estimates with the greatest relative confidence.

The empirical nature of the constructed models hinders predictions for rare/out-of-distribution events. Inspired by Kerdreux et al., 2025, we use successive k-means clustering during training to overweight rare events while reducing redundant data.

## 3.3. RESULTS

We start with a global perspective using several million routine ocean observations acquired with Sentinel-1's WV mode. The small size and discontinuous nature of these vignettes limit instantaneous large-scale analyses. Over limited areas of interest, such as European waters and coastal regions, the WV mode is systematically replaced by the mutually exclusive, larger ( $\sim 1000 \times 230$  km) and continuous IW mode. The enhanced size and observation frequency of IW mode facilitate the study of instantaneous synoptic scales. We show that a minor methodological extension allows us to transfer the FluxSAR retrieval from WV to IW mode, enabling enhanced heat-flux monitoring in coastal and



marginal seas where traditional flux products are known to struggle.

### 3.3.1. GLOBAL WV ANALYSES

On large averaged scales, FluxSAR well captures the variability prescribed by ERA5, as shown in Figure 3.1, allowing it to serve as an independent proxy for heat fluxes: FluxSAR can provide observational indicators for possible unexpected model divergences through time, e.g. when new data are assimilated or the underlying reanalysis model is updated. A point-to-point  $R^2$  of 0.75 and 0.82 for sensible and latent fluxes, respectively, suggests good instantaneous agreement as well (comparing inferences from individual WV vignettes to the nearest ERA5 grid cell). Lower  $R^2$  values of 0.42 and 0.72, respectively, are obtained prior to filtering, as detailed in 3.2.3, confirming the filtering's efficacy.

To illustrate FluxSAR's instantaneous resolving power, a comparison is made to buoy networks in the equatorial seas. As seen in Figure 3.1, the equator experiences little seasonality, which results in heavy  $R^2$  penalization in the presence of minor biases or standard errors. For that reason, the comparison uses a Pearson's correlation. Furthermore, moored buoys are generally assimilated into reanalysis data (Hermes et al., 2019; Hersbach et al., 2020), favoring the buoy-ERA5 comparison.

Buoy co-locations for both sensible and latent heat fluxes, Figure 3.2, reveal the same result: both ERA5 and FluxSAR strongly correlate to the buoys (e.g. same order of magnitude as reanalysis products to different buoys in Bentamy et al., 2017; Sanchez-Franks et al., 2018), yet at first the FluxSAR correlations seem to trail ERA5's by some margin. Things improve significantly when discarding radar scenes classified as containing non-atmospheric textures, and improve further still with increasingly stringent filtering of uncertain FluxSAR estimates.

The first class-based filtering operation discards ~40 % of radar scenes with obvious contamination. The second filtering stage attempts to discard scenes in which the connection between observed radar features and target variables is tenuous, e.g., due to spectral contamination. This is achieved by comparing conformally-calibrated quantile intervals for each prediction, from which the most uncertain predictions—with the largest interval for the same prediction magnitude—may be identified and removed. The fraction of filtered scenes at this stage equals the filter's relative uncertainty threshold, as detailed in Section 3.2.3. These filtering operations alter the target distribution and likely introduce some correlation between difficult conditions and discarded scenes—akin to the removal of cloudy scenes for optical systems—such that the resulting performance becomes conditional and is not representative of the average state.

After such filtering, and for distances closer to the buoy, the average buoy-FluxSAR correlation starts to exceed that from buoy-ERA5. Interestingly, the buoy-FluxSAR correlation for latent heat flux even exceeds that of ERA5-FluxSAR; FluxSAR's observational nature enables it to provide unique and complementary information not captured in the reanalysis product, while still matching the reanalysis at the largest scales. A persistent mismatch between WV acquisition locations and buoy deployments inhibits direct buoy-SAR co-locations. Nonetheless, based on the observed trend, the disparate nature of the various products and the approximate performance parity achieved at 50 km distances from the buoy, we anticipate that direct buoy co-locations are better represented by FluxSAR than by ERA5.

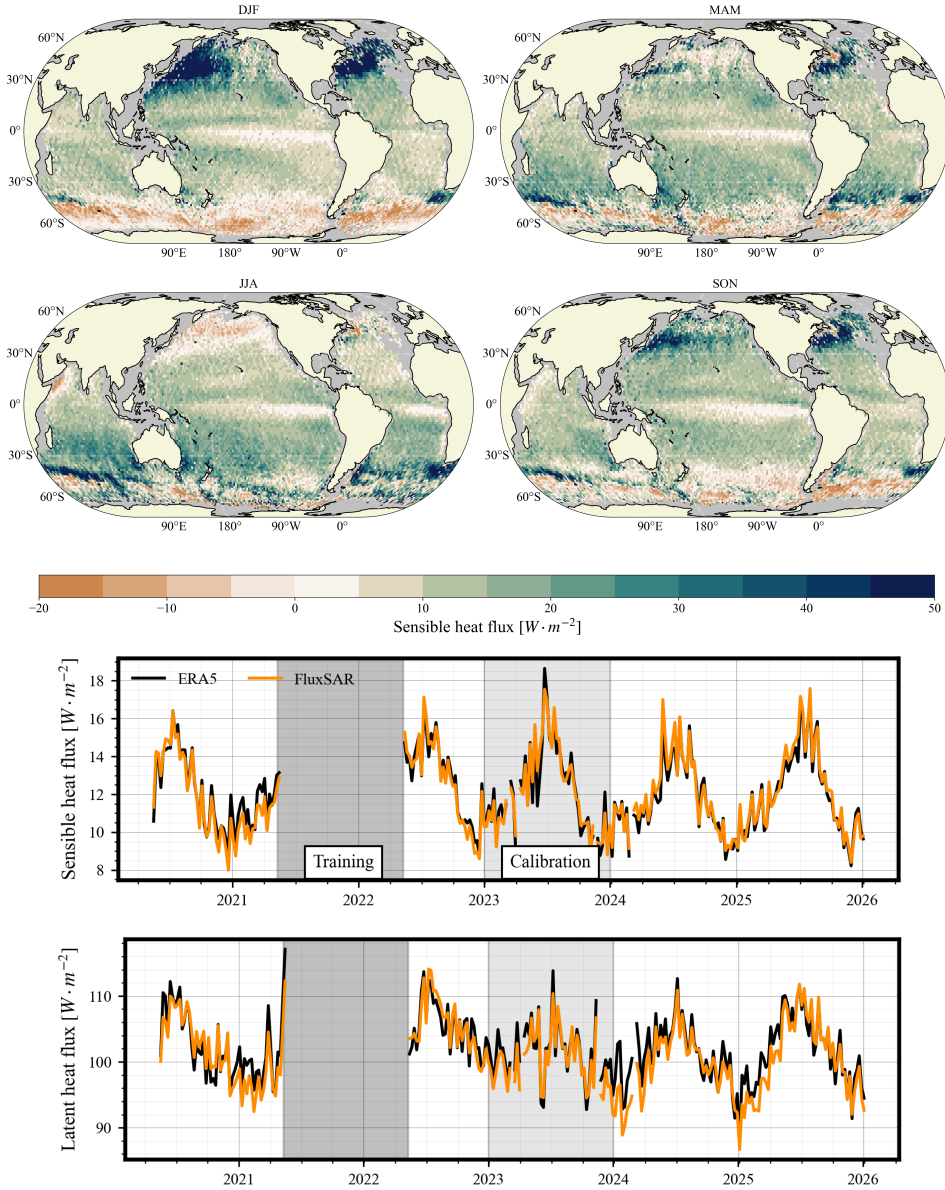


Figure 3.1: Upper) seasonality of mean sensible heat flux estimates on a  $1.5^\circ$  grid using scenes containing dominant atmospheric textures with the highest 50% relative certainty. The boreal winter coincides with strong fluxes over warmer Kuroshio and Gulf Stream currents, whereas the austral winter coincides with an enhanced temperature delta over the Agulhas. The equatorial regions experience little seasonality. Lower) corresponding weekly time series of the above domain for sensible and latent heat fluxes. The seasonal trend for sensible heat is more pronounced, while the magnitude of the latter is much greater.  $R^2$  values for the weekly sensible and latent flux signals are 0.94 and 0.78, respectively. The entire training epoch is used to train the FluxSAR model. A subset of observations made during the calibration epoch is put aside to calibrate the uncertainty estimator, which is used to assess the relative certainty of each inference. Flux anomalies presented in [Figure B.2](#) indicate that the obtained  $R^2$  values remain significant even after discarding the large (semi-)annual cycle.

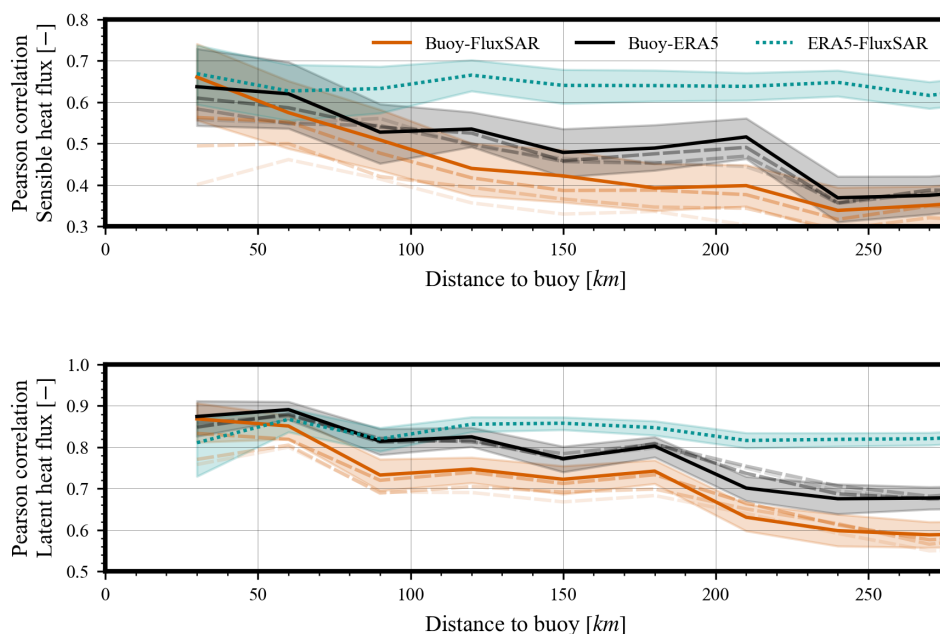


Figure 3.2: FluxSAR's correlation coefficients for Global WV mode sensible (upper) and latent (lower) heat fluxes with TAO/TRITON, PIRATA, and RAMA networks at 30 km binning intervals, starting at 15 km distance, below which negligible co-locations occur. The shaded area indicates the bootstrapped 95% confidence interval. Opacity for the lines increases respectively for: all scenes, omitting scenes classified as contaminated by non-atmospheric textures, additional filtering keeping 50% of scenes with the lowest relative uncertainty, and keeping 30% of scenes with the lowest relative uncertainty. The ERA5-FluxSAR results are included only for the most stringent filtering case. All co-locations are within 29 minutes of hourly buoy datapoints, and ERA5 is co-located with the WV scenes, not the buoy.

### 3.3.2. LOCAL WIDE SWATH ANALYSES

Having illustrated the potential of WV observations, we next turn to the larger, but localized, IW observations. Our methodology easily transfers to IW mode by treating these large scenes as mosaics of smaller 20×20 km sub-vignettes, referred to as tiles, sampled every 10 km (for a 20 km resolution). This minor methodological extension *unlocks* entire new basins for FluxSAR analyses, such as the Mediterranean, over which the more frequent and larger IW mode is systematically acquired. IW-derived FluxSAR time series for the Mediterranean suggest similar large-scale agreement to reanalysis products as compared to the previous global WV mode (included in Figure 3.3), though a difference in autumnal acceleration for latent heat flux hints at a possible disparity in representativeness.

In fact, the discrepancy between estimated and reference latent heat fluxes appears indicative of the inability to retrieve background temperature information needed for correct estimation of specific humidity (the gradients of which drive latent heat flux), see the strong correlation between latent heat flux residuals and temperature information in

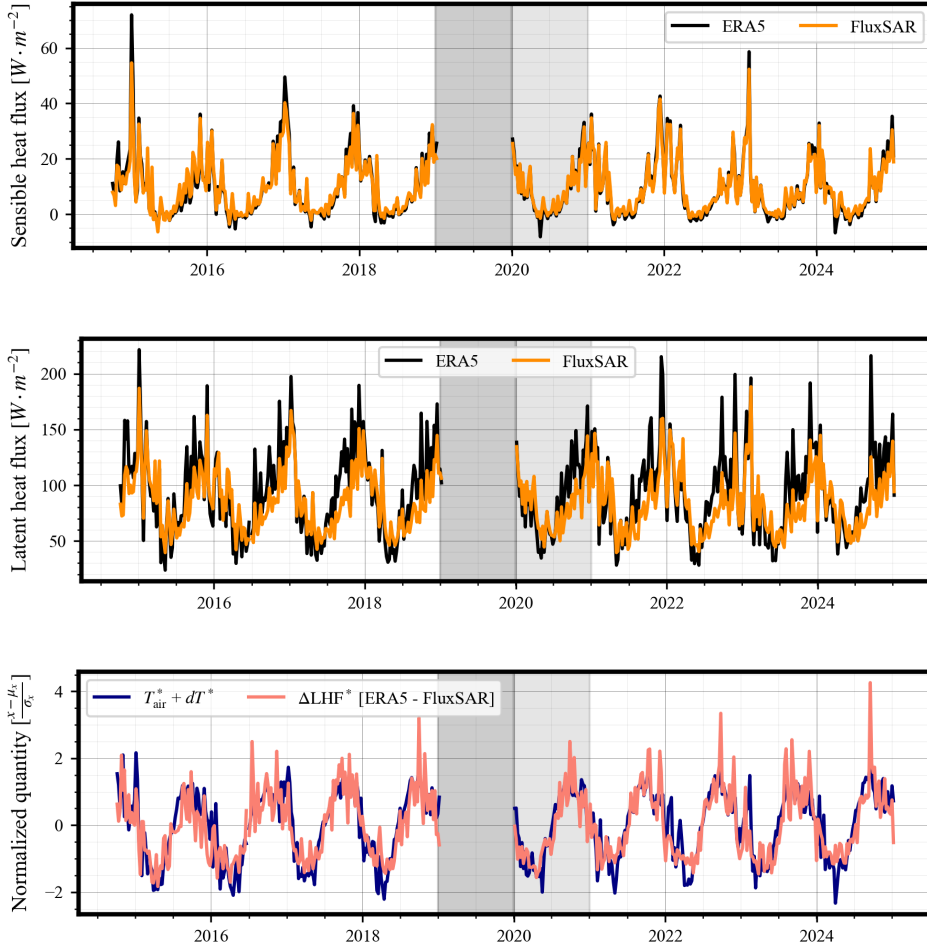


Figure 3.3: Weekly average heat fluxes over the Mediterranean basin from IW scenes for datapoints with the 50% highest relative certainty. Dark and light grey indicate training and calibration epochs, respectively. The point-to-point  $R^2$  is 0.75 and 0.63 (0.70 and 0.60 prior to filtering), and the weekly averaged  $R^2$  is 0.96 and 0.70 (0.88 and 0.66 prior to filtering) for sensible and latent heat fluxes, respectively. Normalized residuals of the latent heat-flux estimate,  $\Delta\text{LHF}^*$ , strongly correlate to the combined sum of ERA5's normalized 2 m air temperature,  $T_{\text{air}}^*$ , plus ERA5's normalized temperature difference between the sea surface and 2 m air temperature,  $dT^*$ , obtaining an  $R^2$  of 0.83.

the bottom panel of Figure 3.3. This suggests that the other components of the latent-heat flux estimation can be estimated successfully, while the background temperature-dependent components leave insufficient tracers in the radar textures. Since the air-sea temperature difference can already successfully be estimated—as is attested by the successful retrieval of sensible heat flux—an additional reference temperature, either of the sea or atmosphere, would thus benefit the retrieval of latent heat flux.

The larger and continuous IW scenes also enable investigations into instantaneous flux variability and phasing of air-sea submesoscale phenomena; by design FluxSAR is constrained to fit the large scales prescribed by ERA5, but informed by observations it retains the freedom to locally diverge, which we illustrate through two case studies in Figure 3.4 (further case studies containing various dynamic examples are included in Appendices B.3 & B.4).

## 3

## MEDICANE BLAS

In the upper half of Figure 3.4, we find decaying medicane Blas headed east. The SAR observation indicates a small storm core of a few tens of kilometers in diameter. This structure is surrounded by energetic winds, radially extending from the storm center by no more than a hundred kilometers.

FluxSAR captures this intricate structure: suppressed sensible heat fluxes occur in both the storm's core and its propagation trajectory, while enhanced fluxes trail the medicane, where the cooler spent air mass lies in the storm's wake.

The reanalysis paints a different picture, with a lull in fluxes across almost the entire storm's footprint. A time series of winds retrieved from ECMWF's Integrated Forecast System (IFS) indicate the source of the flux discrepancy, as is shown interactively on [ovl.oceandatalab.com](https://ovl.oceandatalab.com) (or statically, for ERA5, in Appendix B.5); the reanalysis' limited spatial resolution,  $\mathcal{O}(100\text{ km})$ , results in a misrepresented storm location and structure, obfuscating the mechanics at play.

## ATMOSPHERIC FRONTS OVER THE GULF OF LION

The SAR image in the second row, over the Gulf of Lion, displays two separate atmospheric fronts encroaching on the Mediterranean. In the upper right section, we observe the western Tramontane crashing into strong easterly winds. Towards the interior of the Gulf, and closer to land, few atmospheric signatures are discernible from the SAR image. Meanwhile, further south, curving along the Costa Brava, characteristic atmospheric rolls are aligned north-south along the dominant wind direction. These rolls indicate that turbulent convection is taking place.

Again, FluxSAR traces these evident atmospheric structures: latent heat transport increases from within the relatively stable interior of the Gulf towards the unstable exterior, particularly at the southern extent of the Tramontane. The greatest fluxes are observed over the narrow band of strong easterly winds.

To an extent, the reanalysis aligns with the SAR image, identifying two distinct regions with elevated fluxes. Though a clear phasing offset is present; the apparent Tramontane atmospheric front has yet to exceed the confines of the Gulf, or establish contact with the westerly winds. An ERA5 time series (not shown) indicates that its representation of the Tramontane lags the SAR scene by several hours and that the crashing of fronts is almost entirely overlooked. In addition to phasing issues, ERA5's coarse effective resolution hinders its ability to represent sharp features such as a leading gust front.

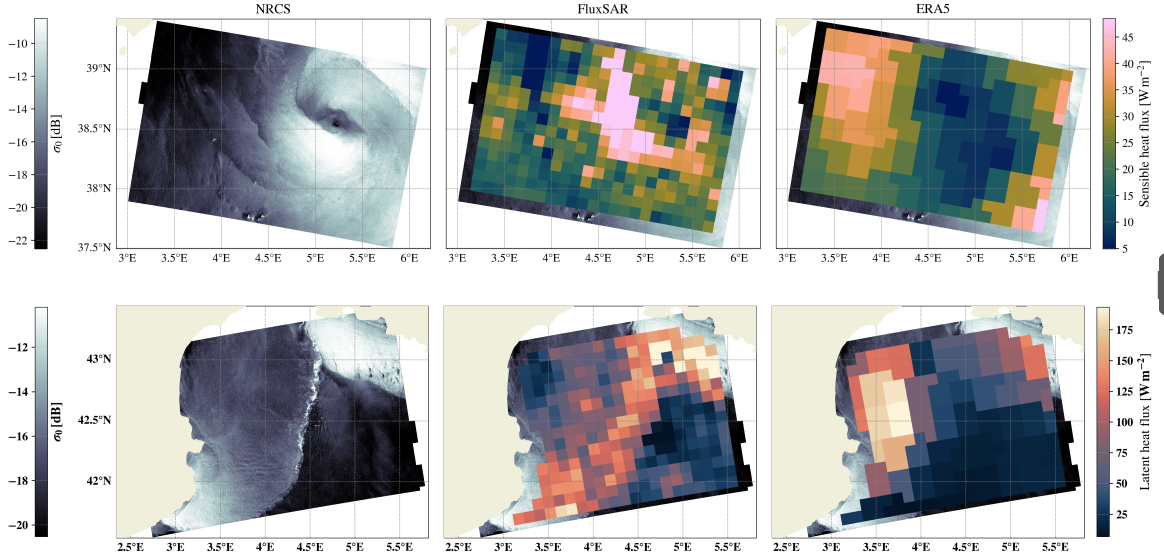


Figure 3.4: Atmospheric regimes as represented by FluxSAR (on IW scenes) and ERA5. Each flux estimate corresponds to the local  $20 \times 20$  km tile (obtained with 10 km overlap to maintain a 20 km spatial resolution). No uncertainty filtering was applied. Top) medicane Blas headed east after deluging the Balearics, 2021-11-13. Note the enhanced fluxes trailing the medicane, where one typically finds depleted, cold, dry air over warmer water. Bottom) westerly Tramontane winds crashing into the easterly winds, over the Gulf of Lion, 2022-03-13.

### 3.4. DISCUSSION AND CONCLUSION

We have now illustrated several FluxSAR use cases, including: the ability to resolve  $\mathcal{O}(10 \text{ km})$  scale flux variability, long-term and independent tracing of basin-wide seasonality, improved agreement with in-situ buoy measurements, and the ability to capture the instantaneous phasing of geophysical phenomena. Yet the objective of these endeavors is not to crown some champion in a contest with reanalysis products, but rather to emphasize the useful and complementary atmospheric information that SARs readily provide. We foresee that future weather forecasting and reanalysis products stand to gain by incorporating this information, either by assimilating observations (e.g. Alexe et al., 2024), or derived variables (e.g. Aouf et al., 2021; Isaksen & Janssen, 2004; Laloyaux et al., 2016; Law-Chune et al., 2021).

The present focus on heat fluxes should not obscure the fact that heat-flux state variables—often more desired in assimilation than the ephemeral fluxes themselves—could likewise be targeted. Repeating the above exercises, we can retrieve the constituent components of heat fluxes (e.g. thermal gradients, as shown in Figure B.6). The limits of such parameter-retrieval capabilities will be the subject of future investigations.

In addition to atmosphere-induced surface roughness, SARs are sensitive to a host of other roughness sources, such as swell waves, internal waves, rain, biological slicks, orography-induced gravity waves, and even wind farms. These could be treated as noise and filtered out, with recent efforts enabling the identification/segmentation for several



of these phenomena (e.g. Santos-Ferreira et al., 2025; C. Wang, Tandeo, et al., 2019; C. Wang et al., 2025). Alternatively, these “contaminants” could themselves be studied to determine heat-flux behavior under deviant conditions, such as under a range of varying sea-state parameters—a domain where bulk flux formulations typically struggle (Cronin et al., 2019).

Perhaps the main advantage of SAR-based heat-flux retrieval is the promise of continuity. With over a decade of Sentinel-1 data, and previous missions like ERS-1/2 and ENVISAT, a substantial archive exists on which climate-scale heat-flux signals can already be assessed. This archive is supplemented daily; as of writing, there are three operational Sentinel-1 SARs imaging our oceans, more than ever before. And with the upcoming Sentinel-1 Next Generation, scheduled for launch in the mid-2030s, decades of future observations are secured. Then there are the Earth Explorer Missions such as Harmony (Lopez-Dekker et al., 2019), Copernicus Expansion Program missions like ROSE-L (Davidson et al., 2021), and non-European constellations such as the Canadian RADARSats (Morena et al., 2004; A. A. Thompson, 2015) or the Chinese Gaofen series (Z. Wang et al., 2025), along with many others still. Few other systems can boast such continuity.

Lastly, there is no substitute for in-situ heat-flux sensors in terms of measurement accuracy and timeliness, and their benefits to weather and climate products are clear (Hermes et al., 2019; Pirani et al., 2024; S. R. Smith et al., 2011). Yet these systems are prohibitively expensive to operate and maintain (even more so when deployed at sea). Hence, heat fluxes are measured where they can be afforded, but not necessarily where they are needed (e.g., high-seas piracy and vandalism preventing buoy deployments, resulting in worse predictions Hermes et al., 2019; McPhaden et al., 2010; S. R. Smith et al., 2011). A spaceborne heat-flux product like FluxSAR could serve as a natural complement to in-situ systems, extending both coverage and continuity. The successful union of these two would certainly aid the democratization of precious heat-flux information.

### 3.5. OPEN RESEARCH

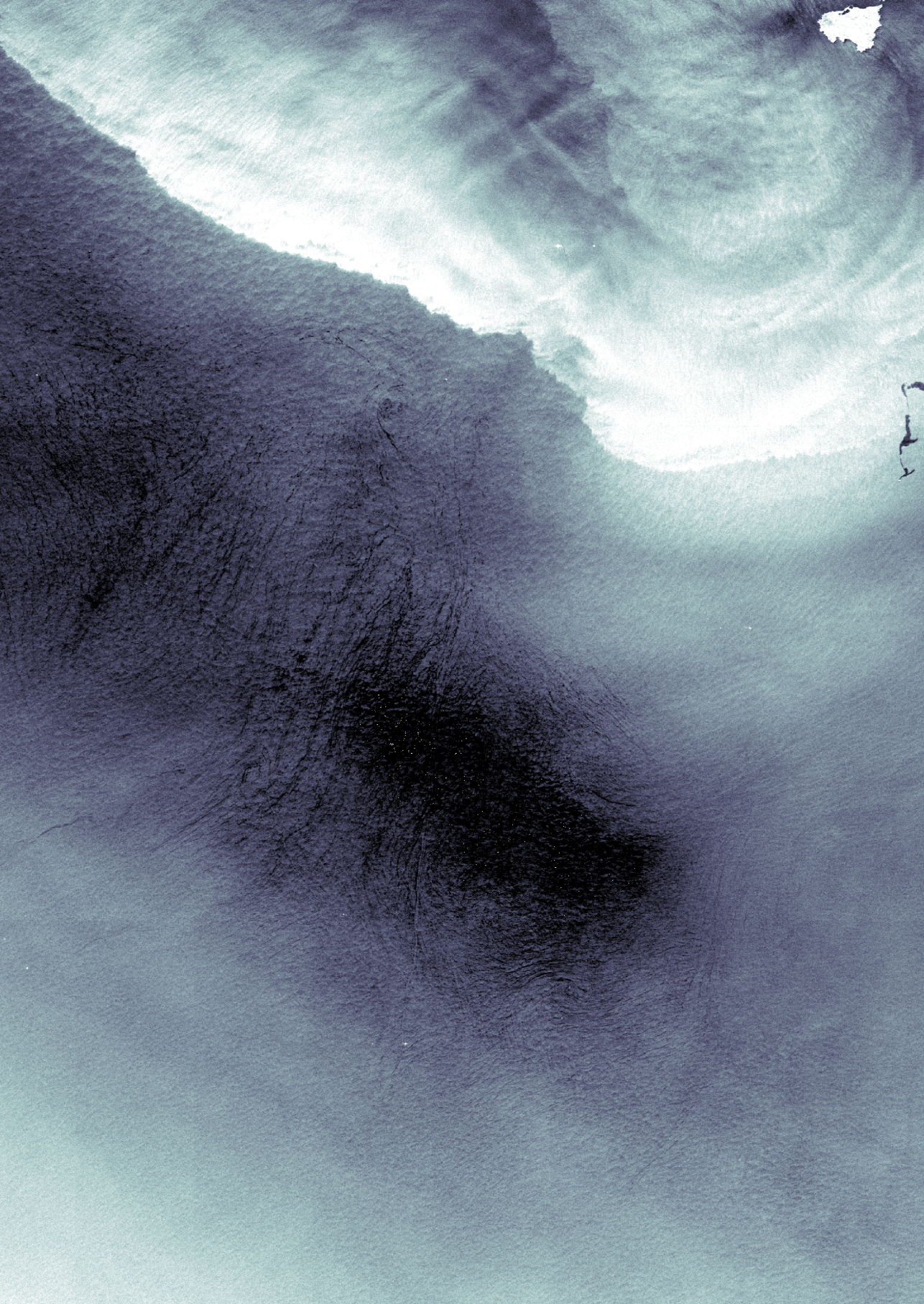
NOAA’s “Global Tropical Moored Buoy Array” data are retrieved from [pmel.noaa.gov/tao/drupal/flux/allsites](https://pmel.noaa.gov/tao/drupal/flux/allsites). ERA5 reanalysis is retrieved from ECMWF’s ERA5 API. The analyses of this study are performed using Copernicus Sentinel-1 data 2014-2025, processed by ESA. These are downloaded through the Alaskan Satellite Facility’s Python API available at [github.com/asfadmin/Discovery-asf\\_search](https://github.com/asfadmin/Discovery-asf_search). These data are accessed using Ifremer’s open source XSAR file reader available at [github.com/umr-lops/xsar](https://github.com/umr-lops/xsar). Jupyter notebooks detailing the generation of here-presented results are included in [github.com/owenodriscoll/FluxSAR-demo](https://github.com/owenodriscoll/FluxSAR-demo).

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# 4

## THE PHANTOM MENACE: LEAKAGE OF GEOMETRICAL DOPPLER INTO GEOPHYSICAL OCEAN MOTIONS OBSERVED WITH DOPPLER SCATTEROMETERS

*I insist that we don't care.*

kb

*The interactions between geometrical Doppler, beam pattern, and normalized radar cross section (NRCS) result in leakage of geometrical Doppler into the perceived geophysical Doppler. Starting from high-resolution synthetic aperture radar (SAR) data we model this leakage for synthesized real aperture radar (RAR) observations of ocean motion. The uncertainty introduced by leakage is  $\sim 1 \text{ ms}^{-1}$ . Corrections proposed in this work using only the synthesized lower-resolution RAR NRCS, decrease this to  $\mathcal{O}(0.1 \text{ ms}^{-1})$ . Further reduction of instantaneous leakage may be achieved through temporal averaging, since the leakage-inducing NRCS gradients appear mostly atmosphere-induced and decorrelate rapidly.*

*The azimuth resolution and number of independent samples determine a system's sensitivity to leakage. C-band systems are inherently prone to suffer from greater leakage and worse corrections than their Ku- and Ka-band counterparts. With DopSCA, the propagated effect of leakage is only secondary compared to the pulse-pair uncertainty. In similar systems where pulse-pair uncertainty is suppressed, leakage will dominate instead.*

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This chapter is adapted with minor edits from O'Driscoll, O., López-Dekker, P., & Payez, A. (2025). *Phantom motion of the ocean: leakage of geometrical Doppler into geophysical motions observed with Doppler scatterometers*. [IEEE Transactions on Geoscience and Remote Sensing](#)

## 4.1. INTRODUCTION

The apparent geophysical surface velocity originating from the interplay between geometrical Doppler, radar beam pattern, and gradients in normalized radar cross section (NRCS), is an undesired contribution to surface-current observations that often flies under the proverbial radar. This phenomenon has primarily been studied in the context of Doppler profilers and Synthetic Aperture Radars (SAR), where it is referred to as “non-uniform beam filling” (Illingworth et al., 2018; Kollias et al., 2014; Schutgens, 2008; Tanelli et al., 2002) and “biased Doppler centroids” (Chapron, 2005; Hansen et al., 2011; Madsen, 1989) respectively. Here we will refer to it as leakage, as the geometrical Doppler seemingly leaks into the geophysical Doppler of interest, causing a phantom motion.

A new generation of Doppler-targeting Real Aperture Radar (RAR) missions has been proposed with the objective of mapping ocean surface motions at hitherto unattainable spatial and temporal scales, such as e.g. SKIM (Ardhuin et al., 2019), WaCM (Rodríguez et al., 2019, rechristened as Odysea), and OSCOM (Du et al., 2021). Such capabilities, and especially their added ability to provide direct observations of ocean surface motions at a global scale for the very first time, are needed to complement and update the mostly indirect contemporary view of ocean surface currents derived from space-borne altimeters (made under the assumption of large-scale geostrophic balance) and highly-localized high-resolution observations (e.g. coastal HF radars, moorings, drifters, or sporadic campaigns such as the recent ESA RVL campaign over the Agulhas NERSC, 2022). SWOT (Morrow et al., 2019) will help bridge the altimetry gap, but it remains an altimeter (albeit a large-swath interferometric one), and currents demand complementary direct observations, in particular in the tropics close to the Equator.

The unique design of the Doppler-targeting systems determines their inherent sensitivity to leakage. For RARs such as SKIM and Odysea, the incurred leakage is fundamentally linked to the width of the beam footprint: a wider beam enables more NRCS gradients to bias the geometric Doppler while stronger gradients further enhance this bias. With both Odysea and SKIM operating at Ka-band, their beam footprints are much narrower than C-band equivalent systems; the anticipated leakage is therefore reduced. For DopplerScat, the airborne counterpart of Odysea, the authors of Rodríguez et al., 2018 estimated the leakage-induced velocity errors to be  $\mathcal{O}(0.01 \text{ ms}^{-1})$ , though sharp NRCS gradients will result in more substantial errors and require correction. SAR platforms such as Harmony receive signals from a much wider C-band footprint (Lopez-Dekker et al., 2019), but the SAR-enabled azimuthal resolving power permits correction for leakage-induced Doppler. Common correction approaches rely on empirical relations (Hansen et al., 2011; Kollias et al., 2014; Schutgens, 2008), iterative procedures (Bamler, 1991), a-priori filtering (Hansen et al., 2011) or spectral filtering (Engen & Johnsen, 2013, 2015).

Given the seemingly benign nature of leakage to these systems, other components of the error budget justifiably take precedence, such as measurement noise, pointing errors and uncorrected wave Doppler.

However, inauspicious combinations of system design parameters will cause a subset of sensors to be particularly prone to suffer from leakage. One of these is DopSCA: an opportunistic mission design proposed under ESA’s DOPSCAT study for scatterometers capable of measuring ocean surface motions (Fabry et al., 2013). This concept is

being investigated as an additional capability for the new MetOp-SG operational C-band fan-beam scatterometer instrument: SCA. With the requirement not to impede the original scatterometer performance of SCA, DopSCA targets the estimation of ocean surface velocities inferred from sub-pulse-pair phase differences (Hoozeboom et al., 2018).

However, constrained by prioritization given to the scatterometer mission aspect, the C-band fan-beam design—with a large azimuthal beam footprint—is inherently sensitive to leakage. As such, the previously unconsidered NRCS gradients may yet irreversibly hinder the estimation of ocean surface velocity vectors.

Thus, to assess the viability of C-band Doppler scatterometers, we must quantify their sensitivity to leakage. DopSCA will be considered as a relevant case study. First, we aim to quantify the expected leakage using high-resolution SAR observations. These provide us with high-resolution NRCS gradients. Then, we assess corrections for the incurred leakage using synthesized low-resolution scatterometer observations.

Next, we illustrate the practical implications of residuals after correction on a limited dataset with surface current estimates over the Agulhas. Lastly, mitigation strategies are considered with the aim of overcoming residual leakage.

Through these analyses we intend to answer the following questions: to what extent are Doppler scatterometers sensitive to uncertainty introduced by leakage? Can leakage be reduced to acceptable levels through correction? What alterations to the instrument/observation mechanism could aid uncertainty reduction?

## 4.2. THEORY AND METHODOLOGY

### 4.2.1. DOPPLER CENTROID AND LEAKAGE VELOCITY

Following Raney, 1986, the Doppler centroid (DC) for a single range bin can be expressed as

$$f_D = \frac{2}{\lambda} \frac{\int \sigma_0 G_{2\text{-way}} (\vec{v}_p - \vec{v}_s) \cdot \hat{r}_{\text{LoS}} d\text{Az}}{\int \sigma_0 G_{2\text{-way}} d\text{Az}}, \quad (4.1)$$

where  $\vec{v}_p$  is the platform velocity vector (considered constant but left inside the integral for ease of notation),  $\vec{v}_s$  the spatially-varying surface motion of interest,  $\lambda$  the radio wavelength,  $\sigma_0$  the spatially-varying NRCS,  $G_{2\text{-way}}$  the two-way antenna gain pattern and  $\hat{r}_{\text{LoS}}$  the Line of Sight (LoS) unit-vector representing the satellite viewing geometry within the azimuthal domain represented by Az. For notational convenience, references to azimuth coordinates are dropped.

From (4.1) it follows that both the geometric and geophysical contributions of relative motion ( $\vec{v}_p$  and  $\vec{v}_s$  respectively) are weighted by the local NRCS and antenna gain. In the absence of geophysical motion, the DC is only governed by the antenna pattern, NRCS, and the observation geometry, as shown in Figure 4.1. Meanwhile, in the along-track interferometry case not considered here, the platform's velocity-induced geometric Doppler drops out, because we observe the surface from the same location. For pulse-pair systems, it is necessary to explicitly estimate and remove this geometric component instead. Assuming a simplified scenario where a perfectly right-looking RAR system observes a uniform NRCS field with a symmetric beam footprint, then the even weighting of the positive and negative geometric Doppler would effectively cancel out the integral terms corresponding to  $\vec{v}_p$ , yielding only the LoS-average geophysical Doppler of inter-



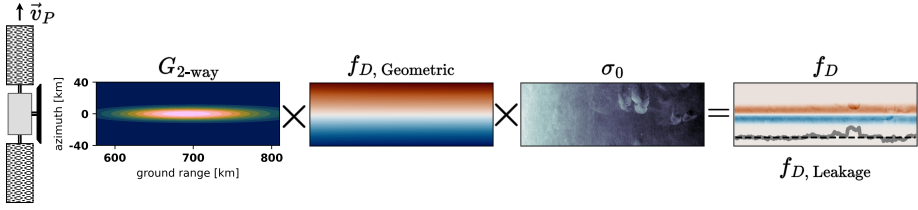


Figure 4.1: Overview of the leakage mechanism for a single RAR pulse. The geometric Doppler, caused by platform motion  $v_p$ , is weighted by the beam pattern and NRCS fields, resulting in a characteristic Doppler Centroid,  $f_D$ . Where NRCS gradients occur, the Doppler Centroid's azimuthal average—here within a single azimuthal resolution cell—becomes non-zero. Under the false assumption that the geometric Doppler is symmetric and will cancel out, this phantom signal,  $f_{D, \text{Leakage}}$ , could erroneously be interpreted as a geophysical motion instead.

4

est. However, for more realistic scenarios containing along-azimuth  $\sigma_0$  gradients within the beam footprint, one can expect compounding and non-zero interactions between  $\sigma_0$ ,  $G_{2\text{-way}}$  and the geometric Doppler that result in spurious and undesired Doppler contributions that bias the Doppler centroid—leakage. This phenomenon is illustrated in Figure 4.1.

The sensitivity to  $\sigma_0$  gradients is determined by the gain pattern. To calculate this sensitivity analytically we first identify in (4.1) convolutions of NRCS with distinct impulse response functions in both the numerator and denominator. Assuming no surface motion ( $\vec{v}_s = 0$ ), a stationary beam pattern and geometric Doppler, and discarding changes in NRCS due to changes in viewing geometry, then (4.1) can be approximated as

$$f_D = \frac{2}{\lambda} \frac{(\sigma_0 * h_1)}{(\sigma_0 * h_2)}, \quad (4.2)$$

with  $*$  being the convolution operator and

$$h_1 = G_{2\text{-way}} \vec{v}_p \cdot \hat{r}_{\text{LoS}} \quad (4.3)$$

$$h_2 = G_{2\text{-way}}. \quad (4.4)$$

After resolving these impulse response functions in the spatial domain, the convolutions in (4.2) can conveniently be resolved in the azimuthal wavenumber domain as

$$f_D = \frac{2}{\lambda} \frac{\mathcal{F}^{-1}(\Sigma_0 H_1)}{\mathcal{F}^{-1}(\Sigma_0 H_2)}, \quad (4.5)$$

where  $\mathcal{F}^{-1}$  indicates an inverse azimuthal Fourier transform of the product of the NRCS wavenumber domain transfer functions,  $\Sigma_0$ , with the respective wavenumber domain transfer functions  $H_1$  and  $H_2$ . The expression in (4.5) is computationally more efficient than the convolution-laden (4.1), with which it differs negligibly (not shown), but it hinges on the aforementioned additional assumptions.

The Doppler resulting from leakage is converted to the horizontal component of leakage velocity following

$$v_L = \frac{\lambda}{2} \frac{f_D}{\sin(\theta_i)}, \quad (4.6)$$

with  $\theta_i$  being the incidence angle. Successive pulses retrieved at multiple range bins yield  $\nu_L(t, \tau)$  as a function of fast and slow time, respectively.

#### 4.2.2. TOWARDS AN INTUITIVE WAVENUMBER INTERPRETATION, AND MOTIVATION FOR EMPIRICAL ANALYSES

From (4.1) and (4.5) several properties of leakage can already be deduced. Yet the division of convolutions thwarts a convenient wavenumber-domain interpretation. Aiming to that end, we decompose  $\sigma_0$  into a mean and space-varying component (Cumming & Wong, 2005)

$$\sigma_0 = \bar{\sigma}_0 + \bar{\sigma}_0 \delta \sigma_0, \quad (4.7)$$

such that (4.2) becomes

$$f_D = \frac{2}{\lambda} \frac{\bar{\sigma}_0 (h_1 * 1 + h_1 * \delta \sigma_0)}{\bar{\sigma}_0 (h_2 * 1 + h_2 * \delta \sigma_0)}. \quad (4.8)$$

Since the mean backscatter terms cancel, and convolutions with an identify field yield the mean impulse response, i.e.  $h_1(x) * 1 = H_1(0)$ , we can rewrite as

$$f_D = \frac{2}{\lambda} \left[ \frac{H_1(0)}{H_2(0) + h_2 * \delta \sigma_0} + \frac{h_1 * \delta \sigma_0}{H_2(0) + h_2 * \delta \sigma_0} \right]. \quad (4.9)$$

The latter fraction can be approximated as

$$\frac{h_1 * \delta \sigma_0}{H_2(0) + h_2 * \delta \sigma_0} = \frac{h_1 * \delta \sigma_0}{H_2(0)} \frac{1}{1 + x} \quad (4.10)$$

$$x = \frac{h_2 * \delta \sigma_0}{H_2(0)}. \quad (4.11)$$

Using a Taylor expansion for  $\frac{1}{1+x}$  we can linearize, yielding

$$f_D = \frac{2}{\lambda} \left[ \frac{H_1(0)}{H_2(0) + h_2 * \delta \sigma_0} + \frac{h_1 * \delta \sigma_0}{H_2(0)} \cdot \left( 1 - \frac{(h_2 * \delta \sigma_0)}{H_2(0)} + \frac{(h_2 * \delta \sigma_0)^2}{H_2(0)^2} - \dots \right) \right]. \quad (4.12)$$

This form provides insight into the effects of various magnitudes of NRCS gradients. Firstly, and based on Figure 4.2, leakage will be greater for smaller wavenumbers (for the same beam impulse response) as the power of NRCS gradients decreases towards greater wavenumbers. Then, in the limit when only weak gradients are present, such that

$$\lim_{\delta \sigma_0 \rightarrow 0} (h_2 * \delta \sigma_0) = \lim_{\delta \sigma_0 \rightarrow 0} (h_1 * \delta \sigma_0) = 0, \quad (4.13)$$

it follows from (4.12) that  $f_D \propto \frac{H_1(0)}{H_2(0)}$ , which is the geometric Doppler. Conversely, for non-zero NRCS gradients things become more complicated: the geometric Doppler term is gradually suppressed through division by  $h_2 * \delta \sigma_0$ , and the multiplication of various higher order terms with  $h_1 * \delta \sigma_0$  leads to scale interactions across wavenumbers. For a symmetric beam and geometric Doppler, such as considered here,  $H_1(0) = 0$ , leaving only the terms resulting from scale interaction. The resulting spectra of  $\nu_L$  approach the

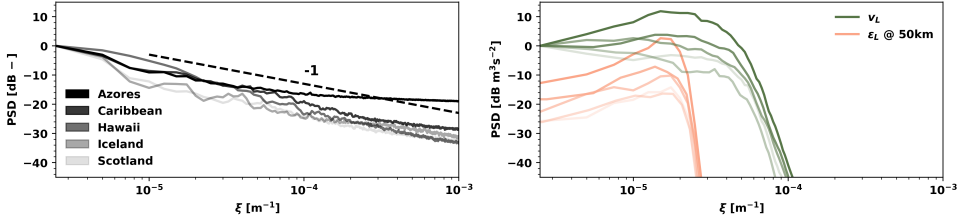


Figure 4.2: Left) relative azimuthal spectra of high-resolution NRCS. Right) native resolution leakage,  $\nu_L$ , and residual leakage after correction,  $\epsilon_L$ , averaged to a 50 km ground-projected spatial resolution. Spectra are estimated along a 400 km azimuthal section and averaged across range for each case study in Table C.1. Spectra of residual leakage are relative to the original leakage. The presented spectra are anecdotal but illustrate the prevailing decreasing gradients in NRCS at smaller scales as well as the consistent behavior of (residual) leakage. The sharp cut-off in residual leakage for wavenumbers beyond  $2 \cdot 10^{-5} \text{ m}^{-1}$  is caused by the aforementioned spatial filtering. Spatial filtering is needed to reduce speckle's inhibitory effect on leakage estimation. The gradual roll-off in  $\nu_L$  traces the beam footprint's frequency response.

spectrum of the corresponding beam pattern, see the right half of Figure 4.2 where the shared and gradual roll-off occurs at the limit of the footprint's spatial resolution. The calculation of presented (residual) leakage spectra will be covered later.

Despite making several simplifying assumptions, no convenient expression results from the procedures described above; to quantify  $f_D$  one still needs the fields  $h_1$ ,  $h_2$  and  $\delta\sigma_0$ , warranting an empirical approach.

#### 4.2.3. DATA SYNTHESIS AND LEAKAGE CORRECTION

Since leakage is the result of NRCS gradients, any observations of the NRCS field can be combined with a known beam pattern and geometrical Doppler to estimate the incurred leakage. We use the high-resolution Sentinel-1 NRCS and (4.1) to approximate the true incurred leakage. It does not matter that the Sentinel-1 NRCS has a finite resolution, as the spatial scales most prone to leakage—those at the limit of the scatterometer resolution—are well captured, see Figure 4.2. Next, we synthesize a coarse scatterometer-observed NRCS with which we aim to correct for the estimated incurred leakage. The data synthesis and correction steps are detailed in Figure 4.3.

Artificial fan-beam scatterometer data are synthesized by stitching together several Sentinel-1 frames along azimuth, simulating a range-subset of the continuous scatterom-

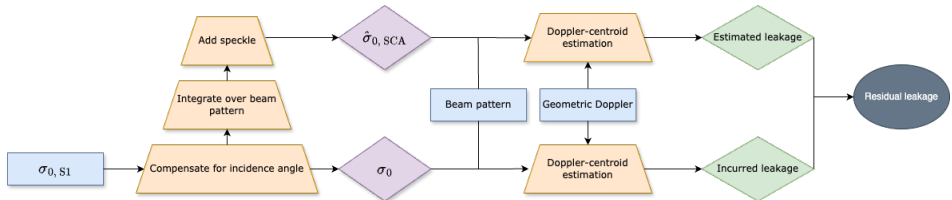


Figure 4.3: Flow chart for the retrieval of estimated, incurred and residual leakage; starting from the high resolution NRCS, beam pattern and geometric Doppler. For our symmetric beam and stationary surface, the estimated Doppler centroid is the leakage.

Table 4.1: The following platform parameters are assumed, respectively retrieved from: antenna dimensions and altitude Fois et al., 2015; antenna elements Rostan et al., 2016; waveform and WVC parameters Hoogeboom et al., 2018.

| Parameter                           | Quantity               |
|-------------------------------------|------------------------|
| Platform altitude                   | 823 km                 |
| Platform velocity                   | 6800 m s <sup>-1</sup> |
| Antenna height broadside            | 0.32 m                 |
| Antenna length broadside            | 2.87 m                 |
| Antenna elements azimuth            | 4                      |
| Antenna elements elevation          | 1                      |
| Beam footprint azimuthal truncation | 80 km                  |
| Ground yaw angle                    | 0°                     |
| Boresight elevation angle           | 40°                    |
| Considered swath elevation angles   | 35° - 45°              |
| Wavelength                          | 5.5 cm                 |
| Nr. of subpulses                    | 2                      |
| Sub pulse bandwidth                 | 1 MHz                  |
| Slant range resolution              | 150 m                  |
| Maximum total pulse length          | 1.15 ms                |
| Time between sub-pulses             | 0.115 ms               |
| Sub-pulse SNR                       | 1                      |
| PRF at broadside                    | 3.942 Hz <sup>1</sup>  |
| Surface spatial resolution          | 50 km                  |

eter observations. The Sentinel-1 NRCS data ( $\sigma_0, s_1$ ) is mapped to the stress-equivalent neutral winds ( $U_{10, n}$ ) using wind directions from ERA5, and these winds are translated back to a high-resolution DopSCA-equivalent NRCS ( $\sigma_0$ ) using the CMOD5.N Geophysical Model Function (Hersbach, 2010). This compensates for their respective viewing geometries. The high spatial and radiometric resolution of  $\sigma_0$  allows it to be used as a reference and starting point from which to estimate the much coarser NRCS observed by DopSCA ( $\sigma_{0, \text{SCA}}$ ) based on the parameters listed in Table 4.1. Computations are simplified by assuming a rectilinear geometry; no squint, pitch, yaw or roll; and neglecting any Earth-rotation effects. Furthermore, range cell migration is assumed to have been corrected for.

The  $\sigma_0$  field is sampled at a uniform 75 m ground-range spacing  $\Delta x_{\text{ground}}$  to generously comply with Nyquist for DopSCA's 150 m slant range resolution. In order to compute  $\sigma_{0, \text{SCA}}$  we need to momentarily convert to a uniform slant-range spacing  $\Delta x_{\text{slant}}$ , which is equivalent to a variable ground-range projected spacing. Spacing conversions are performed with linear interpolators indicated by

$$\begin{aligned} \mathcal{A}_{g \rightarrow s} : \Delta x_{\text{ground}} &\rightarrow \Delta x_{\text{slant}} \\ \mathcal{A}_{s \rightarrow g} : \Delta x_{\text{slant}} &\rightarrow \Delta x_{\text{ground}}, \end{aligned} \quad (4.14)$$

<sup>1</sup>For discretization ease we deviate from the frequently referenced 4 Hz

where the sequence of  $\mathcal{A}_{g \rightarrow s}$  and  $\mathcal{A}_{s \rightarrow g}$  results in a variable low-pass filtering along ground range with worse ground-range resolution for lesser elevation angles. The variable ground-range-projected slant-range spacing is computed as

$$\Delta x_{\text{slant}} = \frac{\Delta x_{\text{ground}}}{\sin(\theta_i)}. \quad (4.15)$$

The simulated true-value of the scatterometer-observed NRCS is computed as

$$\sigma_{0,\text{SCA}} = \mathcal{A}_{g \rightarrow s} \left( \frac{\int_{\eta} \sigma_0 G_{2\text{-way}} d\text{Az}}{\int_{\eta} G_{2\text{-way}} d\text{Az}} \right), \quad (4.16)$$

which integrates the high-resolution  $\sigma_0$  within the truncated azimuthal beam footprint at azimuthal intervals defined by the Pulse Repetition Frequency (PRF). Azimuthal truncation is performed for computational reasons such that the truncated along-azimuth coverage is a constant 40 km to the front and rear of boresight represented by  $\eta$  following

$$\eta = \text{Az}|_{\pm 40\text{km}} \quad (4.17)$$

where Az refers to the entire azimuthal extent. Increasing the truncation extent had little effect on results. Depending on the beam pattern, a variable azimuthal truncation should be considered as a function of elevation angle.

The azimuthal component of  $G_{2\text{-way}}$  can be approximated as a function of antenna length  $L_A$  (Cumming & Wong, 2005). Usually tapered beam patterns are used, widening the main beam and reducing side lobes. For instance, ASCAT's side-lobes required attenuation in order to avoid signals reflecting from parts of the satellite itself (Gelsthorpe et al., 2000). Azimuthal beam tapering employed in this study increases the beam width of  $G_{2\text{-way}}$  from  $0.69^\circ$  to  $0.78^\circ$ .

To simulate a realization of the *observed* NRCS, random speckle is added to the *true* NRCS. We model multiplicative speckle,  $\mathcal{S}$ , as a unit power circular-Gaussian band-limited random signal, and compute the observed NRCS as:

$$\hat{\sigma}_{0,\text{SCA}} = \mathcal{A}_{s \rightarrow g} (\sigma_{0,\text{SCA}} \cdot |\mathcal{S}|^2). \quad (4.18)$$

With multiplicative speckle added, the data are interpolated back to a uniform 75 m ground-range spacing.

From the observed  $\hat{\sigma}_{0,\text{SCA}}$  and using (4.1) we compute an estimate of the leakage velocity,  $\hat{\nu}_{L,\text{SCA}}$ . In the case that we have no geophysical motions and the theoretical DC is zero, the difference in leakage estimated from  $\sigma_0$  and  $\hat{\sigma}_{0,\text{SCA}}$  yields the residual leakage

$$\epsilon_L = \nu_L - \hat{\nu}_{L,\text{SCA}}, \quad (4.19)$$

which represents the incorrigible error introduced by leakage. After averaging to typical scatterometer product resolutions, the magnitude of residuals is in the order  $\mathcal{O}(0.1 \text{ ms}^{-1})$ , and locally up to  $\mathcal{O}(1 \text{ ms}^{-1})$ . The power of these residuals is reduced at all scales with respect to the original leakage spectra, see Figure 4.2, illustrating successful leakage reduction.



#### 4.2.4. PULSE-PAIR MEASUREMENT UNCERTAINTY

Likely the greatest velocity uncertainty of Doppler scatterometers results from the pulse-pair observation mechanism. We simulate and add this uncertainty so that it can quantitatively be compared to leakage velocity. Making the best estimates of pulse-pair uncertainties falls outside the scope of this study. Since the derivation is non-trivial, it is documented in Appendix C.1 (with slight deviations from the literature).

Uncertainty can be reduced by averaging over independent samples. In the particular case of DopSCA, Hoogeboom et al., 2018 used the equivalent number of independent samples present within a 25 km slant-range window, reducing line-of-sight uncertainty to  $\sim 1 \text{ ms}^{-1}$ . The wide spectral response of an unweighted 25 km moving-average operation is similar to that of a 50 km Hann low-pass filter, which we use in this study. Approximately  $2 \text{ ms}^{-1}$  instantaneous pulse-pair uncertainty can be expected at a ground-projected 50 km resolution for the considered range of incidence angles and based on an expected pulse-pair phase coherence of 0.39 estimated in Appendix C.1.

#### 4.2.5. CASE STUDIES

Several sequences of Sentinel-1 observations are used to emulate scatterometer scenes. We focus primarily on a longer sequence of successive observations near the Azores. Metadata for these case studies can be found in Table C.1.

In addition, we utilize a time series of observations made over the eastern Agulhas for which a dataset of surface-current estimates is available (NERSC, 2022). This dataset contains calibrated Doppler centroid anomalies (DCA) and estimates of the wind-wave Doppler. These are compensated to account for the differing incidence angles between Sentinel-1 and the synthesized scatterometer. The retrieved DCA is corrected for the estimated wind-wave Doppler and converted to a surface current. In turn, this current is interpolated to the  $\sigma_{0,\text{SCA}}$  coordinates and integrated over the beam- and backscatter-weighted footprint to the scatterometer's spatial resolution, yielding the total surface current as would be observed by DopSCA:  $u_{\text{TSC}}$ .

### 4.3. RESULTS AND DISCUSSION

The analyses presented in this section intend to assess the magnitude of uncertainty introduced by leakage velocity, our ability to correct for this uncertainty, and the implications of residual uncertainty on mission objectives. Results are presented as ground-projected velocities at a 50 km spatial resolution over the shared spatial extent.

#### 4.3.1. INSTANTANEOUS LEAKAGE VELOCITY AND CORRECTION

The Azores case study presents azimuthal NRCS gradients at varying scales, see subfigures A & B in Figure 4.4. One can identify strong leakage in subfigure C wherever azimuthal inhomogeneities or trends in NRCS are present. Prevalent in particular is the bias of positive leakage towards the upper half of the domain.

With an RMSE of  $1.20 \text{ ms}^{-1}$ , the uncertainty introduced by leakage would easily compare to the signal of strong surface currents. Correcting for leakage improves results: the RMSE of residual leakage in subfigure D drops to  $0.38 \text{ ms}^{-1}$  and the prevailing leakage bias has vanished. Using the coarse, scatterometer-observed NRCS it is thus feasible to

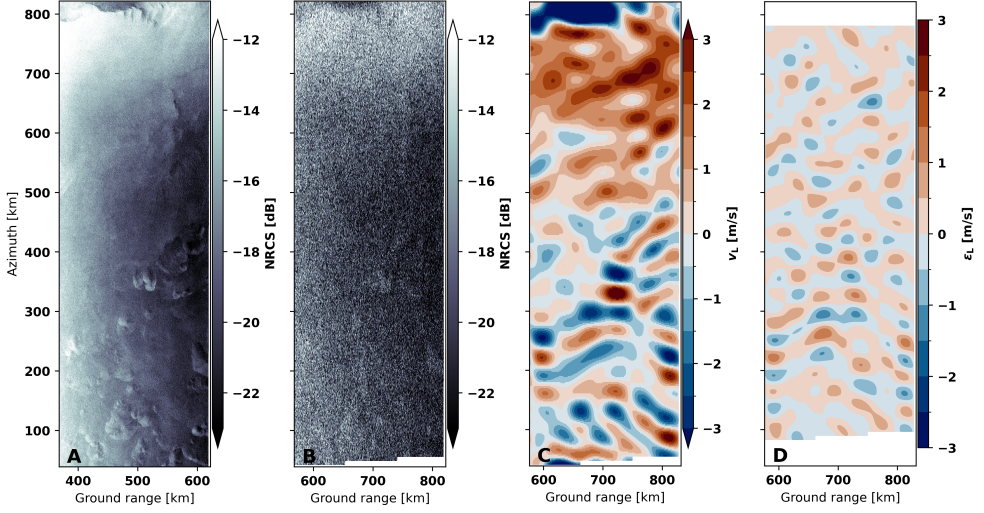


Figure 4.4: Case study near the Azores of five stitched Sentinel-1B acquisitions taken on 2020-11-27 at 19:39. A) original Sentinel-1  $\sigma_{0,S1}$ , B) synthesized scatterometer realization  $\hat{\sigma}_{0,SCA}$  where the different viewing geometry w.r.t. Sentinel-1 results in a different equivalent ground-range coverage (azimuth is cropped due to beam integration extending outside of  $\sigma_{0,S1}$  domain), C) incurred leakage velocity  $v_L$ , D) residual leakage velocity post correction  $\epsilon_L$ . RMSEs for figures C & D are  $1.20$  and  $0.38 \text{ ms}^{-1}$  respectively at a  $50 \text{ km}$  spatial resolution over their shared spatial extent.

reduce leakage uncertainty to  $\mathcal{O}(0.1 \text{ ms}^{-1})$ .

For DopSCA the presented instantaneous effect of leakage would be masked by the dominant instantaneous pulse-pair uncertainty, whose realization for this case study had an RMSE of  $2.12 \text{ ms}^{-1}$ —about twice that of leakage. Nonetheless, the combined RMSE of leakage and pulse-pair uncertainty drops from  $2.40 \text{ ms}^{-1}$  to  $2.18 \text{ ms}^{-1}$  after leakage correction. Thus, correcting for leakage shaves of several  $\text{dms}^{-1}$  worth of errors. Systems capable of suppressing pulse-pair uncertainty would see an increased sensitivity to leakage and may even be dominated by it.

#### 4.3.2. TEMPORAL PERSISTENCE OF LEAKAGE

Residual leakage (and pulse-pair uncertainty) may be reduced further through temporal averaging. Since leakage is correlated to NRCS gradients, the stochastic behaviour of these gradients determines the behaviour of leakage. Currents are known to be long-lived and sources of NRCS gradients, so they might impart their temporal persistence onto the residual leakage. To then consider performance on a temporal scale, we next assess the persistence of residual leakage with respect to a time series of surface-current observations.

The eastern Agulhas is characterized by a strong and relatively stable total surface current (TSC), see Figure 4.5. The rare availability of co-located and calibrated Doppler measurements over the Agulhas enables a relative comparison of leakage velocity with respect to the observed surface current.

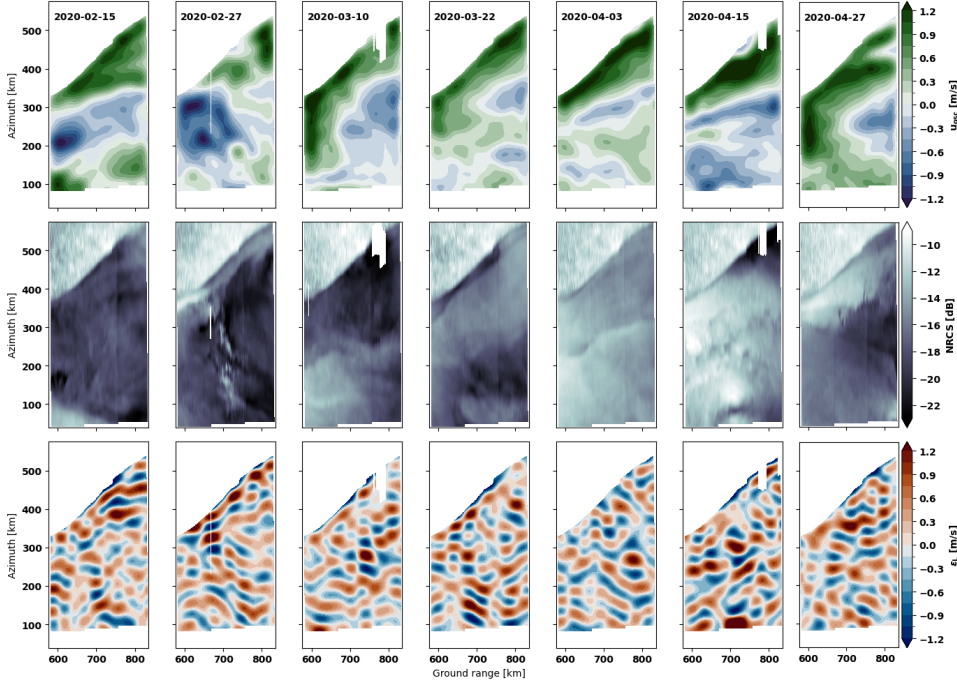


Figure 4.5: Total surface currents from Sentinel-1 integrated over the scatterometer beam at 50 km spatial resolution (upper). Scatterometer  $\sigma_{0,SCA}$  (without the addition of speckle) at native resolution for a time series over the eastern Agulhas (center). Residual leakage velocity at 50 km spatial resolution (bottom).

To show that the TSC is persistent across realizations while the random residual leakage component is not, we compare the mean standard deviation of realizations,  $\langle \sigma_x \rangle$ , to the standard deviation of the mean realization,  $\sigma_{\langle x \rangle}$ . For random, uncorrelated processes,  $\sigma_{\langle x \rangle}$  will decrease by a factor  $\sqrt{N}$  with respect to  $\langle \sigma_x \rangle$ , with  $N$  being the number of independent samples, i.e., realizations.

As shown in Table 4.2, the mean standard deviation of TSCs over the seven presented days,  $\langle \sigma_{u_{TSC}} \rangle$ , is  $0.44 \text{ m s}^{-1}$  and the standard deviation of the temporal mean TSC,  $\sigma_{\langle u_{TSC} \rangle}$ , is  $0.33 \text{ m s}^{-1}$ . Were the TSC random and uncorrelated in time, the standard deviation of its mean realization would have decreased by a factor  $\sqrt{7}$  to  $0.17 \text{ m s}^{-1}$  instead. Unlike for the TSC, such a reduction is observed in the residual leakage velocity, whose mean standard deviation,  $\langle \sigma_{\epsilon_L} \rangle$ , is  $0.45 \text{ m s}^{-1}$  while the standard deviation of the temporal mean  $\sigma_{\langle \epsilon_L \rangle}$ , is  $0.21 \text{ m s}^{-1}$ . The latter is much closer to the  $0.17 \text{ m s}^{-1}$  expected for an uncorrelated, random process (following  $\langle \sigma_{\epsilon_L} \rangle / \sqrt{N}$ ). Thus, despite significant temporal autocorrelation in the TSCs, at the considered temporal scales, currents do not actually introduce persistent leakage. This therefore enables further reductions of the residual leakage through temporal averaging.

The lack of temporal autocorrelation in residual leakage may be explained by two compatible hypotheses: few of the unresolved NRCS gradients are caused by temporally persistent currents such that they impart little of their persistent nature onto the residu-

Table 4.2: Variability of total surface currents and residual leakage velocity for the Agulhas case study when considering and omitting the addition of speckle to the synthesized scatterometer NRCS for  $N = 7$  samples. Only considering data points available on all dates. Columns indicate: average temporal standard deviation  $\langle \sigma_{u_{TSC}} \rangle$ , standard deviation of the temporal average surface current  $\sigma_{\langle u_{TSC} \rangle}$ , Average temporal standard deviation of residual leakage  $\langle \sigma_{\epsilon_L} \rangle$ , standard deviation of the temporal average residual leakage  $\sigma_{\langle \epsilon_L \rangle}$ . All units in  $\text{ms}^{-1}$ .

|              | $\langle \sigma_{u_{TSC}} \rangle$ | $\sigma_{\langle u_{TSC} \rangle}$ | $\langle \sigma_{\epsilon_L} \rangle$ | $\sigma_{\langle \epsilon_L \rangle}$ | $\langle \sigma_{\epsilon_L} \rangle / \sqrt{N}$ |
|--------------|------------------------------------|------------------------------------|---------------------------------------|---------------------------------------|--------------------------------------------------|
| With speckle | 0.44                               | 0.33                               | 0.45                                  | 0.21                                  | 0.17                                             |
| No speckle   | 0.44                               | 0.33                               | 0.27                                  | 0.14                                  | 0.10                                             |

als, or leakage estimation and correction are inhibited by the random speckle present in the synthesized scatterometer NRCS. The first hypothesis is difficult to test as it requires precise knowledge of what NRCS is related to which phenomena. The second hypothesis is assessed by omitting the addition of speckle when producing synthetic scatterometer data. Summary results from this second analysis over the Agulhas are also presented in Table 4.2. In the absence of speckle the residual leakage drops significantly from  $0.45 \text{ ms}^{-1}$  to  $0.27 \text{ ms}^{-1}$ . Nonetheless, the remaining signal still behaves as an uncorrelated random variable; the standard deviation of the temporal mean residual leakage at  $0.14 \text{ ms}^{-1}$  approaches the expected  $0.10 \text{ ms}^{-1}$  for an uncorrelated random variable. It then follows that the first hypothesis is likely responsible for the majority of the residual leakage's lacking temporal autocorrelation.

#### 4.3.3. IMPLICATIONS TO SYSTEM DESIGN

Given the above observations, we can consider what system design parameters ought to minimize exposure to residual leakage, focusing in particular on azimuthal resolution and the number of independent samples. The number of independent samples determines how much spatial averaging can be performed to reduce speckle's inhibitory effect on corrections, whereas the azimuthal resolution sets the sensitivity to the range of unsampled spatial frequencies. And, as observed in Figure 4.2, smaller spatial scales contain less energy and can thus be expected to lead to less leakage.

To illustrate the relative importance of both aspects, we assess performances for the case studies listed in Table C.1 with varying hypothetical antenna lengths, which directly affects the azimuthal resolution. The number of independent samples can be enhanced by increasing the pulse bandwidth (yielding a greater range resolution) and PRF (yielding more samples in azimuth). Both options are computationally expensive to simulate. Instead, no speckle will be added for a run of analyses to simulate the effect of a sufficient number of independent samples capable of nullifying speckle in the limit.

These simulations, summarized in Figure 4.6, corroborate results obtained for the Agulhas case, with a marked decrease in correction capabilities in the presence of speckle. A consistent exponential decay is observed, permitting the inference of performance for other Doppler scatterometers. For instance, at the same 50 km spatial resolution, pencil-beam scatterometers operating at Ku-band with a PRF in the kHz range should expect a similar sensitivity to residual leakage as the equivalent DopSCA setup with no speckle (assuming that speckle reduction is enabled through the greater PRF) and a three

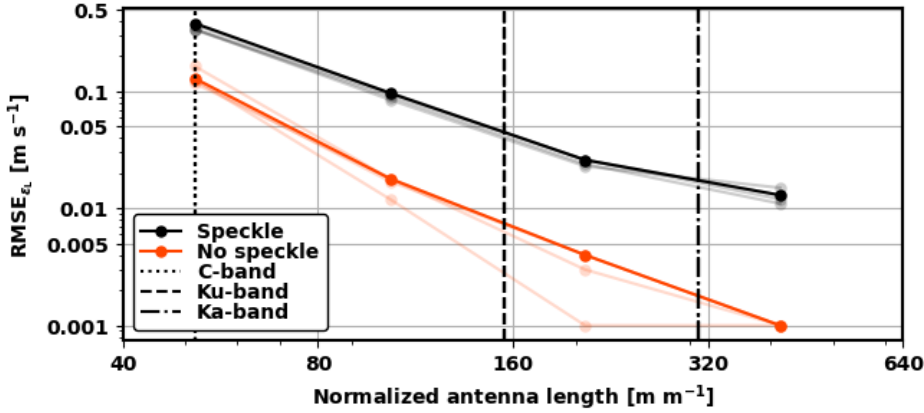


Figure 4.6: Residual leakage for case studies as a function of wavelength-normalized antenna lengths. Reference values are indicated for C-, Ku- and Ka-band systems assuming a tapered beam for a 2.87 m long antenna. Performance for the Azores case is highlighted with the other case studies listed in Table C.1 grayed out. The "No speckle" case represents the limit in residual-leakage reduction due to spatial averaging. A greater along-azimuth extent  $\eta$  and sampling is required to provide representative results outside the range of normalized antenna lengths between 40 and 640 respectively.

times longer antenna. These results also illustrate limitations of conventional C-band scatterometer designs, as a kHz PRF may all but eliminate pulse-pair uncertainty and speckle, yet residual leakage will remain significant (unless SAR processing is possible). Azimuthal resolution is thus key when aiming to mitigate leakage.

Other mitigation strategies could include narrowing the beam footprint by reducing its tapering. This lowers the sensitivity to NRCS gradients at the expense of reduced side-lobe suppression. Alternatively, a squinted viewing geometry could decrease the effective geometric-Doppler gradient and subsequent leakage. And, under highly favorable conditions, a squinted geometry would also enable leakage cancellation through sign reversal by combining observations from opposing squints, e.g., fore and aft. However, alterations to the viewing geometry and beam pattern are prone to conflict with other mission considerations.

## 4.4. CONCLUSION

In this study we assess the sensitivity to leakage velocity with the aim of answering whether this source of uncertainty could jeopardize the performance of Doppler scatterometers. A theoretical analysis does not yield a convenient expression as leakage is the result of non-linear processes. Therefore, an empirical analysis is performed instead, using emulated scatterometer observations.

Results indicate that, over the considered range of elevation angles and if uncorrected, the instantaneous leakage velocity for DopSCA-like sensors would lead to  $\sim 1 \text{ m s}^{-1}$  uncertainty in surface velocity estimates at a 50 km ground-projected spatial resolution. After correction—which consists of estimating the leakage from the observed  $\hat{\sigma}_{0,SCA}$  and the known geometric Doppler and beam pattern—the leakage uncertainty reduces to



$\mathcal{O}(0.1 \text{ ms}^{-1})$ . Sub  $\mathcal{O}(0.1 \text{ ms}^{-1})$  performance is unlikely for any C-band RAR system due to the relatively large beam footprints.

Temporal averaging effectively further reduces the instantaneous residual leakage through a two-fold process. Firstly, temporal averaging reduces speckle's inhibiting effect on the estimation and correction of leakage. Secondly, since residual leakage experiences little autocorrelation from potential current-NRCS interactions—which suggests that leakage-inducing NRCS gradients are primarily caused by imprints of the fast-decorrelating atmosphere—it too is reduced successfully through temporal averaging. This holds over the strong and persistent surface currents of the eastern Agulhas, but it may not transfer to other spatiotemporal domains or scales.

For DopSCA, leakage is a second-order effect compared to the dominant pulse-pair uncertainty. However, where pulse-pair uncertainty is effectively reduced by averaging over more independent samples, this is not the case for leakage velocity, making leakage particularly relevant for systems where pulse-pair uncertainty is successfully suppressed.

Future missions could minimize their exposure to leakage and its residuals by targeting adequate combinations of independent observation samples and azimuthal resolution. When design alterations are unfeasible due to specific constraints, e.g., resolution trade-offs, power requirements, and other limitations, then temporal averaging remains a broadly applicable and effective mitigation strategy.

#### 4.5. DATA AVAILABILITY

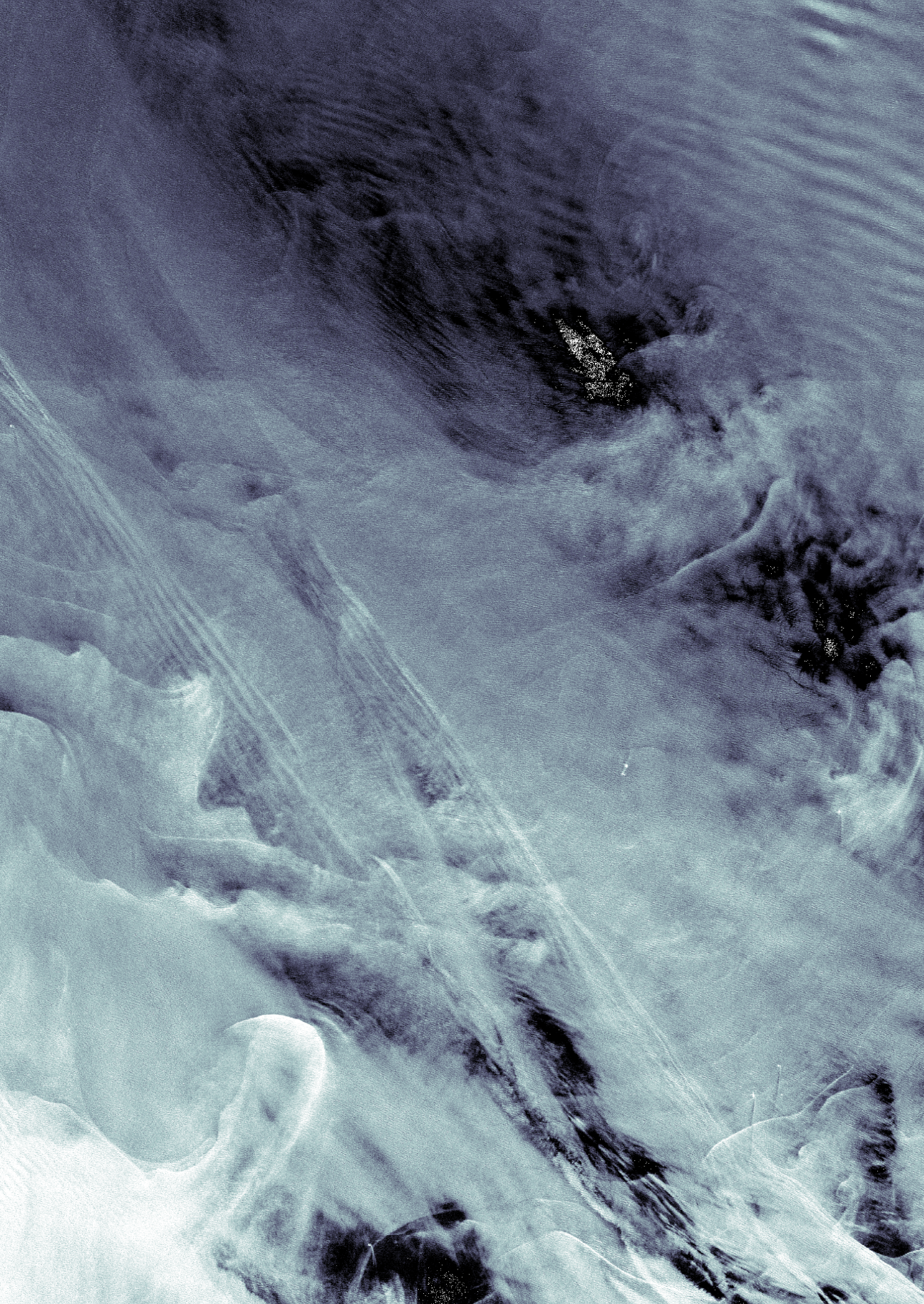
The analyses of this study are performed using Ground Range Detected Copernicus Sentinel-1 data 2020/2023, retrieved from ASF's API on 03-03-2024, processed by ESA. This data are accessed using Ifremer's open source XSAR file reader available at <https://github.com/umr-lops/xsar.git>. Beam patterns were generated using <https://gitlab.tudelft.nl/drama/drama>. The CMOD5.N implementation was used from <https://gitlab.tudelft.nl/drama/stereoid>. Reference wind fields needed to run CMOD5.N were retrieved through ECMWF's ERA5 API (Hersbach et al., 2020). Calibrated Doppler measurements from the Agulhas campaign were obtained from the ESA WOC project (NERSC, 2022). A repository containing the used algorithms is available at [https://github.com/owenodriscoll/DopSCA\\_leakage](https://github.com/owenodriscoll/DopSCA_leakage).

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# 5

## DISENTANGLING CURRENTS AND WAVES: EXPLOITATION OF POLARIZATION DIVERSITY FOR WAVE-DOPPLER ESTIMATION

*Only dead fish follow the current*

Chinese proverb

*Surface velocities measured by Synthetic Aperture Radar (SAR) contain contributions from both mean surface motion—referred to as total surface current (TSC)—and the often more prominent sea-state-induced wave motions. Most modern SAR systems cannot distinguish between these phenomena, which has stifled TSC retrieval from SAR for decades.*

*We propose a new framework to separate TSC and wave-motion components by leveraging polarization diversity, exploiting the tendency of each phenomenon to imprint distinct signatures on orthogonal polarizations. Building on a foundational signal model, we derive four source-separation algorithms. To address the model's theoretical limitations, we introduce empirical extensions via symbolic regression, guided by varying levels of theoretical insight.*

*The developed algorithms are evaluated using simulated C-band SAR data, and benchmarked against a reference geophysical model function (GMF) implementation. Our methods demonstrate comparable overall performance, with errors on the order of  $\mathcal{O}(0.1 \text{ m s}^{-1})$ , and notably outperform the GMF in resolving kilometer-scale spatial features—a domain where traditional GMFs generally struggle.*

*Preliminary results obtained on TanDEM-X observations confirm the generalizability of our approach. These findings highlight the potential of future SAR missions with polarimetric capabilities, such as Harmony, to achieve high-resolution separation of surface-motion sources using polarization diversity.*

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## 5.1. INTRODUCTION

The potential of Synthetic Aperture Radar (SAR) to retrieve surface Doppler—and thus surface velocity—has been investigated by many authors (Caldarella et al., 2022; Frasier & Camps, 2001; Goldstein & Zebker, 1987; Romeiser et al., 2002; Romeiser et al., 2014; Toporkov et al., 2005). The observed surface velocity should be understood as an average of the line-of-sight (LoS) projection of the instantaneous velocities of each *scatterer* on the surface, weighted by their radar cross-sections. Ocean waves modulate the local normalized radar cross section (NRCS). The main contributors to this modulation, tilt and hydrodynamic modulation, affect different parts of the wave to different degrees (Chapron, 2005; Hansen et al., 2012). The ensuing correlation between modulated NRCS and orbital velocities results in an effective Doppler velocity, often referred to as the wave Doppler, even in the absence of any mean surface motion (D. R. Thompson & Jensen, 1993). Indeed, it is well established that the Doppler can be used to infer the surface wind. In general, the measured Doppler velocity due to wind-driven waves is in the order of 10% to 20% of the surface wind (Chapron, 2005).

Aside from this wave Doppler, the measured Doppler velocity also includes the LoS projection of the actual mean surface motion, often referred to as the Total Surface Current (TSC).

Naturally, one would need to distinguish between wave Doppler and the TSC Doppler when interested only in the latter. Considering that the wave Doppler magnitude may easily exceed the TSC Doppler, an accurate separation is paramount.

The wave Doppler also has intrinsic value beyond its use in targeting a TSC; it captures information on the wave state which relates to a host of air-sea coupling processes (e.g. Cavaleri et al., 2012; S. Chen et al., 2018; Huang & Qiao, 2010) and, due to its close correlation to surface winds, it can also be used in improved surface-wind estimation (Mouche et al., 2012; Saïd & Johnsen, 2014).

Contemporary wave-Doppler estimation techniques use empirical Geophysical Model Functions (GMF). These models, such as CDOP, XDOP and KaDOP (X.-M. Li & Lehner, 2014; Mouche et al., 2012; Yurovsky et al., 2019), are tuned to provide a good average fit as a function of wind speed. Theory (e.g. Hansen et al., 2012; V. Kudryavtsev et al., 2005) tells us that the wave Doppler depends on the wave spectra and wave-breaking fraction and that these depend on many factors, including wave-current and wave-wave interactions. Neglecting departures from the mean state for these factors may inadvertently lead to models capable of estimating wave Doppler only when no surface-current gradients are present—an undesirable trait.

More holistic models (e.g. Moiseev et al., 2020, 2022) consider additional information relating to the wave state, making them more suitable to disentangle the convoluted Doppler signals. Still, these models implicitly rely on the nonexistence of wind-wave-current interactions or require ancillary data such as directional wind, wave, and swell information.

In this work we rely on an untapped resource for the estimation of the wave Doppler: polarization diversity. It is known that the measured Doppler velocity is polarization-dependent, which should be generally attributed to a polarization dependence of the wave-Doppler. This dependence has previously been exploited to estimate the surface wind (Saïd & Johnsen, 2014).



The potential to exploit polarization diversity in this sense was already anticipated in the literature (Chapron, 2005; Wollstadt et al., 2017), and was incorporated in the original SEASTAR system concept (Gommenginger et al., 2019), which was conceived as a hybrid-polarimetric system (Raney, 2007). The Harmony mission (Lopez-Dekker et al., 2019) also features a bistatic equivalent to a hybrid polarized system.

From a signal model based on the Doppler-shift considering Radar Imaging Model (DopRIM, Hansen et al., 2012; V. Kudryavtsev et al., 2005), we derive a closed-form expression for wave Doppler as a function of polarized observables. We assume that the Doppler originating from the TSC is polarization-independent. Therefore, the polarized Doppler difference removes the TSC component, providing direct insight into the wave-Doppler contributions. Through careful weighting of this difference, we obtain a quantitative estimate of the wave-Doppler. We further introduce a simplified approximation tailored to practical use.

The scarce nature of clear validation data hinders the assessment of estimated wave- and TSC-Dopplers; measurements of two-dimensional surface currents are lacking, and no existing dataset dissects the sources of NRCS and Doppler at relevant scales. To overcome this obstacle, we rely on simulated data by employing Harmony's Scientific Work Bench (SWB) to simulate relevant contributions towards the total NRCS and Doppler budgets (Conroy et al., 2026; Kleinherenbrink et al., 2026). This simulator combines state-of-the-art radar scattering models with ancillary data from a coupled air-sea model. Afterwards, the developed methodology is applied on a limited quantity of observational data obtained with TanDEM-X (Krieger et al., 2007).

Our signal model is presented in Section 5.2, from which idealized separation of scattering sources can be deduced. The signal model will be applied to simulations and observations, these are detailed in Section 5.3, with the results of this application, and a discussion thereof, presented in Section 5.4. Conclusions and perspectives are shared in Section 5.5.

## 5.2. SIGNAL MODEL

We follow V. Kudryavtsev et al., 2014; V. N. Kudryavtsev et al., 2013 in assuming that the normalized radar cross section for a co-polarization PP (in this paper HH or VV) can be written as the sum of a polarized scattering term,  $\sigma_r^{PP}$ , well described by rough surface scattering theory, and a non-polarized scalar term,  $\sigma_s$ , assumed to be caused by specular scattering associated with localized steep slopes caused by breaking waves:

$$\sigma_0^{PP} = \sigma_r^{PP} + \sigma_s. \quad (5.1)$$

The first term has often been associated with *Bragg* scattering within a two-scale model. Given the difficulties inherent to such a model, with a somewhat arbitrary division of scales, we opt to follow the symbol convention used in V. Kudryavtsev et al., 2005, referring to it as a regular surface  $\sigma_r^{PP}$ , instead of  $\sigma_B^{PP}$ . Note that (5.1) implicitly assumes that the complex-valued contributions of the two types of scatterers are uncorrelated.

As in V. N. Kudryavtsev et al., 2013 we define the polarization ratio, which can be estimated from the data

$$p = \frac{\sigma_0^{HH}}{\sigma_0^{VV}}. \quad (5.2)$$

For convenience, we can also define the fraction of scalar (wave-breaking) scattering for any polarization, for example

$$f_s^{HH} = \frac{\sigma_s}{\sigma_0^{HH}}, \quad (5.3)$$

or, at vertical polarization

$$f_s^{VV} = p f_s^{HH}. \quad (5.4)$$

We now extend this decomposition to the geophysical Doppler velocity,  $v^{PP}$ . This Doppler velocity can be derived from an Along Track Interferometry (ATI) phase, or from a Doppler Centroid Anomaly (DCA). We will assume that the Doppler velocity can be written as

$$v^{PP} = v_{WD}^{PP} + v_{TSC}, \quad (5.5)$$

the sum of a so-called wave-Doppler component and a term associated with the TSC. Conceptually, this decomposition assumes that the waves propagate relative to a medium that moves with a velocity given by the TSC vector. One could reasonably assume that wave-current interactions affect different waves differently, and, in turn, different waves affect both polarizations differently. We assume this effect is minimal, such that  $v_{TSC}$  can be considered polarization independent. Furthermore, possible complications associated with a non-constant vertical current profile are ignored, and we assume that the Doppler velocities can be traced uniquely to either source.

The non-polarimetric TSC assumption could lead to a persistent, but minor, underestimation of the TSC, given that Stokes drift—the net horizontal motion resulting from wave undulations, and a component of the TSC—likely exhibits some polarimetric sensitivity. This component would then be erroneously attributed to wave Doppler instead. Given the generally small magnitude of Stokes drift (between 1-1.8% of the wind speed according to Ardhuin et al., 2009), and the existing ability to estimate it with reasonable precision from wind speed measurements (Ardhuin et al., 2018), even a complete misattribution of Stokes drift is unlikely to introduce errors exceeding  $0.01 \text{ m s}^{-1}$  to  $0.10 \text{ m s}^{-1}$ .

The wave-Doppler velocity component can be written as the weighted average of the Doppler velocities associated with the regular surface,  $v_r$ , and to wave breaking,  $v_s$ , where the weighting is given by the scattering fractions:

$$v_{WD}^{PP} = v_r^{PP} \cdot (1 - f_s^{PP}) + v_s \cdot f_s^{PP}, \quad (5.6)$$

Considering two co-polarized measurements only, (5.5) and (5.6) involve four unknown velocity contributions with two velocity observables.

Since the surface current is polarization independent, its contribution is removed by studying the velocity difference, which, when written in terms of the predefined variables, yields

$$\begin{aligned} v^{HH} - v^{VV} &= v_r^{HH} (1 - f_s^{HH}) - v_r^{VV} (1 - f_s^{VV}) \\ &\quad + v_s (f_s^{HH} - f_s^{VV}). \end{aligned} \quad (5.7)$$

In general, all components will depend on the observation geometry and sea state. We can, however, always define the ratios of the wave-Dopplers with respect to one of them.

This way we introduce

$$k_r = \frac{\nu_r^{HH}}{\nu_r^{VV}}, \quad (5.8)$$

and

$$k_s = \frac{\nu_s}{\nu_r^{VV}}. \quad (5.9)$$

These ratios are generally positive, though changing wind directions may yield local negative values.

Now the resonant scattering can be isolated. When written in terms containing only HH polarization, by combining (5.7) with (5.4), (5.8) and (5.9), this yields

$$\nu_r^{HH} = \frac{(\nu^{HH} - \nu^{VV})}{1 - f_s^{HH} - \frac{1}{k_r} (1 - p) f_s^{HH} + \frac{k_s}{k_r} f_s^{HH} (1 - p)}. \quad (5.10)$$

We next rearrange (5.10) and combine it with (5.6) to yield a closed-form expression for the wave Doppler

$$\begin{aligned} \nu_{wD}^{HH} &= \nu_r^{HH} (1 - f_s^{HH}) + \nu_s f_s^{HH} \\ &= \nu_r^{HH} \left( 1 - f_s^{HH} + \frac{k_s}{k_r} f_s^{HH} \right) \\ &= \left( 1 - f_s^{HH} + \frac{k_s}{k_r} f_s^{HH} \right) \cdot \frac{(\nu^{HH} - \nu^{VV})}{1 - f_s^{HH} - \frac{1}{k_r} (1 - p) f_s^{HH} + \frac{k_s}{k_r} f_s^{HH} (1 - p)}. \end{aligned} \quad (5.11)$$

The obtained formulation is a weighted polarized Doppler difference, which, following (5.5) should be free from contamination by the TSC Doppler. In this rather cumbersome form,  $k_r$ ,  $k_s$  and  $f_s^{HH}$  are still unknown. Their variability will be investigated in Section 5.3.1.

The same derivation can easily be made using  $\nu_r^{VV}$  instead of  $\nu_r^{HH}$  by combining (5.10), (5.8) and (5.6), yielding

$$\begin{aligned} \nu_{wD}^{VV} &= (1 - f_s^{VV} + k_s f_s^{VV}) \cdot \frac{(\nu^{HH} - \nu^{VV})}{k_r \left( 1 - \frac{f_s^{VV}}{p} \right) - 1 + f_s^{VV} \left( k_s \frac{1-p}{p} + 1 \right)}. \end{aligned} \quad (5.12)$$

Though practically the same as (5.11), this formulation is less convenient to simplify, as will be shown later in (5.25).

### 5.3. DATA OVERVIEW

Lacking ground truth measurements, we instead rely on simulations obtained with Harmony's Scientific Work Bench (SWB). Details on the simulator are provided in Section 5.3.1.

Next, we apply the developed framework to a limited dataset of dual-polarized along-track interferometry (ATI) observations made with TanDEM-X. These observational data are described in Section 5.3.2. Additional processing details are provided in Appendix D.1.

### 5.3.1. SIMULATION DATA

#### SCIENTIFIC WORK BENCH

The SWB employs state-of-the-art versions of the Radar Imaging Model (RIM) (V. Kudryavtsev et al., 2005; V. Kudryavtsev et al., 2003) and Doppler RIM (DopRIM) (Chapron, 2005; Hansen et al., 2012; Johannessen et al., 2008; V. Kudryavtsev et al., 2023) to simulate polarimetric Normalized Radar Cross Section (NRCS) and Doppler for bi- and monostatic spaceborne observations of the ocean surface (Conroy et al., 2026; Kleinherenbrink et al., 2026). SWB inputs include modeled surface currents, sea surface temperatures (SST), wind/stress and interior currents. For the simulations in this paper, we use SWAN (Simulating WAVes-Nearshore, Booij et al., 1999) to generate the long-wave directional spectra, with the limit between what we consider long and short waves set at ten times the wavenumber of the spectral peak,  $10k_p$ . Subsequently, the RIM model generates the short wave spectra and the breaking wave fraction, considering the long wave spectrum, the local wind, and modulations due to surface current gradients.

The forward model simulates observations based on the Sentinel-1 Interferometric Wide swath (IW) mode. Specular reflection can be ignored at this range of incidence angles (e.g. Figure 2 in V. Kudryavtsev et al., 2005); the NRCS is fully attributed to resonant regular scattering and wave breaking, as in (5.1), with the wave-breaking fraction, hydrodynamic modulation and wave tilting all taken into account.

We emulate a hypothetical dual co-polarized ATI mode for Sentinel-1. Representative noise at burst level is added to the NRCS. A 2 Hz Gaussian uncertainty is added to the simulated Doppler, in-line with a pessimistic ATI performance (e.g. Romeiser et al., 2014). Model outputs are provided at a 1 km by 1 km grid spacing.

#### DopRIM GMF

In addition to the forward model, the SWB uses DopRIM to provide a Look Up Table (LUT) for the expected Doppler and NRCS given a wind magnitude/direction, incidence angle, polarization and wave age—much like conventional GMFs such as CDOP and CMOD. The estimated wave-Dopplers will be compared to those predicted by this purpose-built LUT, referred to as the DopRIM-GMF.

DopRIM-GMF and the SWB forward model are closely related: DopRIM-GMF is generated from the SWB forward model using an Elfouhaily long wave spectrum (Elfouhaily et al., 1997)—as opposed to the SWAN-derived long-wave spectrum for the reference SWB runs—, zero currents, a homogeneous wind and a constant inverse wave age. The latter we approximate by 1.2, which corresponds to a developing sea.

Since both DopRIM-GMF and the SWB forward model use DopRIM, we expect no biases between these models (excepting local biases that may result from disparate parameterization of wave-wave and wave-current interactions). This enables a fairer illustration of GMF performance, as in practice biases can be fixed by tuning.

Furthermore, in all uses of the DopRIM-GMF the "true" model winds are used, representing a highly idealized GMF performance.

#### CASE STUDY

The SWB simulation covers a region off the Californian coast where a spatially varying system of currents and winds causes a dynamic range of local conditions. An overview of the coupled input parameters to the SWB and SWAN is presented in Figure 5.1.

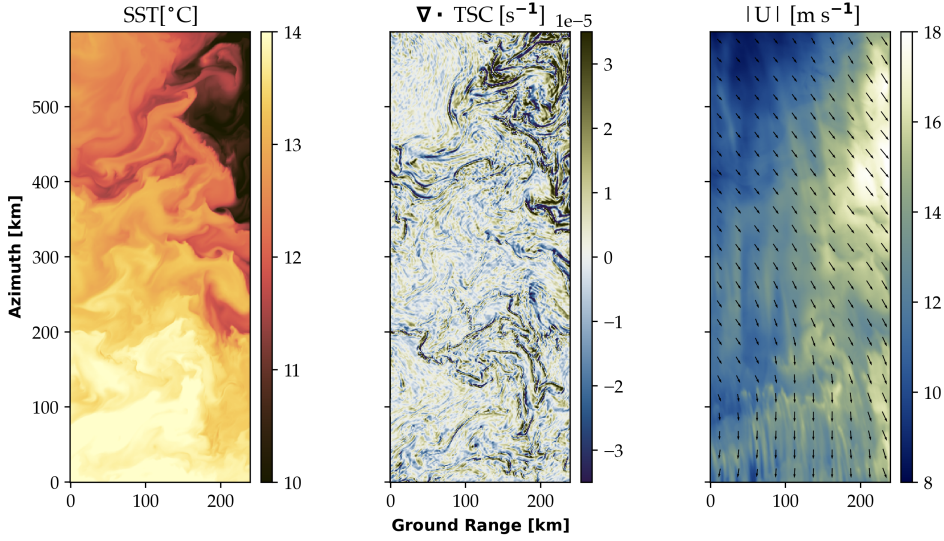


Figure 5.1: Overview of model inputs for the Californian case study overlapping with the forward model output. Coordinates follow those of the simulated right-looking observation system. True North is oriented approximately 15° clockwise from azimuth. Left) sea surface temperatures. Center) divergence of the total surface current. Right) wind-field magnitude at 10 m with corresponding directions.

The upper right-hand side of the domain contains regions with colder sea surface temperatures associated with the Californian coastal upwelling. The resulting swirling system of surface currents locally exceeds  $1 \text{ ms}^{-1}$ . In addition to the surface currents, distinct wind regimes reign supreme: winds accelerate towards the coast, nearing  $20 \text{ ms}^{-1}$  towards the east, and a shift in wind direction towards the south coincides with several streak-like figures. The dynamic wind speed range exceeds  $10 \text{ ms}^{-1}$ .

#### VARIABILITY OF UNKNOWNNS

Using the SWB we obtain a closed budget for the NRCS and Doppler contributions. Namely, how much regular scattering and wave breaking contribute to the would-be-observed NRCS and Doppler. It should be noted that the Doppler originating from wind-wave-current interactions is fully ascribed to the wave Doppler even though its conception necessitates the presence of surface-current gradients. The Doppler budget contains an additional signal originating from the total LoS-projected surface current.

Working with modeled data gives us access to the terms  $k_r$ ,  $k_s$  and  $f_s^{\text{HH}}$ , as defined in Section 5.2. Distributions of these spatially varying quantities are presented in Figure 5.2. The calculation of the therein presented  $\bar{k}_s$  will be discussed later. The targeted wave Dopplers converted to a surface-projected velocity vary from approximately  $0 \text{ ms}^{-1}$  in cross-wind conditions to  $1\text{-}2 \text{ ms}^{-1}$  over the remainder of the domain.



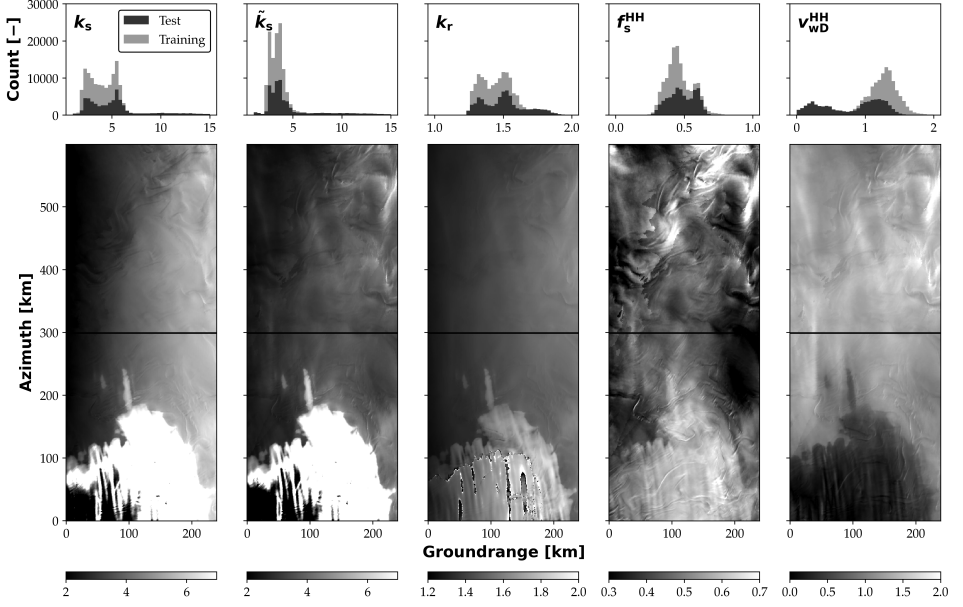


Figure 5.2: Absolute values for various parameters. Upper) distribution of unknowns in (5.11) and (5.25) as simulated under noise-free conditions. Lower) corresponding spatial distribution. The black horizontal line separates the north/south training/test data, respectively. Exploding values of  $k_s$  and  $\tilde{k}_s$  in the southern half are caused by a cross-wind, resulting in the Doppler magnitude approaching zero.

### 5.3.2. OBSERVATIONAL DATA

In addition to simulations, we apply our signal model on a unique dataset of dual polarized Along Track Interferometry (ATI) observations obtained with TanDEM-X (Krieger et al., 2007) in a formation configuration optimized for along-track interferometry. No in-situ validation is available for these observations, enabling a qualitative analysis only.

The TanDEM-X data was acquired in descending passes between 2014-08-30 and 2014-09-15 at around 06:00 UTC, over the coastal region East of Cap de Creus, on the Catalan sea. The system was operated in a dual co-polarized stripmap mode, interleaving horizontally and vertically polarized transmit pulses in order to provide simultaneous interferometric pairs of HH and VV images. Results are presented for the scenes acquired with a  $41^\circ$  incident angle, for which strong polarimetric signatures are expected.

## 5.4. RESULTS AND DISCUSSION

Results are separated into two categories: first introducing the developed retrieval algorithms in 5.4.1, followed by the results of these algorithms applied on SWB data in 5.4.2. The analyses made using the SWB aim to assess the validity of our signal model, the variability of presumed constants, and the suitability of proposed approximations. Next, we apply the approximation learned from model data to real data. Since no quantitative validation data exists for the TanDEM-X case study, a qualitative assessment is performed instead in 5.4.3.

### 5.4.1. RETRIEVAL ALGORITHM DESIGN

The analytical forms in (5.11) and (5.12) contain too many unknowns for them to be applied without a-priori knowledge. As a workaround we establish various simplified versions which require no a-priori information and could thus be applied on any dual-polarized data. The first such method will discard the variability of  $k_r$ ,  $k_s$  and  $f_s^{HH}$ , and approximate them by a constant. The similar second and third methods aim to predict the previously discarded variability by means of symbolic regression with the radar observables, thus forming a hybrid model that relies on empiricism as well the analytical formulations. The fourth and final method relies on an additional assumption which reduces the number of unknowns in (5.11) from three to one. The last remaining unknown can then be approximated by a constant, like in the first method, or by a proxy GME, like in the second and third methods. This fortuitous cancellation of unknowns does not transfer to  $\nu_{wD}^{VV}$  from (5.12), such that it can only be provided for  $\nu_{wD}^{HH}$  from (5.11).

All empirical values needed for these four simplified versions are obtained from the upper half of the California domain, which serves as the training data. This area covers the full range of incident angles and includes a region with wind-wave-current interactions. The lower half, on which empirical methods are assessed, also contains currents as well as a transient wind regime. The latter is unsampled in the upper half and thus provides insight into the transferability of empirical methods. Then, we re-simulate a new realization of the California scene under a different viewing geometry—a descending instead of ascending orbit—for an overlapping section of the original scene. This re-simulated scene covers most of the original test area, along with a sliver of the training area, and it enables us to assess the generalizability of models trained and calibrated under different observation conditions. Development details for the individual models follow below.

#### CONSTANTS

We ignore the variability in  $k_r$ ,  $k_s$  and  $f_s^{HH}$ , and ascribe to them a constant value. These constants are obtained by selecting the median value over the training subset of the simulation, as shown in Figure 5.2. They are listed in Table 5.1.

#### HYBRID-A

Much of the variability in  $k_s$  and  $k_r$  is incident-angle dependent, as follows from their formulations and Figure 5.2. Similarly, following the formulations of  $f_s^{PP}$ , these are related to a ratio of scattering components. Thus, we next construct a hybrid model using the original analytical model supplemented by empirical components to predict known sources of parameter variance.

Table 5.1: Anecdotal C-band coefficients for the four considered simplification methods.

| 1) Constants    | 2) Hybrid-A | 3) Hybrid-B                | 4) simplified      |
|-----------------|-------------|----------------------------|--------------------|
| $k_s$ 3.76      | $c_1$ 2.04  | $c_1$ 2.04                 | $\tilde{k}_s$ 3.32 |
| $k_r$ 1.42      | $c_2$ 0.73  | $c_2$ 0.73                 | $k_r$ -            |
| $f_s^{HH}$ 0.43 | $c_3$ -0.35 | $c_5$ 1.69                 | $f_s^{HH}$ 1       |
| $f_s^{VV}$ 0.23 | $c_4$ 1.09  | $c_6$ $1.54 \cdot 10^{-2}$ | $f_s^{VV}$ -       |

To that end we employ symbolic regression in combination with the radar observables, yielding various functional approximations of the unknowns in question. Constructing robust empirical relations on a single case study is unfeasible. We discard suggested functional formulations that appear to make no physical sense, instead selecting those that balance simplicity (and therefore, hopefully, transferability) as well as accuracy. The selected functional forms are

$$k_s \approx e^{c_1 \cdot \theta_i} \quad (5.13)$$

$$k_r \approx c_2 \cdot e^{\theta_i} \quad (5.14)$$

$$f_s^{HH} \approx \sin(p_{dB}^{-1} - c_3) \quad (5.15)$$

$$f_s^{VV} \approx \cos(c_4 \cdot p_{dB}) \quad (5.16)$$

with the respective coefficients presented in Table 5.1. The exact functional forms for  $k_s$  and  $k_r$  are not particularly important, more so that they can be considered constant at a given incidence angle. The formulations for  $f_s^{HH}$  and  $f_s^{VV}$  are more specific: the (co)sines prevent nonphysical values greater than one, while the (co)sine content represent a rescaled ratio of backscatter (with backscatter in dB), much like the formulation in (5.3).

#### HYBRID-B

Alternatively, and building on V. N. Kudryavtsev et al., 2013, we can substitute the empirical expressions for  $f_s^{PP}$  with one infused with theoretical understanding. First the scalar scattering is formulated as a function of radar observables

$$\sigma_s = \sigma_0^{VV} - \frac{(\sigma_0^{VV} - \sigma_0^{HH})}{1 - p_r} \quad (5.17)$$

where the ratio of resonant scattering is indicated by

$$p_r = \frac{\sigma_r^{HH}}{\sigma_r^{VV}} \quad (5.18)$$

A Taylor expansion for  $p_r$  is given in V. N. Kudryavtsev et al., 2013 as

$$p_r \approx \frac{|G_H|^2}{|G_V|^2} \left[ 1 + (g_H - g_V) \cdot \overline{s^2} \right] \quad (5.19)$$

where  $\overline{s^2}$  refers to the mean squared slope and  $g_p$  to the second order derivatives of  $|G_p|$ , which in turn are defined as

$$G_V = G_V(\theta - \zeta(\overline{s^2})) \quad (5.20)$$

$$G_H = G_H(\theta - \zeta(\overline{s^2})) + \left( \frac{\zeta(\overline{s^2})}{\sin \theta} \right)^2 G_V(\theta) \quad (5.21)$$

with  $\zeta$  indicating the tilting of presumed isotropic Gaussian slopes for waves with wavelengths several times greater than that of the resonant wavelengths (V. Kudryavtsev et al., 2003).

To make use of this method, an a-priori estimate of  $\overline{s^2}$  and wave spectra (for weighting) are needed. But these quantities are non-trivial to obtain in practice. Therefore, we create a surrogate expression that initially ignores the impact of  $\overline{s^2}$  by replacing the original tilt-considering  $G_P(\zeta, \theta)$  with  $G_P(\theta)$ . Then, a compensation is added to account for the previously discarded  $\overline{s^2}$ . This compensation is again determined by symbolic regression, with the resulting formulations being

$$p_r \approx \frac{|G_H(\theta)|^2}{|G_V(\theta)|^2} [c_5 + c_6 \cdot \text{dB}(\sigma_0^{VV})] \quad (5.22)$$

Essentially, this formulation substitutes  $\overline{s^2}$  with an alternative compensation dependent on NRCS—a known  $\overline{s^2}$  proxy. The magnitude of  $\sigma_0^{VV}$  at a given incidence angle is influenced by a multitude of other factors (primarily the relative wind direction with respect to the sensor), which may unfavorably affect  $p_r$  estimation.

Combining (5.22) with (5.17) results in

$$f_s^{HH} = \frac{\sigma_0^{VV}}{\sigma_0^{HH}} - \frac{(\sigma_0^{VV} - \sigma_0^{HH})}{\sigma_0^{HH}(1 - p_r)} \quad (5.23)$$

$$f_s^{VV} = 1 - \frac{(\sigma_0^{VV} - \sigma_0^{HH})}{\sigma_0^{VV}(1 - p_r)}. \quad (5.24)$$

#### SIMPLIFIED

In the preceding approaches we have attempted to account for three unknowns. This was done either by assuming their invariability or, conversely, by attempting to predict their variability. Here we proceed along a different approach, which aims to reduce the complexity by selecting fortuitous and canceling combinations of the unknowns in questions. The resulting simplified approximation exclusively applies to the estimation of  $\nu_{wD}^{HH}$ , which should pose no limitation as any estimate of  $\nu_{TSC}$  in combination with (5.5) enables estimation of the  $\nu_{wD}^{VV}$  as well.

If we assume that  $f_s^{HH}$  has a constant value of 1, which implies that  $\sigma_s = \sigma_0^{HH}$ —an unlikely condition, and not observed in Figure 5.2—we eliminate unknown  $k_r$ . This approximation takes the form

$$\nu_{wD}^{HH} = \frac{\tilde{k}_s}{\tilde{k}_s - 1} \frac{1}{1 - p} (\nu_D^{HH} - \nu_D^{VV}), \quad (5.25)$$

where we can still use the equality sign because  $k_s$  has been exchanged with  $\tilde{k}_s$ , the only remaining unknown. To account for errors introduced by the above assumption, the distribution of the new  $\tilde{k}_s$  has necessarily changed with respect to the “real”  $k_s$ , see Figure 5.2. This also obscures an intuitive physical interpretation of  $\tilde{k}_s$ . Yet the spread in  $\tilde{k}_s$  decreases under idealized no-noise conditions as compared  $k_s$ , making it easier to estimate. Thus, not only does this approach decrease the number of unknown parameters (from  $k_r$ ,  $k_s$  and  $f_s^{HH}$  to only  $\tilde{k}_s$ ), it simultaneously decreases the spread in the remaining target parameter ( $\sigma_{\tilde{k}_s} < \sigma_{k_s}$ ). Such gross approximations also negate potential exploding

uncertainties resulting from compounding interactions between erroneous estimates of  $k_r$ ,  $k_s$ ,  $f_s^{HH}$  and  $f_s^{VV}$ .

The challenge then, is finding a suitable value for  $\tilde{k}_s$ . Fortunately this formulation is relatively insensitive to uncertainty; reasonable results are obtained even when fixing  $\tilde{k}_s$  to the tail ends of the  $\tilde{k}_s$  distribution in Figure 5.2 (not shown). The value used here is again obtained from the median value over the training subset.

#### 5.4.2. QUANTITATIVE MODEL ANALYSES

The four approaches are compared to the wave Dopplers predicted by the SWB. Baseline estimates are also provided by the DopRIM-GMF, whose performance, as illustrative of GMFs, is added for comparison with the presented polarimetric methods.

Distributions of errors for the different cases are presented in Figure 5.3. Empirically derived constants are presented in Table 5.1. The results are discussed individually in the subsequent subsections. Model performance is calculated at 1 km grid spacing, with the displayed results representing the distribution of mean values selected on a coarse-grained 3 by 3 km grid.

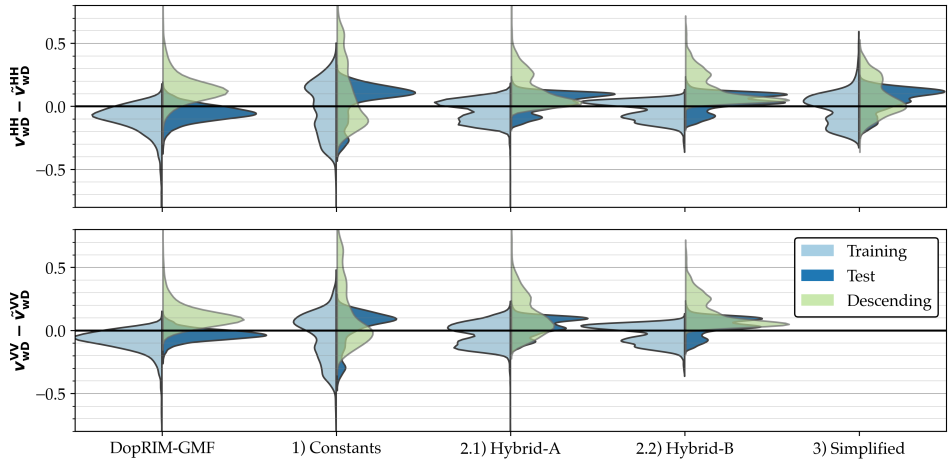


Figure 5.3: Summary of analyses on the California case study using ascending (Training + Test) and descending simulations with no noise. DopRIM-GMF) using idealized model winds in combination with the DopRIM-GMF; Constants) using the full analytical model but replacing the unknowns with constants; Hybrid-A and Hybrid-B) using the full analytical model but replacing the unknowns with empirical relationships; Simplified) using the simplified analytical model and replacing the single unknown with a constant. Model performance is calculated at 1 km grid spacing, with the displayed results representing the distribution of mean values selected on a coarse-grained 3 by 3 km grid. The colored areas are weighted by relative occurrence. The total area of descending data differs from that of training and test as the descending orbit does not fully overlap with the original domains. In the presence of noise, as defined in 5.3.1, the standard deviation of residuals over the test area for the various scenarios increases from (left to right ) 0.07, 0.14, 0.07, 0.07 and 0.09  $\text{ms}^{-1}$  to 0.07, 0.20, 0.16, 0.16 and 0.18  $\text{ms}^{-1}$  for HH and 0.05, 0.14, 0.07 and 0.07  $\text{ms}^{-1}$  to 0.05, 0.17, 0.13 and 0.13  $\text{ms}^{-1}$  for VV.



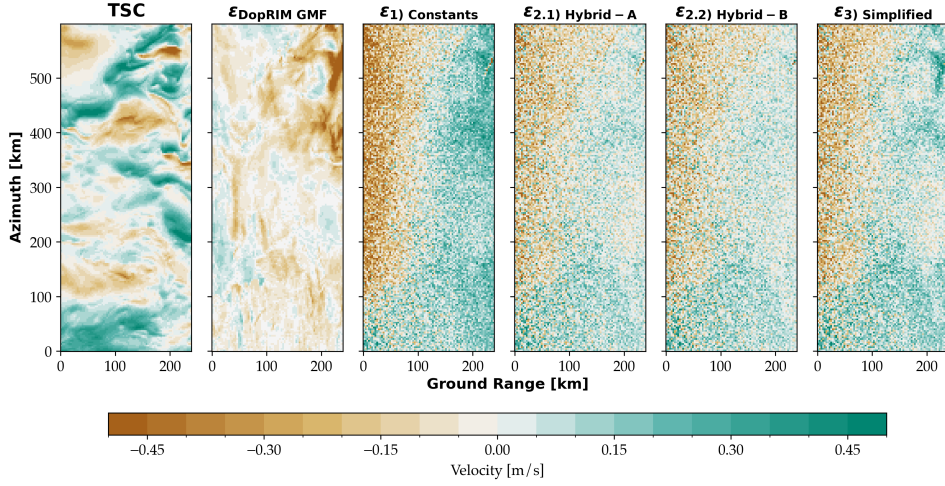


Figure 5.4: Ground-projected total surface currents along with spatial residuals,  $\epsilon_x$ , of  $v_{\text{WD}}^{\text{HH}} - \hat{v}_{\text{WD}}^{\text{HH}}$  under noisy conditions for the different retrieval models. Following (5.5), these residuals would directly translate to errors in the surface-current estimation. Results are coarse-grained to a 3 by 3 km grid. Notably, there are ample geophysical structures present in the residuals for DopRIM-GMF, while these are absent in methods reliant on polarization diversity. The prevailing along-range trend for these latter four methods is attributed to complications pertaining to the SWB implementation. A several Hz Doppler bias was observed during the SWB development for steeper incident angles as compared to CDOP due to incompatibilities between CMOD and CDOP (Kleinherenbrink et al., 2026), which results in an overestimation of Dopplers at steep incidence angles. This bias is known to be a function of the prevailing wind direction, as observed in the southern turning winds.

5

### CONSTANTS

The majority of errors resulting from the fixed-value approach are contained within  $\pm 25 \text{ cm s}^{-1}$ . By design no bias is present in the training area, and only a minor bias appears in the test data. More problematic is the increased standard deviation, which is particularly prevalent in the elongated tails of the residuals for the descending orbit. This indicates that the constants approach is poorly transferable.

A more encouraging picture is revealed in Figure 5.4: the constants-approach extracts most of the local geophysical gradients, though leaving an along-range trend behind. Thus, even though the variability in unknowns is ignored, the gross simplifications still yield distributions in line with an idealized GMF, while the spatial performance enables enhanced retrieval of local features.

### HYBRID-A & -B

As shown in Figure 5.3, the resulting hybrid models A & B yield a narrower distribution around zero for the training data (as expected) which transfers well to both the test and descending cases, even when compared to the idealized DopRIM-GMF results. Observed uncertainties at  $\mathcal{O}(0.1 \text{ m s}^{-1})$  are an order of magnitude lower than the  $\mathcal{O}(1 \text{ m s}^{-1})$  variance of the signal of interest.

Thus, using radar observables it is possible to predict much of the variability in  $k_r$ ,  $k_s$  and  $f_s^{\text{PP}}$ . A representative dataset could be used to develop a suitable and globally

representative GMF-like algorithm for these unknowns.

The obtained forms and corresponding coefficients are anecdotal and not intended to be interpreted as a de facto GMF. Rather, it should be observed that taking into account but a few parameters (incidence angle, the polarization ratio and a proxy for mean squared slope) explains much of the observed variability. Such a minimal empirical addition to the existing domain knowledge—which is infused in the analytical form—enables a superior level of prediction.

#### SIMPLIFIED

The simplified analytical method yields results in line with the idealized DopRIM-GMF implementation, with low variability and good transferability to different regimes and observation geometries. A particular benefit over the previous hybrid approaches is the lessened sensitivity to overfitting, since only one parameter demands estimation. Thus, this simplified approach should better extend to unsampled conditions, which is why it is next applied on the entirely different observations acquired with TanDEM-X.

### 5.4.3. QUALITATIVE OBSERVATIONAL ANALYSES

Of the four methods developed on the California simulation, the simplified method, being the most generalizable, is next applied on two dual-polarized ATI observations, see Figure 5.5. The same approximation and constants obtained from the C-band California simulation are expected to transfer well to X-band observations since the wavelength dependence is limited, as observed experimentally in Martin et al., 2016. Indeed, simulations run at X-band (not shown) yield an X-band estimate of  $\tilde{k}_s = 3.60$  while  $\tilde{k}_s = 3.97$  results in the lowest mean value for the upper 80 km along-azimuth extent—a region for which a zero-mean TSC may be expected. Following (5.25), this latter value results in an approximately 20 % difference with respect to  $\tilde{k}_s = 3.32$  as estimated at C-band.

2014/08/30

The streaks in the intensity data are oriented along the direction of the surface wind estimated by ECMWF's Integrated Forecast System (IFS), coming from west-northwest at around  $7 \text{ ms}^{-1}$  at the northern part of the image and from north at around  $10 \text{ ms}^{-1}$  in the southern part, see the left half of Figure 5.5. The drop in intensity towards the south is consistent with the turning wind direction and is further enhanced by shadowing from the cape.

For the Doppler velocities, several aspects need to be noted. Firstly, the Doppler velocity at HH is feature-rich, as highlighted by the features annotated with **A**, **B**, and **C**. These features are absent or muffled in  $\tilde{v}_{\text{WD}}$  and  $\Delta v^{\text{PP}}$ . A feature poor  $\tilde{v}_{\text{WD}}$  is in-line with expectation for an homogeneous offshore wind field. The orientation of **A** is offset with respect to the wind streaks. Both  $\tilde{v}_{\text{WD}}$  and  $\Delta v^{\text{PP}}$  suggest that this region should experience homogeneous wave Doppler, such that the anomaly is attributed to a minor surface current instead. In  $\Delta v^{\text{PP}}$ , one can still identify **B** due to it nearly canceling out with respect to the background. The additional polarization weighting in  $\tilde{v}_{\text{WD}}$  compensates this effect such that a relatively homogeneous wave Doppler is maintained without introducing striking artifacts in the estimated surface current. Thus, through the polarimetry-enabled weighting, this component is identified as being of non-current origin, which

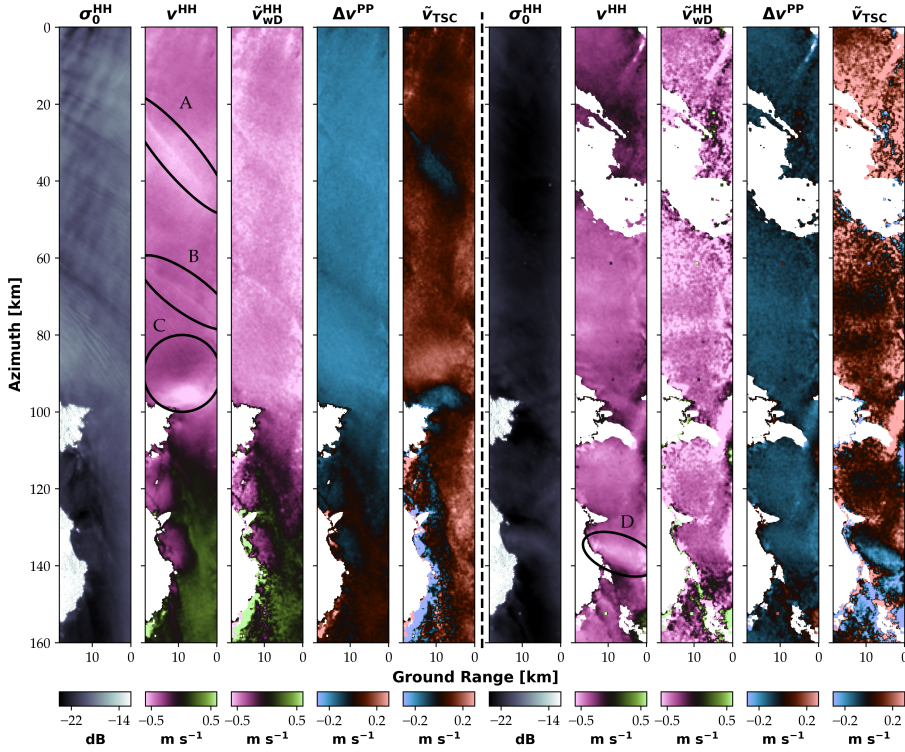


Figure 5.5: Observations and inferences over the French Gulf of Lyon in the north, and the Spanish Gulf of Roses towards the south on 2014-08-30 (left half) and 2014-09-10 (right half). Bright targets and areas with poor signal-to-noise ratios have been removed. The estimated wave Doppler  $\tilde{v}_{WD}^{HH}$  is obtained using the simplified method with  $\tilde{k}_s = 3.32$ . The unweighted Doppler difference ( $\Delta v^{PP} = v^{VV} - v^{HH}$ ) is generally feature poor compared to the individual velocities and intensity data, suggesting that the deviations observed in  $v^{HH}$  are of oceanographic origin (with the exception of potential bathymetric effects and wave-wave interactions near the coastline). Particularly noteworthy areas are: **A**) a sharp striation prevalent in the Doppler and not parallel to the main wind-induced streaks present in NRCS, suggesting a current-related origin; **B**) a striation coinciding with NRCS gradients with a minor influence on the wave Doppler and TSC; **C**) a dipole-like structure located at the tip of Cap de Creus where the coastal and weak Gulf of Lion surface current crashes into the stronger Liguro-Provençal-Catalan surface current; **D**) an anomalously strong velocity observed at the mouth of the river Ter and coincident with the start of several days of elevated river discharge (Agència Catalana de l'Aigua, 2025).

could not be concluded before. Lastly, the dipole structure annotated by **C** is identified as purely current driven: it is entirely absent in  $\tilde{v}_{WD}$ , such that it is much amplified in the estimated TSC. Indeed, the location of this dipole coincides with the likely merging of two orthogonal surface currents.

#### 2014/09/10

The low winds coinciding with the later date, see the right half of Figure 5.5, result in low NRCS, low signal-to-noise ratio (SNR), and unreliable interpretations. Nonetheless, both this scene and the preceding scene from 2014/08/30 experience similar mean Dopplers

and estimated wave Doppler. Methods reliant on backscatter intensity would struggle to reconcile this behavior.

One region with elevated NRCS and SNR is annotated by **D**. The observed plume-like structure connects to the mouth of the river Ter. Elevated river discharges were recorded for the Ter on this date (Agència Catalana de l'Aigua, 2025), suggesting the observed Doppler to be a manifestation of surface currents. Indeed the  $\tilde{v}_{\text{WD}}$  does not rise beyond its background value, whereas a much sharper increase is observed in the estimated surface current.

## 5.5. CONCLUSION AND PERSPECTIVES

This study aims to retrieve the wave-Doppler component of the Doppler budget using polarimetric diversity. Based on a signal model rooted in scattering theory, we exploit the propensity of surface currents and wave Doppler to each impart a characteristic signal onto orthogonal polarizations.

Various approximated forms are presented that provide new and practicable methods for wave-Doppler estimation using dual-polarized observations. And, although shown only using ATI observations, there are no methodological constraints to preclude its application to Doppler Centroid Anomaly (DCA) observations. Though the latter is generally noisier, necessitating more spatial averaging (e.g. Romeiser et al., 2014).

Of the four presented approximation methods, the first three rely directly on the analytical formulation presented in (5.11) and try to *fill in the blanks* using empirical information. The fourth method, though also rooted in empiricism, relies on a simplified analytical form as presented in (5.25). This makes it less cumbersome and well generalizable, as confirmed by the direct applicability to X-band observations.

Quantitative assessments on simulated case studies provide encouraging results: even with gross approximations, wave-Doppler estimation uncertainties—which transfer one-to-one as TSC-estimation uncertainty—are low compared to the dynamic range of the signal of interest, biases are reduced with respect to a reference DopRIM-GMF, and performance transfers well between the different ascending and descending geometries.

Furthermore, compared to the residuals of the reference DopRIM-GMF method, there are few discernible geophysical features in the residuals presented in Figure 5.4. This is perhaps the main benefit of the proposed methods compared to contemporary GMFs—they enable the extraction of much higher resolution geophysical signals. This fact is not directly evident from the aforementioned summary statistics, which suggests a parity in performance instead. And, based on Figure 5.4, much of the residuals in the summary residuals of the proposed methods are in fact related to a known SWB bias permeating into the simulation data as an along-range slope.

Of course the four proposed methods are sensitive to noise in Doppler in addition to NRCS, as opposed to the more robust NRCS-reliant GMFs. But it is exactly this sensitivity that enables a more holistic characterization of surface motion. Depending on the scales of interest, one could opt to spatially filter the input Doppler fields in order to reduce noise. Little spatial resolution has to be traded in this manner as the wave-Doppler is generally smooth compared to NRCS modulation (e.g. see Figure 5.5).

Qualitative assessments of real data yield results consistent with expectations. Even for a case with low-wind conditions, the residual Doppler budget—retrieved by remov-

ing the estimated wave Doppler from the total Doppler budget—highlights distinct areas with probable surface-current activity.

The results of the quantitative and qualitative analyses illustrate the potential of dual-polarized Doppler and NRCS observations to infer contributions to the Doppler budget for a complex and dynamic set of wind-wave-current conditions. These approximated forms are particularly adept at inferring high-frequency spatial deviations from the mean wave-Doppler field—something contemporary GMFs struggle with by their very nature. There is then an opportunity to combine polarization diversity with existing GMFs in a sort of multi-scale model, leveraging the high-frequency resolving power of polarization diversity in combination with the average validity of contemporary GMFs. Indeed, initial testing (not shown) suggests that a union of the two disparate models (SWB-GMF + Hybrid A-B) surpasses any of the previously considered models when using a simple scale separation in the frequency domain.

Results of this study open several opportunities in dual-polarized observations of surface motion. Future studies could do away with the approximations made in this study by investigating alternative retrievals of  $k_s$ ,  $k_r$  and  $f_s^{PP}$ .

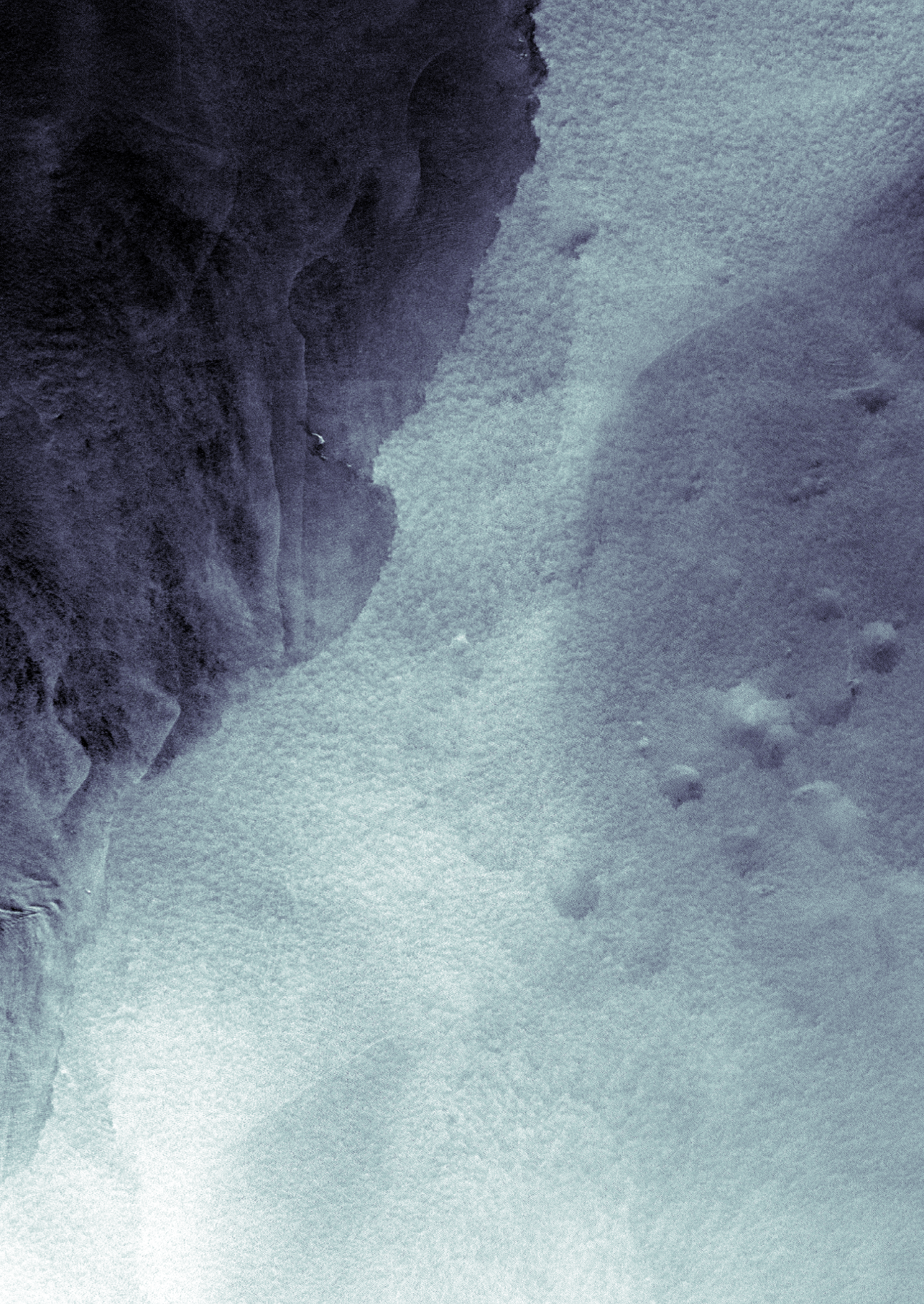
Extending from V. N. Kudryavtsev et al., 2013, one could also aim for wave-Doppler and TSC retrieval using only polarized NRCS. This necessitates the capability to attach an expected Doppler to an associated scattering mechanism. Such an approach would be particularly useful when neither ATI nor DCA Dopplers are available.

Future missions stand to gain from polarization diversity as well. Due to the angular diversity between the Sentinel-1 transmitter and Harmony's receivers, the received signal contains a dual-polarized component (in addition to cross-polarization) (Iannini et al., 2022). This in spite of the fact that the transmitter operates at the conventional co-polarization mode. The signal-to-noise ratio for the minor polarization will be significantly reduced (and may even be suppressed by cross-polarization) compared to systems that interleave polarized signals. Therefore, significant averaging may be needed to suppress noise, which, as mentioned above, does not necessarily come at a great cost to the spatial resolution of wave-Doppler estimation. And, like in Caldarella et al., 2022; Frasier and Camps, 2001; Toporkov et al., 2005, the aforementioned angular diversity may simultaneously enable a unique vector decomposition of the forces of interest.

## ACKNOWLEDGMENTS

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# 6

## CONCLUSION

*We burn way too few books*

A Catalan man

The efforts of the preceding chapters can be separated into the characterization of two phenomena: vertical air-sea interactions (Fluxes, Chapters 2 & 3) and horizontal ocean surface translations (Flows, Chapters 4 & 5). As detailed in Chapter 1, there is a clear scientific demand to enhance the spaceborne retrieval and characterization of these phenomena. The subsequent sections reflect on the progress towards that end, followed by a synthesis of contributions and recommendations for future investigations.

### 6.1. REVISITING THE RESEARCH OBJECTIVES

SAR OBSERVATIONS CONTAIN SIGNIFICANT QUANTITIES OF ATMOSPHERIC INFORMATION, THOUGH PRE-EXISTING ANALYTICAL METHODS STRUGGLE TO CAPTURE THIS.

In the first chapter we attempt to follow a theoretical framework outlined by Young et al., 2000, for the estimation of atmospheric stability. The backbone of this framework relies on a fundamental property of radar oceanography: radar backscatter at  $\mathcal{O}(10\text{ km})$  scales strongly correlates to wind speeds at similar scales. It is then assumed that this relation holds on much smaller scales,  $\mathcal{O}(0.1\text{ km})$ , such that high-resolution radar images can provide high-resolution wind fields. Unfortunately, this is not the case, and high-resolution wind-field estimation is mired in numerous difficulties that remain unsolved. This disrupts the core tenets underpinning Young's theoretical framework: without high-resolution wind fields, one can't obtain accurate power spectra, and relying on higher-order moments, such as power spectra, quickly amplifies any errors introduced. As such, the direct applicability of this theoretical framework is limited.

Despite this apparent setback, Young's proposed framework opens the door for alternative approaches. After all, radar backscatter does relate to wind, and backscatter variations at  $\mathcal{O}(0.1\text{ km})$  scales do relate to high-resolution wind-field variations at similar scales. The exact transfer function between the two simply isn't known.

Chapter 2 illustrates that atmospheric stability information can still be derived, and more successfully so, by abandoning the theoretical framework and embracing empirical methods instead. By learning the correlation between simple summary statistics derived from SAR observations, such as mean estimated stress-equivalent neutral wind

speed, it is already possible to predict ~50% of the targeted stability parameter's variability for a subset of radar scenes. This fraction approaches ~80% when supplying additional second-order moments. These results indicate that ocean SAR observations can encode significant quantities of atmospheric information, and that this information can be extracted using relatively simple methods.

**SAR-DERIVED ATMOSPHERIC INFORMATION IS SUFFICIENTLY RICH TO TRACE REANALYSIS-PRESCRIBED HEAT-FLUX VARIABILITY ON LARGE SPATIOTEMPORAL SCALES, WHILE SURPASSING REANALYSIS IN THE REPRESENTATION OF LOCAL AND SMALL-SCALE FEATURES.**

Building on Chapter 2, in Chapter 3 we aim to illustrate the potential value of atmospheric information extracted from SAR observations. In order to meet a perceived popular demand (e.g. Cronin et al., 2019), we switch from stability- to heat-flux retrieval.

A straightforward illustration of SAR's flux-retrieving prowess would be the surpassing of other state-of-the-art retrieval methods against some ground truth. But few retrieval alternatives exist, and there are significant gaps in ground-truth observations ("truth" being a generous suffix). For the most part, we can only assess retrieval performance compared to coarse-scale reanalysis fluxes. Given these restrictions, how does one discern performance with respect to the *truth*?

6

We tackle this challenge through a series of experiments that, combined, illustrate that SAR-derived heat fluxes provide new and complementary insights compared to existing reanalysis fluxes. We first show that estimated heat fluxes, on average, closely match those prescribed by the reanalysis. This is significant since, at large scales, reanalysis data provide the best globally available heat-flux benchmark. Then, based on comparisons with a limited set of tertiary validation points, we can infer that radar-derived fluxes may locally exceed the reanalysis at small-scale representativeness. Lastly, using a series of qualitative case studies, we illustrate the added value of the radar's greater spatial resolving power on various dynamic geophysical phenomena.

These experiments suggest that high-resolution radars can retrieve more air-sea parameters than previously considered, such as heat fluxes, and that the quality of this retrieval—when aided by proper filtering—can set a new state of the art. Since Sentinel-1's historic catalog already contains many millions of observations, our SAR-based flux retrieval would immediately constitute one of the largest global datasets of observation-based air-sea heat-flux estimates, particularly for undersampled regions, such as the Southern Hemisphere.

There are, of course, limits to the retrieval of heat fluxes from high-resolution radar imagery. We show, for instance, that a model trained on IW scenes from select geographical regions struggles to generalize the retrieval of latent heat flux. This lack of predictive "skill" appears strongly correlated with background temperature information, suggesting that radar-retrieved textures trace only part of the variability in latent heat flux. The retrieval of latent heat flux would thus benefit from systems capable of measuring both surface temperature and roughness texture, such as Harmony.

LOW-RESOLUTION DOPPLER-TARGETING SCATTEROMETERS ARE PRONE TO SUFFER FROM UNWANTED DOPPLER “LEAKAGE”. FORTUNATELY, CORRECTIONS CAN REDUCE MUCH OF THIS ERRONEOUS SIGNAL SUCH THAT IT NO LONGER DOMINATES.

In Chapter 4, we investigate the susceptibility of Doppler scatterometers to leakage of geometrical Doppler into the targeted surface Doppler. We focus on the novel Doppler scatterometer, “DopSCA”, as its design makes it uniquely sensitive to leakage.

Complications in the analytical derivation of leakage warrant an empirical approach. Therefore, we rely on ubiquitous, high-resolution Sentinel-1 data to simulate the leakage incurred by DopSCA due to azimuthal NRCS gradients. Results indicate that DopSCA’s sensitivity to leakage is significant, and even rivals the dominant pulse-pair uncertainty—which itself is a product of DopSCA’s Doppler-retrieval mechanism. However, unlike pulse-pair uncertainty, leakage is not easily reduced by averaging independent samples, since the signal contains significant spatial correlations.

Fortunately, leakage is deterministic and can be corrected using a second estimate of leakage obtained with DopSCA’s low-resolution observed NRCS, which differs from the incurred leakage computed using Sentinel-1’s high-resolution NRCS. We show that such corrections greatly reduce the incurred leakage uncertainty, and that these residuals are susceptible to further reduction through spatiotemporal averaging, as the large-scale deterministic components have been removed and mainly random uncertainties remain. After such corrections, DopSCA’s residual leakage can be considered irrelevant by virtue of another, more significant source of uncertainty.

Although Chapter 4 focuses specifically on leakage—which transfers to any Doppler-targeting system—rather than the feasibility of the DopSCA system itself, it would be disingenuous to avoid further commenting on DopSCA’s main uncertainty source: pulse-pair self-clutter. This singular uncertainty contribution—estimated at  $\sim 2 \text{ m s}^{-1}$  on 50 km horizontal scales in Chapter 4—immediately precludes DopSCA’s usage for the retrieval of most, if not all, instantaneous TSC processes. It is only the presumed unbiased nature of these measurements and their relatively extensive spatiotemporal coverage that may give DopSCA some utility still, albeit limited to assessing long-term regional TSC biases under specific conditions where altimeters commonly fail. One such use case may be the identification of potential ageostrophic currents at the heart of wind-vector disagreements between scatterometers and forecast/reanalysis (e.g., those reported in Belmonte Rivas & Stoffelen, 2019). Whether such applications warrant DopSCA’s materialization remains under investigation.

POLARIZED NRCS AND DOPPLER OBSERVABLES ENABLE THE SEPARATION OF WAVE DOPPLER FROM THE TOTAL DOPPLER BUDGET. SEPARATION IS PARTICULARLY EFFECTIVE AT FINE SPATIAL SCALES WHERE TRADITIONAL SOURCE-SEPARATION ALGORITHMS STRUGGLE.

In Chapter 5, we outline how polarimetry, when combined with a theoretical model, enables us to disentangle wave-Doppler contributions from the total Doppler budget. In turn, this provides a method to obtain surface currents, assuming that the total Doppler budget consists solely of wave-Doppler and surface-current Doppler.

Despite having to overcome several existing theoretical gaps, the proposed Doppler separation methods appear robust, even when transferred across frequencies from simulations to observations. Summary statistics of the polarimetric method’s performance

further suggest parity in skill with respect to an optimistic geophysical model function (GMF) implementation.

The greater spatial resolving power of polarization-based source separation is a particularly desirable trait, though it is not immediately evident from the summary statistics. This characteristic is prevalent even in the simplest variant of proposed separation algorithms. Alternative wave-Doppler estimation methods, and especially those that rely on coarse ancillary inputs, are much less able to resolve small-scale current features. Thus, the presented method would be well-suited for the retrieval of intricate and small-scale current features where conventional GMFs typically struggle.

The Achilles' heel of polarimetry-based Doppler separation methods lies in the scarcity of contemporary SAR systems with the required polarimetric capabilities. Fortunately, the next generation of Europe's Sentinel-1 SAR constellation, to be launched sometime in the 2030's, is designed with such polarimetric capabilities in mind, promising many years of high-resolution surface-current measurements. We may get a sneak peek even sooner by exploring options with Harmony's unconventional polarimetric basis instead. Harmony would provide an interesting case study for other reasons as well, as it will be uniquely capable of deriving surface currents using conventional approaches: vector motions converted to currents using a GMF. This mission may thus facilitate the comparison of both approaches, which could then be used to find an optimal mix of methods, e.g. a classical GMF for large scales and polarimetry-based GMF for small scales.

## 6.2. SYNTHESIS OF CONTRIBUTIONS

### 6.2.1. FLUXES

We can't claim to be the first to identify or use atmospheric features in SAR (e.g. Gerling, 1986; Young et al., 2000), nor even the first recently (e.g. Stopa et al., 2022; C. Wang, Tandeo, et al., 2019), but we are the first to systematically extract quantitative air-sea parameters by exploiting SAR texture. We have illustrated that the information content thus extracted is complementary—and can locally even surpass—existing best estimates of specific air-sea parameters. Thus, the main contribution of Chapters 2 & 3 is the expansion of existing SAR capabilities towards the retrieval of additional air-sea related geophysical parameters. The impact of that contribution depends on the extent to which it will be adopted in scientific pursuits. This will be the next challenge.

### 6.2.2. FLOWS

The contribution of Chapter 4 centers on the identification and correction of a previously unconsidered source of uncertainty: leakage. In that sense, the contribution is self-contained; identifying a problem and fixing it. Again, it would be unfair to claim that we are the first to consider this uncertainty. Though ours is likely the most detailed account of the estimation and correction stages, with more elaborate discussions on implications. A transferable contribution of Chapter 4 would be the promotion of using existing satellite data to simulate hypothetical systems, such as the usage of real Sentinel-1 observations to emulate DopSCA's sensitivity to small-scale NRCS gradients. It would certainly be more costly to embark on arduous end-to-end simulation efforts instead.

The contributions of Chapter 5 have greater applicability for surface-current retrieval.



We introduce the first practicable and polarization-based Doppler separation algorithm. This effort builds on an existing theoretical framework and addresses theoretical gaps through empirical extensions. The proposed method provides a new avenue for pursuing the long-standing challenge of surface-current estimation, in particular at higher spatial resolutions than previously permitted.

## 6.3. RECOMMENDATIONS

### 6.3.1. FLUXES

It is easy to concoct a wish-list of recommendations to follow up on Chapter 3. Mine includes some obvious options:

- Consolidating distinct components of the FluxSAR methodology, such as image feature extraction, target source selection (i.e., reanalysis or in situ), and physically-constrained loss-function design. We could, for instance, develop a retrieval using only in-situ observations (e.g., from the global ICOADS archive, Freeman et al., 2017) by employing multiple-instance learning to match sparse observations on basin-wide scales. In this manner, a complete detachment from reanalysis and its biases would be achieved.
- Characterizing performance across regions and geophysical targets to determine limitations and their physical origins. This could include transferring FluxSAR's methodology to Sentinel-1's EW mode (in HH-pol) to expand retrieval over vulnerable, and critically under-sampled, polar regions.

As well as more exploratory ventures:

- Investigating (future) synergies with additional observations from other platforms (e.g., scatterometers for wind vectors; geostationary satellites for cloud fields; CIMR for salinity and SST; EarthCARE for atmospheric profiles; and Harmony for a bit of everything). As we've shown, SARs provide rich information about the lower atmospheric boundary layer. Perhaps combining that with information from a different medium, such as cloud structure at the top of the atmospheric boundary layer, can unlock a more complete characterization of the entire boundary layer. Furthermore, we know that C-band SARs exhibit strong directional sensitivities, which may percolate as directional biases in derived products (akin to the incidence-angle-dependent classification in Figure 6 of C. Wang et al., 2020). Observations with diverse viewing geometries, such as those obtained from Harmony, could be used to study and counteract this effect.
- Expanding the retrieval to the vast historic archive of prior high-resolution radar missions. SARs are unique in their extensive legacy of observations. This resource remains underutilized, but if properly exploited, it could enable the investigation of climate-scale signals, their trends, and perhaps tipping points too.
- Quantifying the assimilation gain of SAR-based air-sea interaction products into weather and reanalysis models. Here it is particularly interesting to assimilate not the ephemeral fluxes, but properties more closely related to state variables, such as  $\Delta T$ , which are also encoded in the observed roughness textures.

- We could even consider the suitability of scatterometers for retrieving air-sea stability parameters by using the spread around the maximum likelihood function of the scatterometer-retrieved wind. This spread indicates wind variability, which could serve as a suitable proxy for changes in air-sea stability (e.g. Y. Chen et al., 2025).

One detail not addressed so far concerns the fixed orbit of conventional SAR systems. These are generally sun-synchronous, revisiting the same location at fixed times (e.g., approximately 6 am or 6 pm local time for Sentinel-1). Such an orbit offers several advantages in terms of predictability, thermal properties, and consistency in sampled environmental conditions. Mornings and evenings also tend to coincide with the sharpest gradients in the diurnal cycle, such that dynamic and interesting conditions are assured of observational priority. Yet, a drifting orbit could introduce several benefits. After all, over the ever-changing oceans, there is no need to revisit the same fixed patch over and over again; each observation is anecdotal and may as well be made several kilometers east or west. Fixed revisit locations can even work disadvantageously. For instance, the current Sentinel-1 orbit results in a systematic mismatch between SAR observations and buoy deployments. Keeping this orbit fixed thus ensures curtailed co-location capabilities indefinitely. Furthermore, and following a similar reasoning, drifting orbits would also enhance the potential to co-locate with other observational systems, such as scatterometers or profilers (e.g., ASCAT, EarthCARE) that operate on different orbital schedules. Lastly, after acquiring sufficient measurements to prevent temporal aliasing, a drifting orbit would enable all times of day to be studied. This would certainly be beneficial if we were to present observation-based fluxes as constraints for the total energy budget. In that case, we would likely need to sample a bit more of the diurnal cycle than just 6 am/pm. These benefits might not weigh up against those afforded by conventional sun-synchronous orbits, but perhaps they are worth bearing in mind. Some SARs from commercial “new space” ventures, such as ICEYE, Capella, or UMBRA, already deviate from the standard observation times to tailor towards consumer demands for sub-daily revisit times. Their data could thus potentially be used to ascertain whether drifting orbits are worth pursuing.

More important than any of the above suggestions, which focus on improving or expanding retrieval skill, is the need to employ the developed retrieval methodology as a tool in scientific investigations. Several investigations may benefit from this tool's unique capabilities. We could, for instance, study the spatial flux distribution across temporal composites of various dynamic geophysical phenomena, i.e., a “centric” analysis focusing on hurricanes, ocean fronts, Madden-Julian Oscillations, atmospheric rivers (akin to Asharaf et al., 2025) or any other type of highly dynamic and localized event. There are plenty of options. These investigations, when combined with the large and growing archive of SAR images, would then shed light on small-scale physical processes throughout the life cycles of such events, which are otherwise challenging to observe. Furthermore, we are more likely to encounter, and thus identify and fix, deficiencies in the flux-retrieval methodology by applying it in scientific investigations across a wide range of phenomena.

### 6.3.2. FLOWS

The investigations into leakage of Chapter 4 are self-contained with a limited objective in mind. Extrapolating the findings to more general recommendations is therefore not straightforward. And, as identified in Chapter 4, radar properties that benefit Doppler retrieval (e.g., high PRF and small footprint) also reduce leakage, such that it would be needless to suggest Doppler scatterometers to optimize systems only with leakage reductions in mind.

Two main recommendations follow from Chapter 5. Firstly, the presented results show encouraging transferability across simulations and observations. But more data is needed to explore the limits of transferability. Unfortunately, few systems provide orthogonally polarized observables *and* accurately measure surface Doppler. Sentinel-1, for instance, does neither, but SAOCOM and some of the RADARSATs might be able to do both. Though their Dopplers tend to be acquired using the generally noisier Doppler Centroid Anomaly (DCA) method, rather than through cleaner Along Track Interferometry (ATI) methods. On the one hand, this poses little issue, as the method proposed in Chapter 5 relies on a weighted Doppler difference between polarizations, such that systematic noise and biases across polarizations cancel out. Yet, this will only yield a clean wave Doppler; if the total Doppler is still noisy, then subtracting a clean wave Doppler cannot prevent the estimated surface current from being contaminated by noise (in fact, most of the noise will then permeate into the surface-current estimate). Future missions such as Harmony and Sentinel-1 Next Generation could potentially provide both necessary elements, but the non-orthogonal polarimetry of the former needs further investigation, while the Doppler provided by the latter may suffer from similar issues as its predecessor.

Secondly, since clean Dopplers are challenging to obtain in practice, we could aim to advance the current-retrieval methodology entirely beyond a Doppler dependence, to rely solely on polarized NRCS instead. It may seem ludicrous to discard motion measurement when the target is a motion, but, as highlighted in V. N. Kudryavtsev et al., 2013, quantitative characterization of surface scattering mechanisms is already possible using only dual co-polarized NRCS observables. Even from single-pol NRCS, one can readily identify strong surface currents through their unique spatial pattern. See, for instance, the sharp but meandering NRCS anomalies that trace surface currents on the front page of Chapter 5. Once we can attach unique (or likely) Dopplers to unique combinations of scattering mechanisms, we could potentially do away with all Doppler measurements. The success of such an approach is not guaranteed, yet the potential rewards may justify the gamble.

But perhaps all these efforts have been in vain, considering the promising surface-current retrieval results recently obtained by optical geostationary systems (Lenain et al., 2025). That is, of course, until a pesky cloud flies by.

## 6.4. SOME MISCELLANEOUS REMARKS AND PERSPECTIVES

### 6.4.1. CIMR-FLUX

Recent efforts by the air-sea interactions community have identified potential synergies for air-sea heat-flux retrieval between ESA's CIMR mission, and a derivative of the

Butterfly mission originally proposed under NASA's Earth-Venture Program. The stand-alone CIMR mission is not designed for heat-flux retrieval, but it measures several state variables needed for conventional bulk-formula retrieval of these fluxes. The Butterfly derivative would trail CIMR in orbit to retrieve the missing variables, thus serving as an optional flux-retrieval add-on for the original CIMR mission, forming the combined entity named CIMR-Flux.

Hopefully, CIMR-Flux materializes, as it would provide unparalleled global coverage of essential variables following an alternative methodology to FluxSAR. As such, CIMR-Flux and FluxSAR would be interesting to compare; CIMR-Flux relies on bulk formulae, whereas FluxSAR is only indirectly dependent on them. Discrepancies between the two methods could then be used to identify regions where bulk formulae struggle or where SAR textures are overly contaminated. In terms of spatial extent, there is perhaps little that SARs could contribute to CIMR-Flux's great coverage, though their enhanced spatial resolution could help characterize CIMR-Flux's retrieval performance for small, sub-mesoscale phenomena. In the temporal domain, the missions are perhaps most complementary. Once CIMR-Flux and FluxSAR are cross-calibrated, the SAR-derived fluxes could retroactively be improved for their multidecadal-spanning archive. In turn, this would provide CIMR-Flux with historical, observational context on regional flux variability and climatological trends. Thus, CIMR-Flux has the potential to benefit from and add value to several decades of observations made with an entirely different sensor—a most interesting prospect.

#### 6.4.2. THE DATA SWAMP

Lastly, each new satellite brings exciting new observations, features, and other novelties, but this dissertation hopefully shows that we are already quite data-rich (in both quantity and quality). It is true that the historic archive does not enable all paths to be tread, and some of the research for this very dissertation was indeed in anticipation of exciting new capabilities. Still, it would appear that ample opportunities are lying dormant in the ever-growing archives, waiting to be exploited.

Unfortunately, the full value of past and present missions often remains locked behind a labyrinth of logistical and engineering issues. As a result, repetitive and wasteful toiling in preparing remote sensing and in-situ data has become an accepted practice. I don't think that this is a consequence of bespoke data preparations needed for each individual project, since even the most basic standardization is often missing (looking at you, in-situ sensors). Meanwhile, the benefits of clean, easy-to-use products are clear, as is attested by the ubiquitous usage of ERA5.

There are examples of data processing and dissemination made easier. For instance, Ifremer's custom Sentinel-1 data reader, XSAR, supported much of the research in Chapters 2-4; were it not for my short stint at Ifremer, I would have likely never known of this tool and, God forbid, would have had to use SNAP instead. Then, in Chapter 3 we used Oceansites flux data from NOAA's "Global Tropical Moored Buoy Array" service, which provides uniformly pre-processed heat-flux data across three different buoy arrays—a unicum! Neither XSAR nor the Oceansites data is flawless, but they make trudging through the data morass a more manageable experience.

It is positively remarkable that so much remote sensing and in-situ data is shared

freely. But one really needs a multi-year timeline to justify the necessary efforts into making sense of the discombobulated data swamp. Perhaps the air-sea interaction community should focus its resources on developing a single, unified data platform. Surely launching such a website is easier than launching new satellites.







## ACKNOWLEDGMENTS

Marcus Aurelius dedicated the whole first chapter of his *Meditations* to acknowledgments. Perhaps he realized that acknowledgments are the most-read section of any work, so it makes sense to get that out of the way first. But apparently, he had never intended to publish his notes. I prefer to think that his extensive acknowledgments reflect him being a nice guy, even thanking the gods for his improficiency in rhetoric and poetry, which freed up time to pursue a career as emperor of Rome. Either way, this dissertation is unlikely to share such a legacy, so let's be curt.

Thank you, Paco, for teaching me so much, some even relating to radars, the ocean, or the atmosphere. I would need more than a few lines to express my gratitude properly. Suffice it to say, it has been a fun few years, and I owe much of that to you.

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To my friends and family who repeatedly inquire how my studies into rocks or bathymetry are going: it's been going great, thanks.

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Lastly, cheers to fate for making some of the science work out.

# A

## APPENDIX FOR CHAPTER 2

This appendix contains an expanded description of data preparation in Appendix A.1, detailing the retrieval of a wind field from SAR imagery, the preparations of both ERA5 and buoy data for use with the COARE.5 algorithm, the decorrelation of ERA5 validation as a result of spatial resolution and a comparison between buoy and ERA5 validation data. Appendix A.2 expands upon the methodology. It details the statistics derived from the two- and one-dimensional spectra and the analysis frameworks used to obtain results. Appendix A.3 provides a supplement to the results. It contains an analysis of the results in a geographical representation, the effects of turbulence scale and viewing geometry on estimation and a variance budget bringing together estimation results and the expected maximum attainable estimation as a result of noise and errors in validation data.

### A.1. DATA PREPARATION

#### A.1.1. WIND-FIELD RETRIEVAL

SAR backscatter intensity is generally related to a stress-equivalent neutral wind field at 10 m above the ocean surface (hereafter simply referred to as “wind field”) through a geophysical model function (GMF). GMFs require an a-priori wind direction, which is provided by the ERA5 global reanalysis product along with information on the SAR viewing geometry. This study employs CMOD5.N, a GMF developed to estimate wind speeds for  $\theta(10\text{ km})$  C-band scatterometer observations (Hersbach, 2010). SAR spatial resolutions are still orders of magnitude greater than that of scatterometers, for which CMOD5.N is designed. Therefore, we cannot discount the possibility that CMOD5.N is incapable of quantifying high-resolution wind-field properties. The GMF assumes the observed backscatter to be solely related to the local wind conditions; any imprints caused by rain bursts, swell, surface slicks or currents can lead to erroneous estimates of the wind field. With the exception of currents, most of these errors can be separated in the frequency domain or avoided by restricting analyses to homogeneous scenes.

#### A.1.2. ERA5 DATA

Included in the retrieved ERA5 data are: 10 m horizontal wind vectors, 2 m air and dew point temperature, sea-surface temperature, surface pressure, surface thermal radiation downwards (long-wave radiation), surface solar radiation downwards (short-wave

radiation) and boundary layer height. Wind vectors are converted to magnitude and orientation relative to North, and relative humidity is computed from the air and dew-point temperatures using the Arden-Buck equation. Parameters such as boundary layer height, long-wave and short-wave radiation have a minimal impact on the computation of  $L_{\text{ERA5}}$ , but are nonetheless required inputs to run the COARE3.5 algorithm. Alternatively, these parameters could be attributed a constant value. No surface-current vectors are available from ERA5 such that the wind speed can not be converted to a current relative equivalent. This being prescribed by the COARE3.5 algorithm.

### A.1.3. BUOY DATA

Buoy data from NDBC, 2022; NOAA, 2022a, 2022b; WHOI, 2022 is used as a secondary validation source. It serves as a check on ERA5's validation capacity and as an independent validation for a small subset of co-located SAR observations. SAR observations are considered co-located with one of 269 buoys if they occur within 4 hours and a 200 km radius of a measurement. To increase the number of co-locations the analysis was performed for 2014-2022/04. During this time window, a total of 7565 co-locations occur between scenes classified as rolls and 103 unique buoys. All buoys measured air/sea temperature, relative humidity (or dew point temperature from which relative humidity can be calculated) and wind speeds/directions. COARE3.5 provides an ideal tool to calculate  $L_{\text{buoy}}$  from buoy measurements as it can take into account the variable measurement heights of each buoy. None of the buoys measured all the required parameters to run the full COARE3.5 algorithm, necessitating supplementary ERA5 data. This includes the spatiotemporal co-located ERA5 data for boundary layer height, long-wave radiation and short-wave radiation. Additionally, only a few buoys measured surface pressure. For consistency, the ERA5 surface pressure values were used for all buoys instead. Similar to ERA5, no (consistent) observations of the currents were made such that the wind speed could not be made current relative.

### A.1.4. ERA5 DECORRELATION

The coarse  $1^\circ \times 1^\circ$  resolution of ERA5 data used here leads to decorrelation between observations and validation. By quantifying this effect, we can determine what fraction of the error budget is controlled by ERA5's resolution and whether or not a finer resolution is required. The average decorrelation is predicted by analyzing the mean difference between an ERA5-retrieved  $L_{\text{ERA5}}$ -field with a (spatially) shifted version of itself by assessing longitudinal differences for neighbouring grid cell. To increase the representability of results for co-location between SAR and ERA5, the analysis is performed between  $-20^\circ$  and  $20^\circ$  latitude (corresponding the highest concentration of observed rolls), all shifted data points involving positive  $L_{\text{ERA5}}$ 's are removed and the distribution of  $L_{\text{ERA5}}$  is further filtered such that it is similar to that of ERA5 co-located with SAR (not shown). Assuming that the decorrelation gradient between an offset of  $0^\circ$  and  $1^\circ$  holds on a sub-grid level, that all offsets are purely longitudinal and that the average offset between observations and the points hypothetically represented by ERA5 within the sub grid is  $0.25^\circ$ , the found maximum achievable  $R^2$  and minimum median absolute error (MAE) on a logarithmic scale are approximately 0.94 and 0.02 respectively.



### A.1.5. BUOY-ERA5 COMPARISON

Comparing a subset of SAR observations co-located with both ERA5 and buoys enables us to assess the validation capabilities of ERA5 with respect to the ground truth measurements from the buoys. Table A.1 contains comparison results. A direct comparison between these two validation sources gives a MAE of 0.202, which is equal to a median relative error of 59%. An  $R^2$  of 0.258 indicates that just over a quarter of the variance from ERA5 is directly explained by validation retrieved from buoys, highlighting the volatility of Obukhov-length estimation. The differences between validation sources may be caused by consistent offsets. To remove the effect thereof, a ML algorithm is trained to regress buoy data (raw measurements and those computed from COARE3.5 but excluding any unique buoy/network identifier) towards  $L_{\text{ERA5}}$ . Indeed, the  $R^2$  value for the predictions of this algorithm,  $\hat{L}_{\text{buoyML}}$ , increases nearly threefold to 0.759: when accounting for consistent offsets, buoys are able to explain approximately 76% of ERA5's variance. This ballpark figure provides a lower bound on the fraction of ground-truth-related atmospheric information contained in ERA5's data set. A separate analysis on a greater buoy-ERA5 co-locations data set yielded slightly better results ( $R^2 \approx 0.8$ , not shown) even after excluding parameters potentially contaminated by ERA5, e.g., parameters calculated through COARE3.5. Therefore, a maximum of approximately 24% of  $L_{\text{ERA5}}$ 's variance remains unexplained of which a minimum of approximately 6%-points are caused by spatial decorrelation (see Appendix A.1.4), leaving a maximum of 18% of  $L_{\text{ERA5}}$ 's variance to be miscellaneous noise. When comparing estimates from the analytical approach,  $\hat{L}$ , with the different validation sources,  $L_{\text{buoy}}$  and  $L_{\text{ERA5}}$ , results are closer to the buoy than ERA5 as indicated by the greater  $R^2$  and lesser MAE. Two new ML algorithms are trained,  $\hat{L}_{\text{MLERA5}}$  and  $\hat{L}_{\text{MLbuoy}}$ , using all the SAR-derived parameters. The former is trained towards validation from ERA5 and the latter towards validation from the buoys. The performance difference between either  $\hat{L}_{\text{MLERA5}}$  or  $\hat{L}_{\text{MLbuoy}}$  and their respective validation is statistically insignificant. This suggests that both validation sources are approximately equally representative of the atmosphere as extracted from SAR imagery. Results appear slightly better when regressing towards validation from ERA5, perhaps because the more precise point-wise buoy measurements experience greater spatiotemporal decorrelation than the large-scale averaged ERA5 values. On a small sample of co-locations, results from the validation comparison substantiate the use of ERA5 for validation: even though ERA5 differs from the buoys, it differs consistently such that predicting ERA5 is akin to indirectly predicting buoy values.

## A.2. SUPPORTING METHODOLOGY

### A.2.1. SPECTRAL COMPUTATIONS

#### TWO-DIMENSIONAL SPECTRUM

First, the resampled SAR-derived wind field is clipped by 5 pixels, thereby removing pixels prone to discontinuities and errors. Next, each wind field is subdivided into four equal-sized tiles, each approximately 10 by 10 kilometers. A two-dimensional Hann window is applied on each wind-field tile, followed by the subtraction of the mean (removing the 0<sup>th</sup> frequency component). Next the Power Spectral Density (PSD) of the windowed and mean-removed wind-field tile is computed in the spatial domain yielding  $S_i(\xi_x, \xi_y)$ ,

where  $\xi$  is the spatial frequency with units of  $\text{m}^{-1}$  in the x-axis and y-axis of the  $i^{\text{th}}$  wind-field tile. The four PSDs per wind field are averaged to create a single smoothed PSD representative of the whole wind field,  $S(\xi_x, \xi_y)$ . The hypothetical power loss due to windowing is compensated. For non-homogeneous scenes, this correction may be insufficient, such that

$$\sigma_{\text{windfield}}^2 \neq \int_{\xi_x} \int_{\xi_y} S(\xi_y, \xi_x) d\xi_y d\xi_x. \quad (\text{A.1})$$

The fraction of variance gained/lost after applying a window correction, as compared to the variance of the original wind field, is kept and will be referred to as the window effect

$$\text{window effect} = \frac{\int_{\xi_x} \int_{\xi_y} S(\xi_x, \xi_y) d\xi_y d\xi_x}{\sigma_{\text{windfield}}^2}. \quad (\text{A.2})$$

This parameter partially captures the inhomogeneity of the wind fields in question. The Cartesian  $S(\xi_x, \xi_y)$  is linearly interpolated to a polar coordinate system giving  $S(\theta, \xi)$  where  $\theta$  and  $\xi$  are the angle with respect to image north (satellite azimuth direction) in degrees and spatial frequency in  $\text{m}^{-1}$  respectively. SAR imagery is resampled to 100 m resolution in both axes ( $\Delta x \approx \Delta y$ ), such that

$$\xi_{\text{Nyquist}} \geq \frac{1}{2 \cdot \Delta x} = \frac{1}{200 \text{ m}}. \quad (\text{A.3})$$

Variance in  $S(\theta, \xi)$  for  $\xi > \xi_{\text{Nyquist}}$  contains high-frequency energy sampled in the corners of the 2D PSD. The total energy in these corners is stored as another parameter.

A wind-streak containing wind field is shown in the upper left of Figure A.1 with its corresponding two-dimensional PSD,  $S(\xi_x, \xi_y)$ , displayed in the upper right. The majority of energy is located at high frequencies ( $\xi > 1/600 \text{ m}^{-1}$ ) with a narrow circular concentration of energy at the maximum vertical extents indicating a swell system. The wind-streak related energy is observed within the bandpass of interest ( $1/600 \text{ m}^{-1} \geq \xi > 1/3000 \text{ m}^{-1}$ ) where the energy concentration is perpendicular to the streak orientation. Energy within the lowpass frequencies ( $\xi < 1/3000 \text{ m}^{-1}$ ) contains information about mesoscale phenomena.

The lower left of Figure A.1 contains annotations of further parameters derived from  $S(\xi_x, \xi_y)$ . The orientation of maximum integrated energy over frequencies within a Gaussian smoothed bandpass gives the energy direction which, being the orientation of the rolls, could be used as a proxy for wind direction (e.g. Figure 3c in C. Wang, Mouche, et al., 2019). The 180° spectral ambiguity is removed by selecting the orientation closest to that from the ERA5 wind direction. The energy direction with respect to geographical North is converted to a direction with respect to the radar range direction  $\delta$  (energy direction in range). A spectral area within 20° to the left and right of the energy direction is referred to as the beam. Variance within this beam and the intersection of the beam with the bandpass are stored as variance beam and variance bandpass beam respectively. Contours are shown for which frequencies greater than  $1/3000 \text{ m}^{-1}$  a cumulative integration of  $S(\xi_x, \xi_y)$  per angle achieves 25%, 50%, and 75% of the average energy

within the bandpass. For each contour, the mean, median, standard deviation, and median absolute deviation in pixels from the center are stored. These zero-dimensional parameters give insight into the spread and directionality of the spectral energy.

### ONE-DIMENSIONAL SPECTRUM

The one-dimensional spectrum  $S(\xi)$  in the lower left of Figure A.1 is computed from the two-dimensional spectrum in the upper right by integrating over  $\theta$  such that

$$S(\xi) = \frac{\int_{\theta=0}^{360} S(\theta, \xi) d\theta}{\Delta\theta} \quad (\text{A.4})$$

where  $\Delta\theta$  is the angular spacing of the polar spectrum in radians. In the two-dimensional example spectrum of Figure A.1 one can see high-frequency energy from swell located perpendicular to the orientation of wind-streak energy within the bandpass. A polar integration over  $\theta$  prevents this energy from projecting itself on the otherwise smooth  $-5/3$  inertial subrange. The one-dimensional spectrum within the bandpass is scaled with  $\xi^{5/3}$  such that the higher frequencies increase in amplitude with respect to the lower frequencies. The peak of this scaled spectrum is selected as the spectral peak. Without scaling one would always select the mesoscale as containing a spectral peak when both a mesoscale and microscale peak are present. Spectral peaks located at  $\xi < 1/1500 \text{ m}^{-1}$  are assumed to fall within the mesoscale whereas peaks at  $\xi > 1/1000 \text{ m}^{-1}$  are assumed to fall within the microscale. Spectral troughs are selected as the lowest point between the spectral peak and  $\xi = 1/300 \text{ m}^{-1}$ .

Estimated spectral peaks and spectral troughs can be located at the same frequency as the latter is not scaled prior to analysis. For these undesirable cases the spectrum is successively scaled with decreasing powers during trough detection such that the amplitude of high frequencies decreases with respect to that of the low frequencies. Though this increases the probability of finding a trough at high frequencies, the quality of the slope between peak and trough for these cases may be of poor quality. Several filtering operations are applied to remove such cases.

The range between peak and trough is assumed to be the inertial subrange with a  $-5/3$  spectral slope. As a quality check this slope is scaled with  $\xi^{5/3}$  which, for a perfect inertial subrange, yields a normalized spectral amplitude identical for each frequency. The frequency-weighted standard deviation of  $S(\xi) \cdot \xi^{5/3}$  is divided by the median value giving a frequency-weighted normalized slope deviation of the inertial subrange,  $z_{S(\xi)}$ . Poorly identified inertial subranges are detected through high values of  $z_{S(\xi)}$  and subsequently removed.

The similarity-theory equations require a PSD as a function of temporal frequency  $S(n)$ , where  $n$  is the temporal frequency with units Hz. Invoking Taylor's hypothesis, temporal frequency  $n$  is calculated from spatial frequency  $\xi$  as

$$n = \xi \bar{U}, \quad (\text{A.5})$$

where  $\bar{U}$  indicates the averaged wind field over the entire imagerie. In order to decrease sensitivity to systematic errors and outliers in the wind field—caused by erroneously attributing the magnitude of observed backscatter to the wind field alone, neglecting

any current-induced effects or due to the inhomogeneity of the estimated wind field—this study uses the median wind speed  $\tilde{U}$  in all places where literature prescribes  $\bar{U}$  or  $U$ . Following Equation 1 from Kaimal et al., 1972, this leads to the calculation of  $S(n)$  as

$$S(n) = \frac{1}{\tilde{U}} S(\xi). \quad (\text{A.6})$$

### A.2.2. ANALYTICAL FRAMEWORK

#### SHEAR COMPONENT

Wind-induced surface stress  $\tau$  is related to friction velocity  $u_*$  and wind velocity following

$$u_*^2 = C_d \bar{U}^2, \quad (\text{A.7})$$

$$\tau = \rho_{\text{air}} u_*^2, \quad (\text{A.8})$$

where  $C_d$  is the drag coefficient,  $\bar{U}$  the mean horizontal wind speed and  $\rho_{\text{air}}$  the air density (Fairall et al., 1996). The drag coefficient  $C_d$  is calculated following

$$C_d = \left[ \frac{\kappa}{\ln(z) - \ln(z_0) - \psi_m} \right]^2, \quad (\text{A.9})$$

where  $z$  is the measurement height (10 m for CMOD5.N),  $z_0$  the aerodynamic roughness length,  $\kappa$  the von Kármán constant (According to Table 2 in Foken, 2006  $\kappa \approx 0.40$ ) and  $\psi_m$  the diabatic wind profile function (Stull, 1988). For neutral conditions ( $zL^{-1} = 0$ ), the  $\psi_m$  term becomes zero and  $C_d$  will be referred to as  $C_{dn}$ . Since stress-equivalent neutral wind speed is retrieved from the GMF,  $C_{dn}$  will be used for all shear-component calculations. In turn the aerodynamic roughness length  $z_0$  can be calculated according to the Charnock relation (Fairall et al., 1996)

$$z_0 = a \frac{u_*^2}{g} + 0.11 \frac{\nu}{u_*}. \quad (\text{A.10})$$

The Charnock constant  $a$  is an empirical measure used to quantify the sea state (S. D. Smith et al., 1996). Young et al., 2000 uses a constant value of 0.011. According to Hersbach, 2011, the  $a$ -value for seas with swell hovers around 0.01 whereas for young steep seas it is closer to 0.04. Typical values fall within this range. For consistency, this study will use a value of 0.011. A constant value of  $9.8 \text{ ms}^{-2}$  is chosen for gravitational acceleration  $g$  and, according to Equation 78 presented in Andreas, 1989, the kinematic viscosity of air  $\nu$  is approximately  $1.5 \cdot 10^{-5} \text{ m}^2 \text{ s}^{-1}$  for an air temperature of 293 K. This series of equations is solved iteratively taking an initial estimate of  $C_{dn}$ . Convergence is achieved within a few iterations. The calculated values for  $z_0$ ,  $C_{dn}$  and  $u_*$  are used in the successive algorithms. Parameters  $\rho_{\text{air}}$ ,  $a$  and  $\nu$  are approximated rather than retrieved from measurements. A summary of the convective algorithm is outlined in Table A.2.

## CONVECTIVE COMPONENT

The convective atmospheric component is estimated from the variance present within the inertial subrange. Therefore a portion of the microscale spectrum must be identified as following the -5/3 power law in the one-dimensional spectrum  $S(n)$ . As the analysis is frequency normalized it does not matter at which frequency in the inertial subrange the analysis is performed, as long as it falls on the same -5/3 slope. Rewriting Equation 4 from Kaimal et al., 1976 yields

$$w_* = \sqrt{\frac{(2\pi)^{2/3} f_i^{2/3} n S(n)}{\alpha \psi^{2/3}}}, \quad (\text{A.11})$$

where  $\alpha$  is the Kolmogorov constant of approximately 0.5 and  $\psi$  the dimensionless energy dissipation rate. Results obtained in Young et al., 2000 used a mixed-layer value of  $\psi = 0.6$ . This study uses  $\psi = 1.0$  which, based on Figure 4 in Kaimal et al., 1976, is deemed more representative of the surface layer. Lastly,  $f_i$  represents the dimensionless frequency calculated following

$$f_i = \frac{n Z_i}{U} \quad (\text{A.12})$$

with  $Z_i$  being the boundary layer height. In further calculation towards Obukhov length, the value of  $Z_i$  will cancel itself out, making its estimation unnecessary. A value for the convective velocity scale,  $w_{*,i}$ , is obtained for each analyzed frequency  $n_i$  within the inertial subrange. These values should be near identical meaning they can be combined using a frequency-weighted average to form a single convective velocity scale,  $w_*$ , representative of the entire inertial subrange. The final value of  $w_*$  is combined with a rewritten version of Equation 4.2a from Stull, 1988 yielding

$$\overline{w' T'_v} = \frac{w_*^3 \overline{T_v}}{g Z_i}. \quad (\text{A.13})$$

Plugging  $\overline{w' T'_v}$  into Equation 5.7c from Stull, 1988 yields Obukhov length  $L$  following

$$L = -\frac{\overline{T_v} u_*^3}{\kappa g \overline{w' T'_v}}. \quad (\text{A.14})$$

The  $\overline{T_v}$ 's cancel out combining Equations A.14 and A.13. Having calculated  $L$ , a stability correction is applied to the original wind field to account for unstable atmospheric conditions. Young et al., 2000 calculates a stability correction factor  $\chi$  as

$$\chi = 1 - \left( \frac{\psi_m \sqrt{C_{dn}}}{\kappa} \right), \quad (\text{A.15})$$

where  $C_{dn}$  is retrieved from the shear algorithm and  $\psi_m$  is computed by plugging the obtained value of  $L$  into

$$x = \left( 1 + 16 \left| \frac{z}{L} \right| \right)^{1/4}, \quad (\text{A.16})$$



followed by plugging  $x$  into (corrected for typo)

$$\psi_m = \ln \left[ \left( \frac{1+x^2}{2} \right)^2 \right] - 2 \tan^{-1}(x) + \frac{\pi}{2}. \quad (\text{A.17})$$

Next  $\chi$  is multiplied with all the mean wind-speed terms in the convective algorithm. Since  $S(\xi)$  captures the variance of  $U$ , its correction becomes  $\chi^2$ . However, following Equation A.6,  $S(\xi)$  is divided by  $U$  (and thus  $\chi$ ) yielding  $S(n)$ , such that the correction for  $S(n)$  becomes  $\chi^2 \cdot \chi^{-1}$ . The values for  $f_i$ ,  $S(n)$  and  $w_*$  are updated iteratively until convergence. A summary of the convective algorithm is outlined in Table A.3.

### A.2.3. MACHINE LEARNING

#### DATA FILTERING

ML algorithms are trained towards matrix  $y$  containing the transformed validation values of Obukhov length  $\text{Log}_{10}(|L_{\text{val}}|)$ , where  $L_{\text{val}}$  is either  $L_{\text{ERA5}}$  or  $L_{\text{buoy}}$ . All observations in  $y$  with a positive  $L$  or a positive heat flux oriented into the ocean are removed; the analytical model is incapable of predicting these phenomena. The remaining  $y$  has size  $m \times 1$  with  $m$  observations.

The matrix of independent variables  $X$  of size  $m \times n$  contains  $m$  observations for  $n$  parameters. The  $n$  parameters in  $X$  are devoid from any validation data (either from ERA5 or buoys) with the exception of the ERA5-retrieved wind direction which is implicitly contained in all wind-field related parameters. Included in  $n$  are zero-dimensional parameters derived from the SAR imagette along with information about the acquisition, e.g.  $\tilde{U}$ ,  $u_*$ ,  $L$ , incidence angle  $\phi$ , etc. Spatiotemporal information (latitude, longitude and time) is withheld from the ML-algorithm to prevent it from fitting to geographical locations or seasons rather than observation.

Observations are filtered prior to training. Primary filtering is performed by thresholding on observed parameters. This includes filtering of observations for which any of the following conditions are not met:  $1.5 \geq \text{window effect} \geq 0.5$ , normalized spectral slope deviation  $z_{S(\xi)} \leq 0.25$ , energy direction from Figure A.1 differs by less than  $30^\circ$  from  $\theta_{\text{ERA5}}$ ,  $200 \text{ m} \leq \text{inertial subrange length} \leq 20\%$  of the peak production wavelength and  $2950 \text{ m} \geq \text{peak production wavelength} \geq 610 \text{ m}$ . The first threshold removes inhomogeneous scenes, the second removes scenes with a poor fit to the spectral -5/3 slope, the third removes scenes with likely classification errors and the fourth and fifth thresholds remove scenes with unlikely inertial subranges. The ensemble of primary filtering operations ensures that only the SAR imagettes are considered for which one could reasonably assume the analytical method to be applicable. In fact, primary filtering slightly penalizes ML results in return for systematically reducing prediction noise (a minor  $R^2$  reduction in return for a significant MAE reduction, not shown).

A secondary and more refined filtering operation aims at removing outliers. First all observation columns  $n$  in  $X$  are scaled by removing the mean and dividing by their respective standard deviations. Next the dimension of  $X_{\text{scaled}}$  is reduced using Principal Component Analysis (PCA). The first principal components explaining a combined 80% of the total variance,  $X_{\text{PCA } 80\%}$ , are used. Outliers in  $X_{\text{PCA } 80\%}$  are found using the unsupervised Local Outlier Factor outlier-detection algorithm with 100 nearest neighbors implemented in Sci-kit learn (Pedregosa et al., 2011). Observations that do not meet the set

thresholds or whose values can be considered outliers are subsequently removed from both  $y$  and  $X$  to maintain identical  $m$ -size. Lastly, both  $y$  and  $X$  are randomly split into 80% training and 20% testing fractions. Performances of the analytical and ML-assisted methods are assessed on the test fraction of the filtered scenes.

For the rolls data set, approximately two-thirds of the data are removed in this manner, leaving a total of 35,907 observations (out of 124,682). The ensemble of filtering operations decreases the proportion of observations for which  $L_{\text{ERA5}}$  indicates near-neutral unstable conditions, conditions under which Obukhov length tends to explode.

For the rolls + cells data set, the energy-direction filtering operation is dropped as the spectral energy orientation of cells cannot consistently be interpreted as a streak orientation. Other filtering operations remain the same. Of the resulting composite data set containing 100,538 observations, approximately two-thirds is classified as cells and one-third as rolls. A greater number of the former pass the filtering operation as the spectral signature of cells tend to be more clearly defined. Additionally, fewer cell observations are removed due to co-located ERA5 indicating non-convective conditions. With rolls being generally less unstable, this plagues them particularly.

## REGRESSION

Regression is performed using a so-called stacked regressor where multiple regressors are trained on the data independently followed by training a final regressor on the output of the original regressors. The idea being that the final regressor learns from the combination of original results, thereby allowing it to make a new and improved prediction. The following independent regressors are used: LightGBM, XGBoost, CatBoost, Bayesian Ridge and Lasso LARS. The former three use state of the art tree-based boosting (T. Chen & Guestrin, 2016; Ke et al., 2017; Prokhorenkova et al., 2018, respectively) which, when trained on sufficient data, consistently outperforms the latter two linear model, which are added to increase diversity for the stacking regressor. The outputs of these five regressors are combined, or stacked, using a final Ridge regressor (implemented by Pedregosa et al., 2011).

Hyperparameters of the independent regressors are tuned using a Tree-structured Parzen Estimator (Bergstra et al., 2011) and hyperband-based pruner (L. Li et al., 2017) implemented in the open-source optimization software Optuna (Akiba et al., 2019). Optimization targets the minimization of the mean MAE between  $y$  and estimate  $\hat{y}$  after a 5-fold cross validation on the training data. Alternatively one could opt for the maximization of  $R^2$  for which results are nigh identical (not shown). The hyperband pruner is called after successively training on 10%, 20%, 30%, 40% and 60% of the training data. Hyperparameter optimization per regressor is constrained to 200 iterations or 40 minutes run time, depending on which condition is met first. Hardware and software specifications are: Python 3.9.12, Ubuntu 20.04.4 LTS, 64 GB of DDR4 at 3200 MHz and an Intel Xeon(R) W-11955M CPU @ 2.60 GHz  $\times$  16.

The optimal preprocessing scaler of the  $X$  matrix is sought in addition to optimizing the regression hyperparameters. Namely, whether to scale all columns of the  $X$  matrix using one (or none) of several common preprocessing scalers available in the Scikit-learn Python package (Pedregosa et al., 2011). Similarly, the optimization procedure decides whether to transform the dependent matrix  $y$  to a normal distribution (and to

how many quantiles this normal distribution should contain) prior to regression. Such a transformation can boost performance when the regressor assumes  $y$  to follow a normal distribution. The  $X$  scalers and  $y$  transformations are selected per independent regressor. Information leakage is prevented by fitting the scalers and transformations on the training data only.

### A.3. SUPPLEMENT TO RESULTS

#### A.3.1. SPATIOTEMPORAL ANALYSIS

Spatiotemporal averages of estimates are shown in Figure A.2. Though the magnitude may be off, spatial features of the analytical results in the upper left overlap with those from validation in the upper right: there is increased instability near the coasts (in particular for the equatorial west coasts), a thin equatorial region with greater instability separates the northern and southern tropical regions with lesser instability, followed by a transition into oceans north and south of  $30^\circ\text{N}$  &  $30^\circ\text{S}$  respectively. Results from the ML-assisted approach in the lower right are qualitatively different from those obtained with the analytical approach and very similar to those from validation.

Spatial differences between  $|\hat{L}|$  and  $|L_{\text{ERA5}}|$ , shown in the upper left of Figure A.3, indicate under estimation of  $|L|$  north of  $30^\circ\text{N}$  and south of  $30^\circ\text{S}$  whereas within these bands there is over estimation. Notable exceptions are the coasts bordering Angola, Ecuador, Senegal and the sea just north of Madagascar. Spatial differences between  $|\hat{L}_{\text{ML}}|$  and  $|L_{\text{ERA5}}|$  can be discerned from the upper right of Figure A.3. The ML algorithm is capable of explaining away most of the original under estimation of  $|L|$  for the seas bordering Angola, Ecuador, Senegal and Madagascar, i.e. observations for these regions contain useful signatures. The fact that error signs of ML results appear regionally correlated indicates that regional phenomena are sources of errors. For instance, the coherent structures of flipping error signs near the equator are located where one would expect equatorial currents in close proximity to the equatorial counter current. These apparent errors could originate from the validation side, as a result of, for instance, not supplying current-relative wind speed to COARE3.5 or poor parameterisation of currents in ERA5's ocean-atmosphere interactions. The error sign of the maps in the top panel of Figures A.3 may fortuitously cancel out, falsely giving the impression of low median errors. This is mitigated by analysing the absolute median errors, provided in the lower panel, which confirm that the magnitude of errors is not significantly affected by sign cancellation.

#### A.3.2. TURBULENCE-SCALE EFFECT

Theoretically the analytical method is only valid for the microscale inertial subrange. In Table A.4 the ML prediction performance is assessed across the mesoscale and microscale in order to determine whether its applicability is also constrained by scale. We separated scales according to the wavelength of the found spectral peak. Scenes with spectral peaks greater than 1500 m are assumed to contain mesoscale convection whereas spectral peaks located at less than 1000 m are assumed to fall within the microscale. Performances are obtained from an ML algorithm retrained on an equal number of scenes for both scales. The difference in  $R^2$  score is statistically insignificant while a statistically significant lower MAE value for the mesoscale suggests that a ML-assisted approach is

systematically better at inferring atmospheric stability from larger-scale turbulence. A sampling difference between scales is the likely cause of this result: the distribution of  $L_{\text{ERA5}}$  within the microscale is broader than that of the mesoscale (not shown), potentially penalizing the MAE metric. Nevertheless, it is evident that the ML-assisted approach is able to extract significant atmospheric information from scenes containing either micro- or mesoscale turbulence. The indifference to scale confirms that little predictive power is extracted from the scale-sensitive parameters derived in the analytical methodology.

### A.3.3. VIEWING-GEOMETRY EFFECT

Radar observations of the ocean surface are generally sensitive to the orientation of surface waves with respect to the sensor. ML-estimation performance is assessed for different bins of ERA5 wind directions with respect to the radar range direction,  $\delta_{\text{ERA5}}$ , in order to determine the effect of this inherent sensitivity to the extraction of atmospheric information. Results are presented in Table A.5. A  $\delta_{\text{ERA5}}$  of  $0^\circ$  indicates wind propagating exactly down (or up) the radar range direction with a maximum value of  $90^\circ$  indicating wind propagating perpendicular to the range direction. The ML algorithm is retrained per  $\delta_{\text{ERA5}}$ -angle bin using an identical number of observations following the same distribution of  $L_{\text{ERA5}}$  (according to a two-sample Kolmogorov-Smirnov test the distributions across bins are insignificantly different with all  $p$ -values greater than 0.95). The small sample size of overlapping  $L_{\text{ERA5}}$ 's across  $\delta_{\text{ERA5}}$ -bins prevents statistically significant results; almost all mean values fall within two standard deviations of all other means. Nonetheless, from the  $18^\circ$ - $36^\circ$  bin onwards the explainable variance  $R^2$  decreases while the median error increases. This suggests that the quantity of atmosphere-related information extracted from SAR imageries decreases for winds propagating at greater angular differences with respect to the radar range direction. A similar observation is made in C. Wang et al., 2020 where the detection of rolls decreases with wind directions propagating perpendicular to the radar orientation, again suggesting a gradual loss of atmospheric information contained in SAR imagery as a function of viewing geometry. The relatively poor performance for the  $00^\circ$ - $18^\circ$  bin might be caused by increased sensitivity exactly down range, systematically picking up noise and/or sampling a broader range of possible parameter values associated with  $L$ . This would also explain the increased uncertainty ranges.

### A.3.4. VARIANCE BUDGET

Analyses of the validation data in Text A.1.5 suggest a maximum of 24.1% of variance observed in the validation data may be ascribed to noise, of which a minimum of 6%-points as a result of spatial decorrelation (Text A.1.4). These ballpark figures lead to an  $R^2_{\text{max}} = 0.759$ . Therefore, with an obtained  $R^2 = 0.673$ , approximately 88% of the explainable variance is resolved. The remaining 8.6%-points of unexplained variance provide an indicative limit for attainable improvement. Resolving all individual uncertainties—such as those related to the high-resolution applicability of CMOD5.N, the inability to capture/extract atmospheric information through the used zero-dimensional parameters or the disregard of surface currents—is unlikely to improve results by more than 8.6%-points, and certainly no more than 26.6%-points (unexplained % + misc. noise %).

An infographic detailing the variance budget for the rolls data set is provided in Figure A.4.

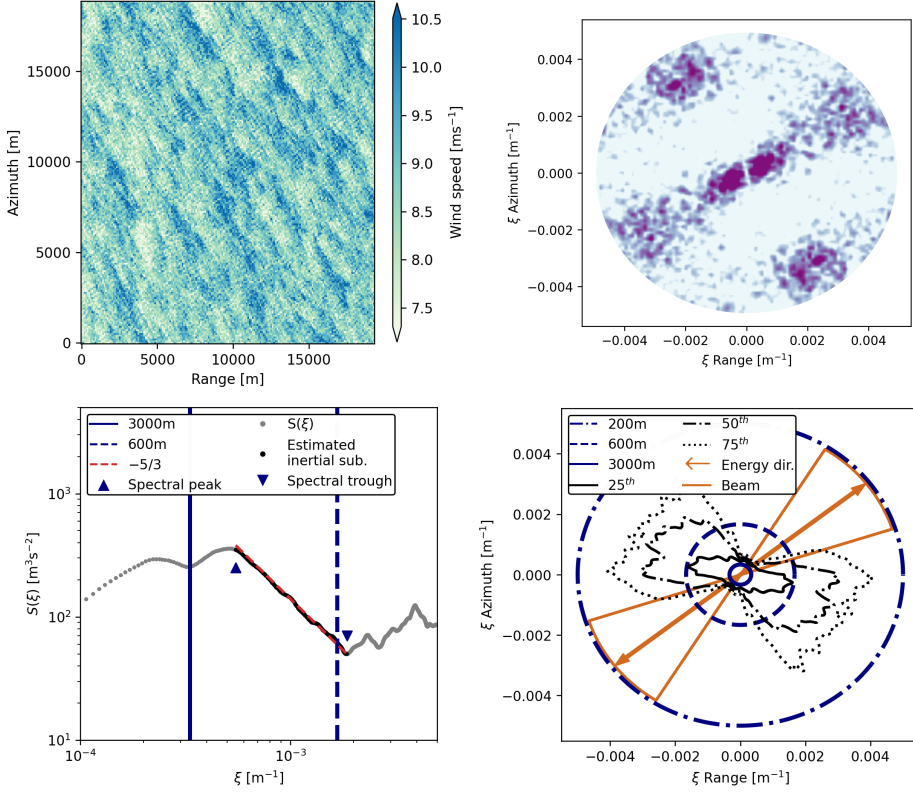


Figure A.1: Spectral example of WV imagette classified as containing rolls. Sentinel-1B, date: 07-07-2021, absolute orbit: 027685, vignette : 42, product unique ID: FF3B. (Upper left) Stress-equivalent neutral wind field as retrieved from the GMF. (Upper right) Logarithm of wind field's 2D PSD,  $S(\theta, \xi)$ . Arbitrary units with more purple indicating greater amplitude. (Lower left) 1D integrated spectrum of 2D PSD,  $S(\xi)$ . (Lower right) Annotations for  $S(\theta, \xi)$ .

Table A.1: Estimation performance between  $\log_{10}(|L_x|)$  and  $\log_{10}(|L_y|)$  where  $\log_{10}(|L_y|)$  is the objective for 2056 observations with both buoy and ERA5 validations. Results are shown for ERA5 validation co-located in space and time with buoy observations rather than SAR acquisitions, allowing for a comparison between buoy and ERA5 validation.

| $L_x - L_y$ | $L_{\text{buoy}} - L_{\text{ERA5}}$ | $L_{\text{buoy}_{\text{ML}}} - L_{\text{ERA5}}$ | $\hat{L} - L_{\text{ERA5}}$ | $\hat{L} - L_{\text{buoy}}$ | $\hat{L}_{\text{ML}_{\text{ERA5}}} - L_{\text{ERA5}}$ | $\hat{L}_{\text{ML}_{\text{buoy}}} - L_{\text{buoy}}$ |
|-------------|-------------------------------------|-------------------------------------------------|-----------------------------|-----------------------------|-------------------------------------------------------|-------------------------------------------------------|
| $R^2$       | $0.258 \pm 0.083$                   | $0.759 \pm 0.047$                               | $-1.374 \pm 0.219$          | $-0.572 \pm 0.134$          | $0.495 \pm 0.053$                                     | $0.396 \pm 0.096$                                     |
| MAE         | $0.202 \pm 0.010$                   | $0.087 \pm 0.007$                               | $0.359 \pm 0.017$           | $0.259 \pm 0.011$           | $0.120 \pm 0.014$                                     | $0.136 \pm 0.013$                                     |



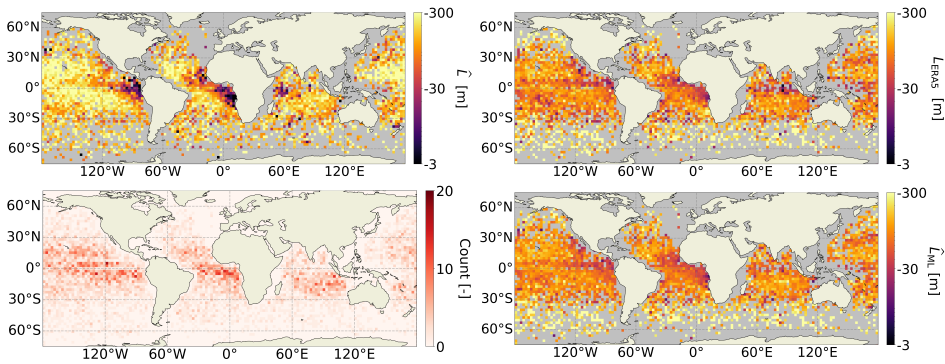


Figure A.2: Global median estimation results on  $2.5^\circ \times 2.5^\circ$  for the 20% testing data set during 2020-2021. Medians calculated on logarithmic scale. (Upper left)  $\hat{L}$  (Upper right)  $L_{\text{ERA5}}$  (Lower left) Scene count (Lower right)  $\hat{L}_{\text{ML}}$ .

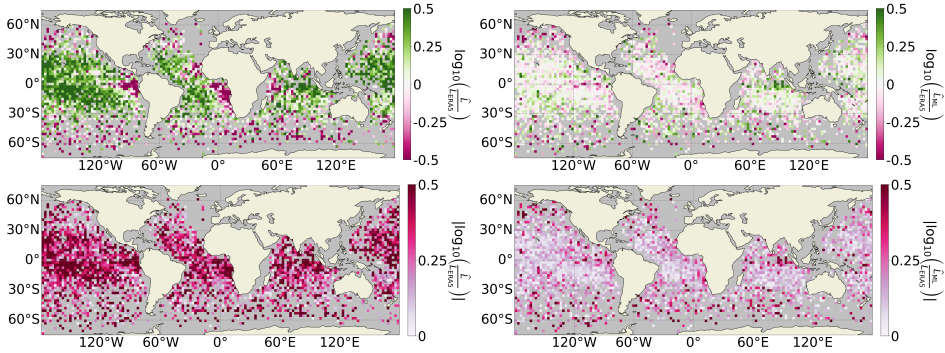


Figure A.3: Global median estimation and validation differences on  $2.5^\circ \times 2.5^\circ$  for the 20% testing data set during 2020-2021. Medians calculated on logarithmic scale. (Upper left) difference  $\hat{L}$  and  $L_{\text{ERA5}}$ . (Upper right) difference  $\hat{L}_{\text{ML}}$  and  $L_{\text{ERA5}}$  (Lower left) Absolute difference  $\hat{L}$  and  $L_{\text{ERA5}}$ . (Lower right) Absolute difference  $\hat{L}_{\text{ML}}$  and  $L_{\text{ERA5}}$ .

Table A.2: Summary of shear algorithm in Text A.2.2

| Step | Equations            | Operations                                                   | Constants              |
|------|----------------------|--------------------------------------------------------------|------------------------|
| 1    | <a href="#">A.7</a>  | $u_* = \sqrt{C_{dn} \overline{U_n^2}}$                       | initial guess $C_{dn}$ |
| 2    | <a href="#">A.10</a> | $z_0 = a \frac{u_*^2}{g} + 0.11 \frac{\nu}{u_*}$             | $a, g, \nu$            |
| 3    | <a href="#">A.9</a>  | $C_{dn} = \left[ \frac{\kappa}{\ln(z) - \ln(z_0)} \right]^2$ | $z, \kappa$            |
| 4    |                      | Iterate till convergence                                     |                        |

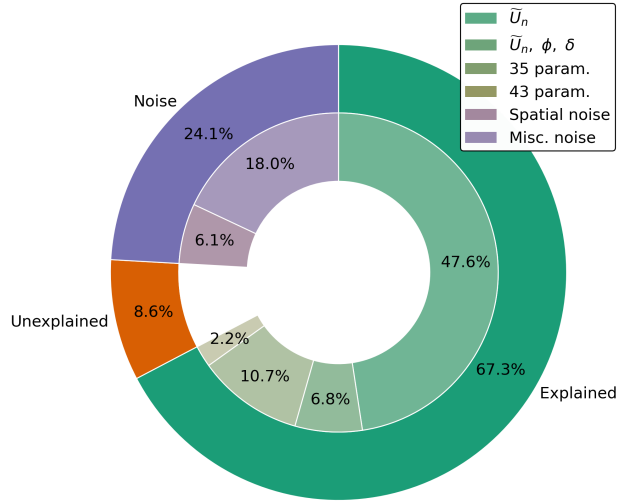


Figure A.4: Approximate explainable variance budget for  $L_{\text{ERA5}}$  estimation on rolls data set. A ML algorithm trained on estimated stress-equivalent neutral median wind speed,  $\tilde{U}_n$ , is capable of explaining 47.6% of variance. Including two viewing-geometry related parameters,  $\phi$  and  $\delta$ , increases the explained variance by 6.8%-points. Including a further 32 parameters (for a total of 35) derived from two-dimensional spectra adds 10.7%-points. Including eight parameters (for a total of 43) uniquely derived in the analytical method adds a mere 2.2%-points. A comparison between buoys and ERA5 indicates that a minimum of 75.9% of ERA5's  $L_{\text{ERA5}}$  is physically based. The remaining 24.1%-points are attributed to noise of which approximately a quarter is attributed to spatial decorrelation. The difference between the 75.9% of  $L_{\text{ERA5}}$  explained by the buoys, and the 67.3% explained by SAR yields 8.6% of unexplained but attainable signal. Results should be seen as ballpark figures representative for the data set of this study. Exact values are likely to vary with the maximum explainable variance being a function of geographical location, data distribution, viewing geometry and or other (unconsidered) factors.

Table A.3: Summary of convective algorithm in Text A.2.2

| Step | Equations | Operations                                                                                      | Constants                                 |
|------|-----------|-------------------------------------------------------------------------------------------------|-------------------------------------------|
| 1    | A.5       | $n = \xi \bar{U} \cdot \chi$                                                                    | $\chi = 1$ for first iteration            |
| 2    | A.12      | $f_i = \frac{n Z_i}{\bar{U} \cdot \chi}$                                                        | Initial estimate $Z_i$                    |
| 3    | -         | $U \rightarrow S(n)$                                                                            |                                           |
| 4    | A.11      | $w_* = \sqrt{\frac{(2\pi)^{2/3} f_i^{2/3} n S(n) \cdot \chi}{\alpha \psi^{2/3}}}$               | $\alpha, \psi$                            |
| 5    | A.13      | $\overline{w' T'_v} = \frac{w_*^3 T_v}{g Z_i}$                                                  | Initial estimate of $\overline{T_v}$      |
| 6    | A.14      | $L = -\frac{\overline{T_v} u_*^3}{\kappa g \overline{w' T'_v}}$                                 | $\kappa, g, u_*$ from the shear algorithm |
| 7    | A.16      | $x = \left(1 + 16 \left \frac{z}{L}\right \right)^{1/4}$                                        | $z$                                       |
| 8    | A.17      | $\psi_m = \ln \left[ \left( \frac{1+x^2}{2} \right)^2 \right] - 2 \tan^{-1}(x) + \frac{\pi}{2}$ |                                           |
| 9    | A.15      | $\chi = 1 - \left( \frac{\psi_m \sqrt{C_{dn}}}{\kappa} \right)$                                 | $C_{dn}$ from the shear algorithm         |
| 10   |           | Iterate till convergence                                                                        |                                           |

Table A.4: ML performance for scenes whose inertial subrange is assumed to lie in either the microscale ( $\xi_{peak}$  [610, 1000] m) or mesoscale ( $\xi_{peak}$ : [1500, 2950] m). A maximum of 7910 scenes occurred within the microscale range. An identical number of scenes with peaks in the mesoscale range was chosen to prevent artificially improving performance.

|       | microscale        | mesoscale         |
|-------|-------------------|-------------------|
| $R^2$ | $0.667 \pm 0.038$ | $0.619 \pm 0.045$ |
| MAE   | $0.150 \pm 0.007$ | $0.124 \pm 0.007$ |

Table A.5: ML performance on a logarithmic scale for the angular difference between ERA5 wind direction and radar range direction,  $\delta_{ERA5}$ . The ML algorithm is retrained per  $\delta_{ERA5}$ -bin on 400 data points. These data points follow a similar validation distribution across the  $\delta_{ERA5}$ -bins with 50  $L_{ERA5}$ 's chosen for each of eight logarithmically spaced ranges between -300 m <  $L_{ERA5}$  < -20 m.

| $\delta_{ERA5}$ | 00-18             | 18-36             | 36-54             | 54-72             | 72-90             |
|-----------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| $R^2$           | $0.573 \pm 0.177$ | $0.666 \pm 0.054$ | $0.570 \pm 0.092$ | $0.554 \pm 0.095$ | $0.394 \pm 0.137$ |
| MAE             | $0.166 \pm 0.037$ | $0.124 \pm 0.029$ | $0.156 \pm 0.010$ | $0.164 \pm 0.018$ | $0.181 \pm 0.021$ |



# B

## APPENDIX FOR CHAPTER 3

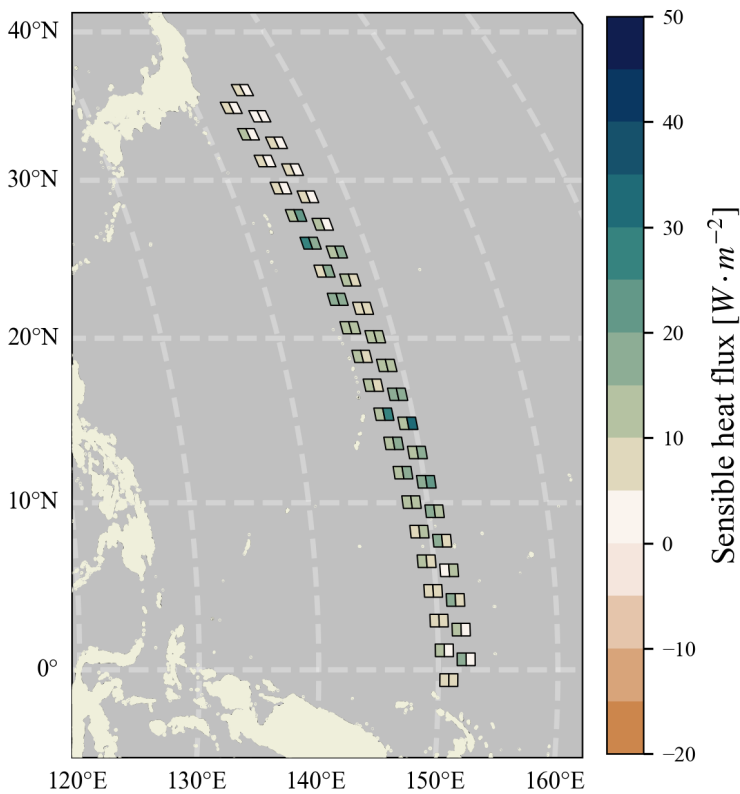


Figure B.1: Example ascending WV track between New Ireland and Japan with alternating steep and far vignettes. The left and right halves of each square represent the SAR and ERA5 reanalysis sensible heat fluxes, respectively. No filtering has been applied, and the squares have been enlarged for illustrative purposes (each vignette is approximately 20×20 km in size originally).



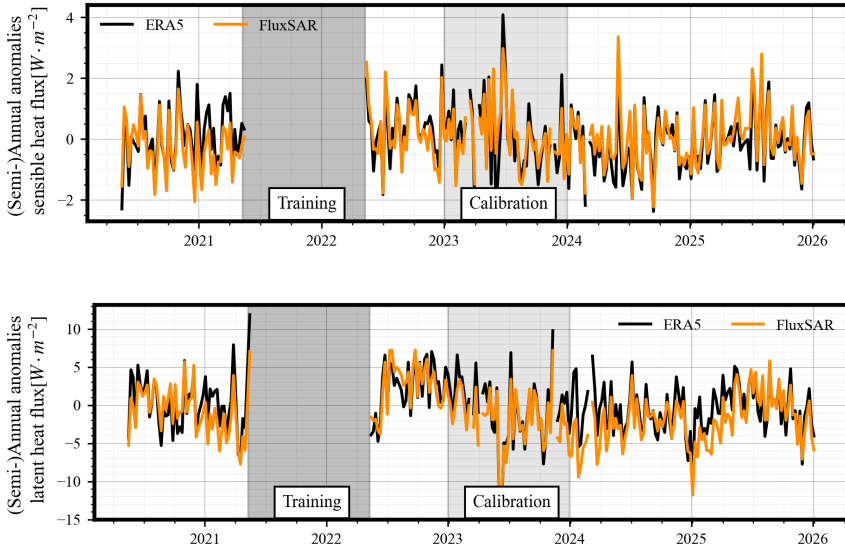


Figure B.2: Heat flux anomalies for Figure 3.1, after removing fixed annual and semi-annual cycles. The weekly-averaged  $R^2$  values are 0.76 and 0.62 for sensible and latent heat flux anomalies, respectively. Some temporal biases appear, particularly during early 2025 for the latent anomalies, suggesting that a more flexible cycle removal may yield greater  $R^2$  values.

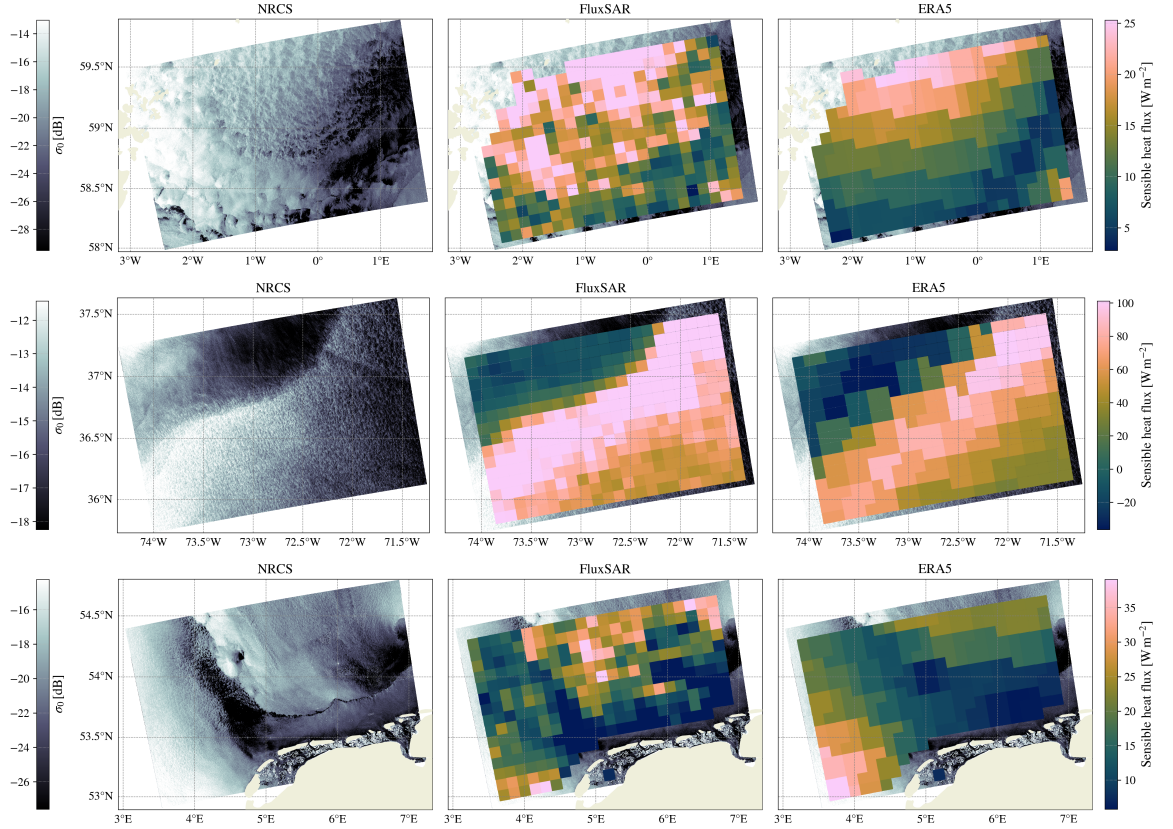


Figure B.3: A selection of dynamic atmospheric conditions with corresponding FluxSAR and ERA5 sensible heat fluxes, without any uncertainty filtering. Top) minor temperature gradients induced by the Gulf Stream's extended tongue, near the Orkney islands, 2025-02-13. Middle) cold continental air from the north west encounters the meandering Gulf Stream, 2024-01-12. Bottom) crashing fronts among the wind farms north of the Netherlands, 2025-02-15.

B

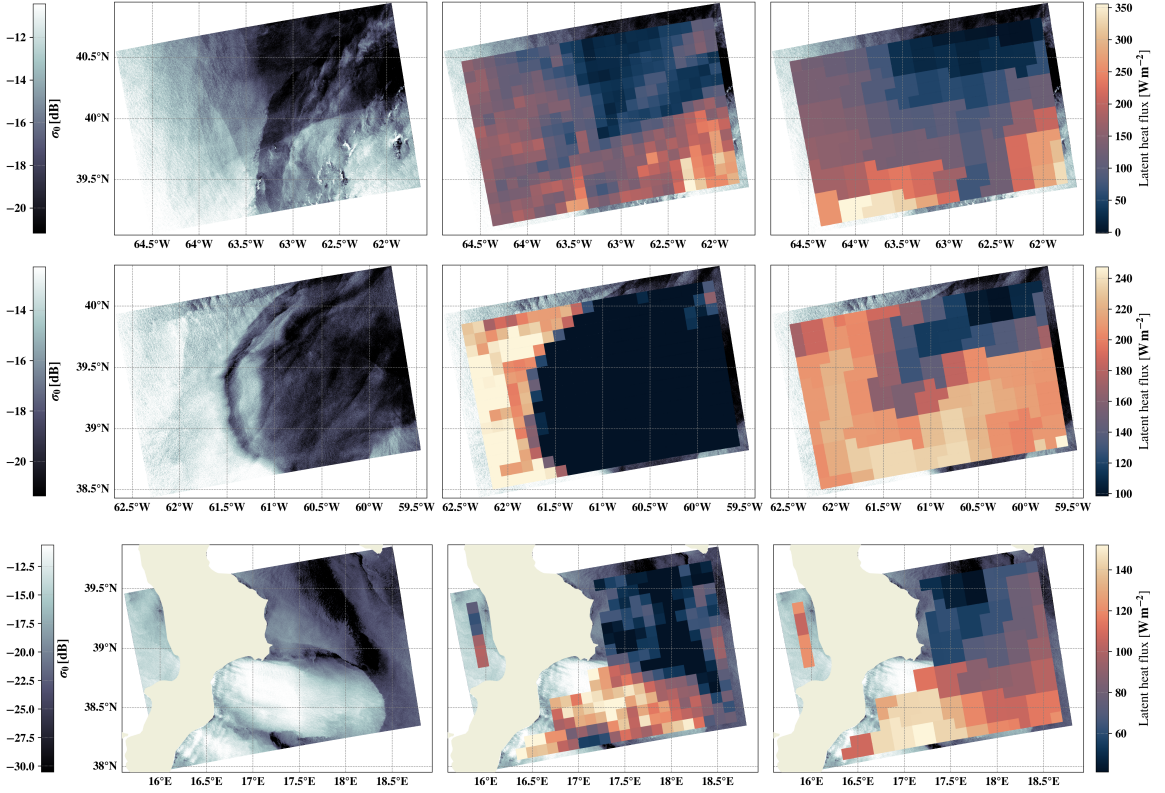


Figure B.4: Continued selection for latent heat fluxes. Top) atmospheric front propagates from the warm south towards the cold north-east ahead of unnamed tropical storm al012023, 2023-01-16. Middle) A cold intrusion from the right enters the Gulf Stream, 2024-05-05. Bottom) orographic winds hailing from the Calabrian coast, 2022-01-30.

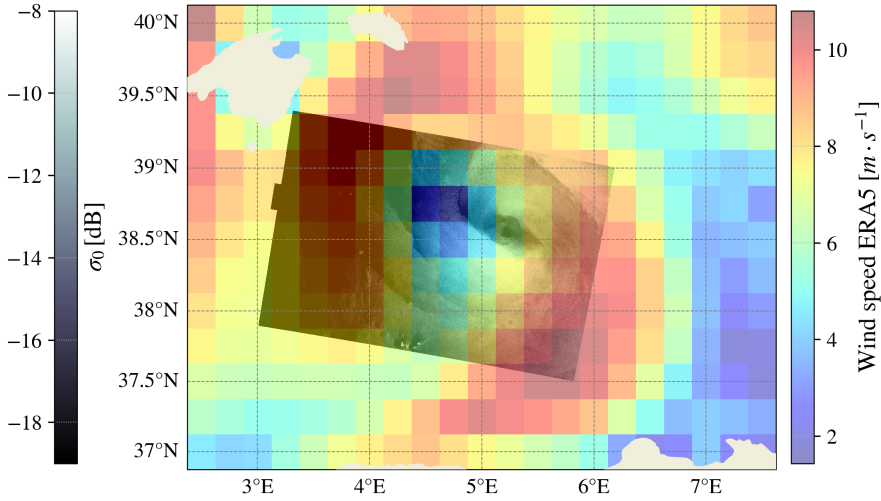


Figure B.5: SAR image of medicane Blas, acquired on 2021-11-13T05:45, superimposed with the ERA5 wind field, representative for 2021-11-13T06:00. The enlarged low-wind area of ERA5, as compared to the confined dark patch surrounding the storm's eye in the SAR image, indicates that ERA5 overestimates the size and misrepresents the structure of this medicane.

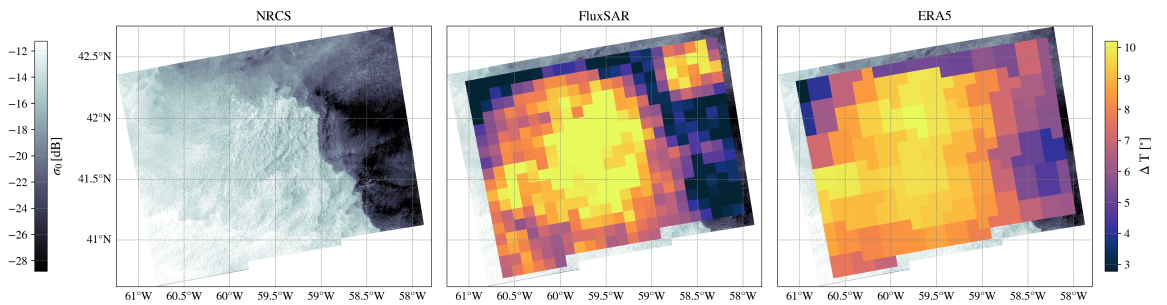


Figure B.6: Illustration of  $T_{SST} - T_{10}$  retrieval, near strong thermal gradients in the Gulf Stream, 2024-01-01. The ERA5  $T_{10}$  is obtained by inserting ERA5 state variables (which includes  $T_2$ ) into the COARE algorithm.

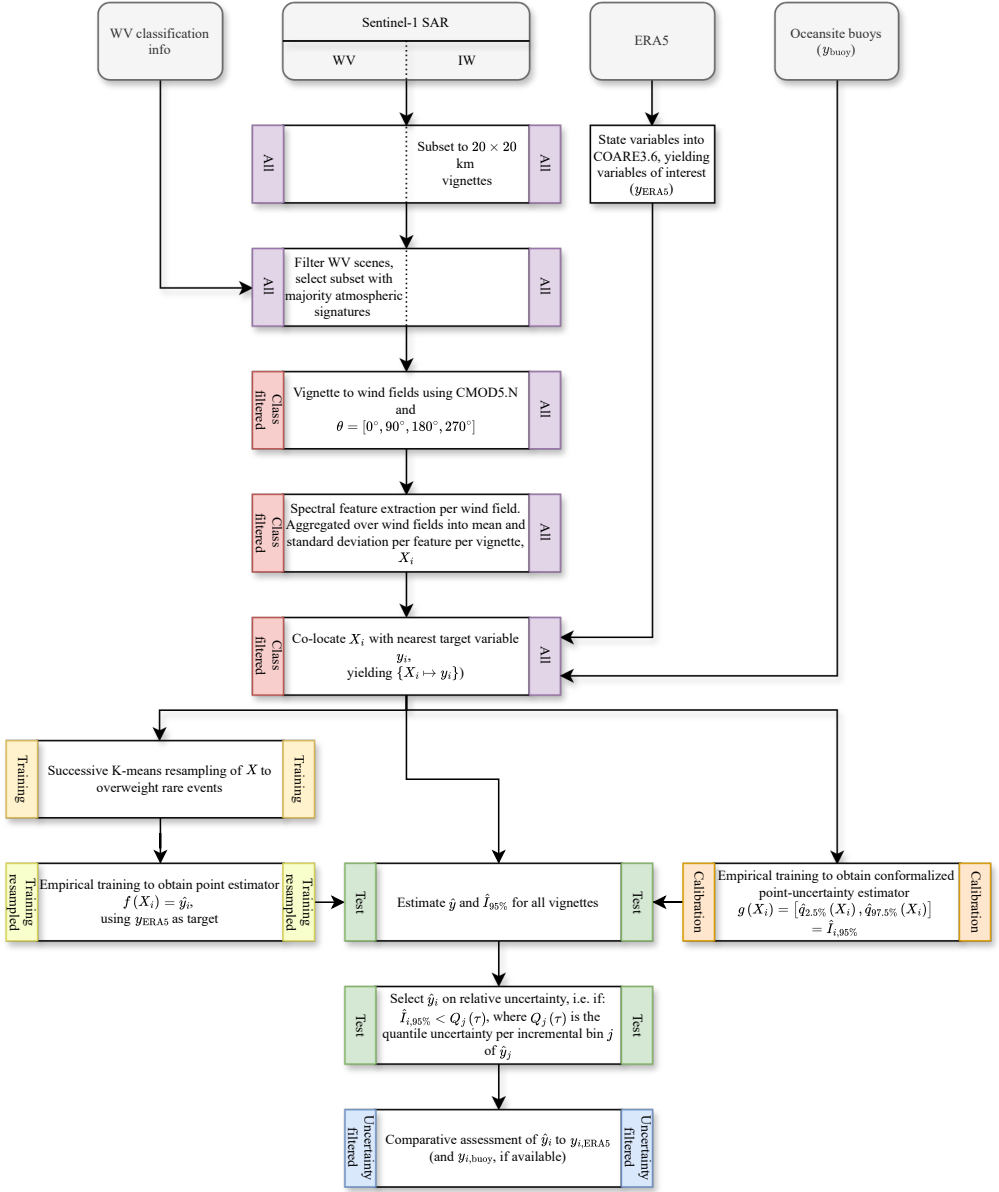


Figure B.7: High-level overview of the FluxSAR processing chain for both WV and IW modes. Vertical colored bars indicate what portion of the data is used at what stage for WV (left) and IW (right). At first, all radar data is considered. Then, using pre-existing class labels, a subset of scenes is selected for the WV mode (class labels are not available for IW mode). In turn, this subset (or all data for IW) is divided into training, test, and calibration fractions. Then, using the uncertainty estimator developed on the calibration fraction, the test data can optionally be filtered on relative certainty prior to a final assessment with target labels.



# C

## APPENDIX FOR CHAPTER 4

### C.1. PULSE-PAIR UNCERTAINTY

We make three simplifying assumptions during the estimation of pulse-pair uncertainty: the signal-to-clutter ratio (SCR) is 1 since overlapping reflections from the first and second pulse yield, on average, equal amounts of clutter and signal (we ignore variations in SCR due to variations in NRCS); we assume a Gaussian beam footprint in the coherence terms despite assuming a tapered beam elsewhere; and we assume clutter dominates over other noise terms such that the coherence loss due to the signal to noise and clutter ratio (SNCR) can be approximated following (Rodríguez & Martin, 1992; Rodríguez et al., 2018)

$$\gamma_{\text{SNCR}} = \frac{S}{S + N + C} \approx \frac{\text{SCR}}{1 + \text{SCR}}. \quad (\text{C.1})$$

The platform motion during the pulse-pair interval,  $\tau_p$ , leads to a relative motion of the scatterers contributing to the radar echo within a resolution cell. The resulting decorrelation is dependent on the ratio of  $\tau_p$  over  $T_D$ , where the latter indicates the time it takes for the satellite to move half the length of its antenna. Following Rodríguez et al., 2018, this coherence can be approximated for a Gaussian beam footprint at broadside (mid beam) by

$$\gamma_D \approx \exp \left[ - \left( \frac{\tau_p}{T_D} \right)^2 \right] \quad (\text{C.2})$$

$$T_D = \left( \sqrt{2} k V_p \sigma_{\phi a} \right)^{-1}, \quad (\text{C.3})$$

where  $k$  is the wavenumber ( $= 2\pi\lambda^{-1}$ ) and  $\sigma_{\phi a}$  the 3 dB beamwidth in the azimuth direction. For SCA,  $T_D$  will be in the order of  $\mathcal{O}(10^{-1})$  ms, but greater than the 0.115 ms sub-pulse separation time  $\tau_p$ .

The ocean surface also decorrelates between sub pulses. This coherence loss depends on the sea state and its wave-motion correlation time,  $T_W$ . Similar to (C.2), it is given by

$$\gamma_{TW} = \exp \left[ - \left( \frac{\tau_p}{T_W} \right)^2 \right], \quad (\text{C.4})$$

where  $T_W$  is approximated as (Tucker, 1985; Wollstadt et al., 2017)

$$T_W \approx 3.29 \lambda U^{-1}. \quad (\text{C.5})$$

For reasonable wind speeds  $U$  observed with a C-band system,  $T_W$  will be in the order of  $\mathcal{O}(10^1)$  ms. This is much greater than either  $\tau_p$  or  $T_D$ , making ocean surface decorrelation a minor source of coherence loss.

We approximate the total coherence as the product of the three components

$$\gamma \approx \gamma_{\text{SNR}} \gamma_D \gamma_{TW}, \quad (\text{C.6})$$

yielding a  $\gamma$  of approximately 0.39. Since,  $1 - \gamma \neq 0$  we are prevented from using the Cramer-Rao bound for pulse-pair velocity uncertainty of Seymour and Cumming, 1994, which is only valid in the high coherence limit (Rodríguez et al., 2018). Instead, we generate pulse-pair velocity uncertainty from the 1-look phase-difference probability density function (PDF) following Lee et al., 1994

$$p(\psi) = \frac{(1 - \gamma^2) \left[ (1 - \beta^2)^{\frac{1}{2}} + \beta (\pi - \arccos \beta) \right]}{2\pi (1 - \beta^2)^{\frac{3}{2}}}, \quad (\text{C.7})$$

where  $p(\psi)$  is the PDF of phase differences valid between  $-\pi < \psi \leq \pi$ , and  $\beta = \gamma \cos(\psi)$ . The phase-difference PDF is converted to velocity following

$$p(\sigma_{pp}) = p(\psi) \frac{1}{2k\tau_p} \frac{1}{\sin(\theta_i)}, \quad (\text{C.8})$$

where the additional sine term converts vectors from line-of-sight to a ground-projected one. Similar to the addition of speckle, band-limited pulse-pair uncertainty is generated at the independent slant-range-spaced sample resolution, interpolated to grid spacing through zero-padding in the Fourier domain and then interpolated back to the ground-range-projected grid spacing.

## C.2. CASE STUDIES

Table C.1: Metadata for case studies excluding the Agulhas.

| Region    | Platform | Date/Time        | Product unique ID            |
|-----------|----------|------------------|------------------------------|
| Azores    | S1B      | 2020-11-27T19:39 | A07B, B01D, CA05, CE1B, E23C |
| Caribbean | S1A      | 2023-11-04T23:08 | 5B80, 75FE, FCE5             |
| Hawaii    | S1A      | 2020-11-06T04:23 | 40AB, 9158, B0E7, B3F4       |
| Iceland   | S1A      | 2023-11-07T18:49 | 026F, 03F2, B5DE             |
| Scotland  | S1A      | 2023-11-09T18:32 | 6D0B, B440, BAFB, CE72       |

# D

## APPENDIX FOR CHAPTER 5

### D.1. ATI FUNDAMENTALS

Here we recall some of the fundamental concepts and relations. In an ATI system, two radars fly separated by a short separation in the along-track direction, providing a temporal aperture  $\tau_{\text{ATI}}$ , for a pair of observations made under nearly identical geometry. The ATI phase and the Doppler velocity are related by

$$v = \frac{\lambda_0 \cdot \phi_{\text{ATI}}}{4\pi \cdot \tau_{\text{ATI}}}, \quad (\text{D.1})$$

where  $\lambda_0$  is the wavelength of the radar signal (3.1 cm in this case) and  $\phi_{\text{ATI}}$  the interferometric phase.

In general, specially in a formation flying system like TanDEM-X, there will also be a cross-track baseline component that introduces a sensitivity of the measured interferometric phase to the surface height. Often, this sensitivity is expressed in terms of the so-called height of ambiguity ( $h_{\text{amb}}$ ), i.e. the height variation resulting in a  $2\pi$  phase variation. The cross-track phase component associated to a height variation  $\Delta h$  can be written as

$$\phi_{\text{XTI}} = \frac{2\pi \cdot \Delta h}{h_{\text{amb}}}. \quad (\text{D.2})$$

This phase can be translated (wrongly) into an equivalent Doppler velocity,

$$\Delta v_{\text{D}} = \frac{\lambda_0}{2 \cdot h_{\text{amb}} \cdot \tau_{\text{ATI}}} \cdot \Delta h. \quad (\text{D.3})$$

The perpendicular baseline was very small, resulting in heights of ambiguity in the order of 400 m or higher. Combined with the temporal lag, this results in a height to velocity conversion factor, as given by (D.3) of less than  $1.5 \text{ cm s}^{-1} \text{ m}^{-1}$  for the second acquisition and of  $1 \text{ cm s}^{-1} \text{ m}^{-1}$  or less for the remainder three.

### D.2. PROCESSING DETAILS

The L1 data was generated by operational processing chain of the German Aerospace Center (DLR), and interferometrically processed using TAXI (experimental TANDEM-X Interferometric processor) (Prats et al., 2010). For each acquisition, the data was provided in 5 frames, which had to be stitched together.

Following common practices in the along-track interferometry community, the interferometric phase was calibrated using the land areas included in the acquisitions to determine a phase offset, assumed constant for the whole acquisition.

The intensity data, and complex interferograms were further multi-looked down to a grid spacing of 750 by 750 m<sup>2</sup>, providing in the order of 60000 independent looks. In order to estimate the normalized radar cross-sections, the estimated noise-floor was subtracted to the averaged intensities. The acquisitions are about 250 km long with a swath width of approximately 15 km.

It is worth noting that the noise floor changed near the end of the fourth frame towards the end of the acquisition. We speculate that this was caused by a change in the azimuth-switched Block Adaptive Quantization scheme (Martone et al., 2014), as the last part of the acquisitions corresponded areas with low NRCS.

The temporal lag between the interferometric acquisitions, the height of ambiguity, and the incident angle for the three data takes are reported in Table D.1. The temporal lags correspond to physical along-track separations between the two satellites ranging from 40 m to 70 m, which is around the optimum value in terms of interferometric performance (Wollstadt et al., 2017).

Table D.1: Acquisition date, along-track temporal lag, height of ambiguity, incident angle, and wind conditions reported by ECMWF's Integrated Forecast System(IFS) for the acquisitions considered.

| Date       | Temporal lag | $h_{\text{amb}}$ | Incident angle | ECMWF IFS wind range    |
|------------|--------------|------------------|----------------|-------------------------|
| 2014/08/30 | 4.6 ms       | > 452 m          | 41°            | 7 - 10 ms <sup>-1</sup> |
| 2014/09/10 | 3.9 ms       | > 433 m          | 41°            | 0 - 4 ms <sup>-1</sup>  |

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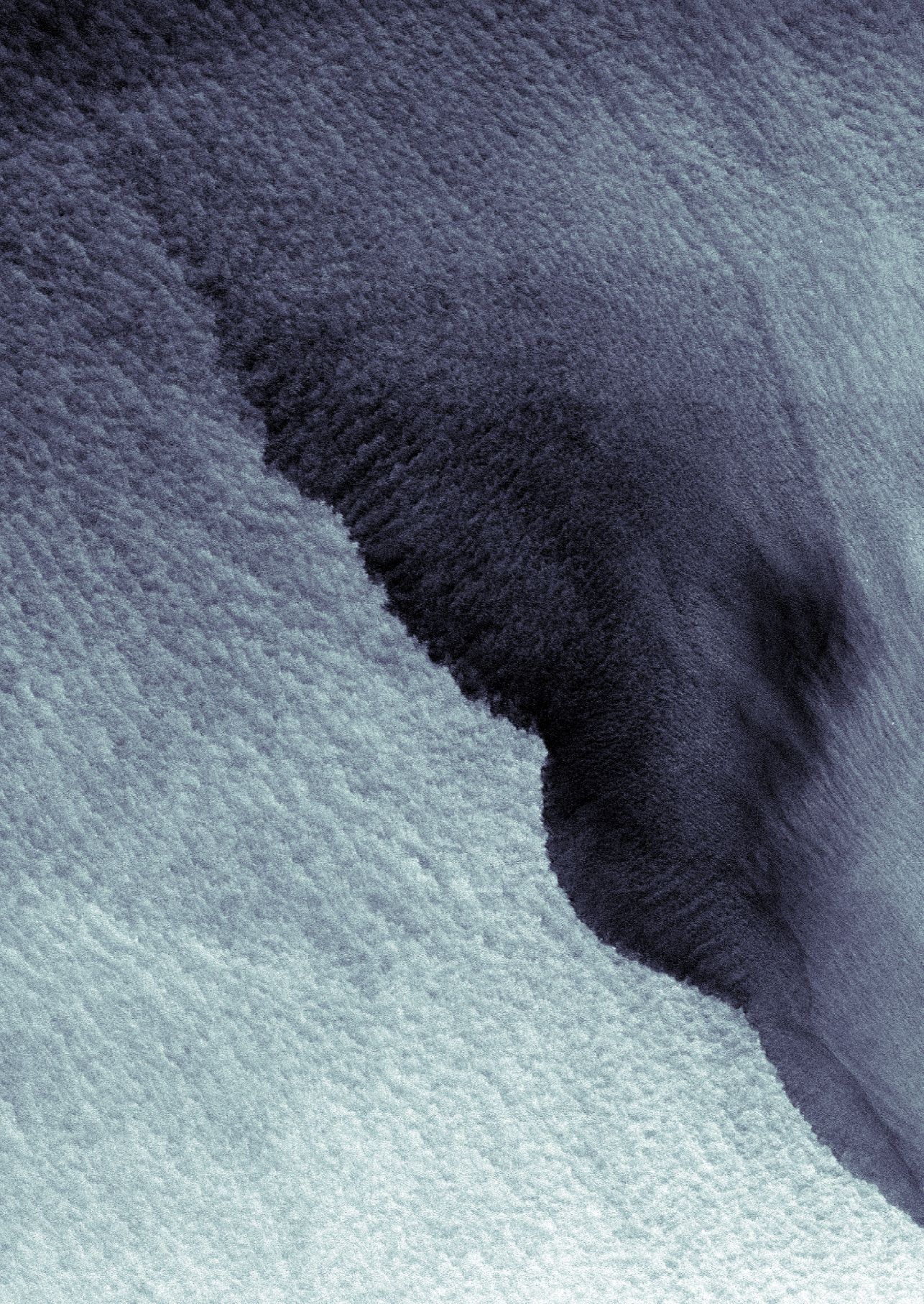
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# LIST OF PUBLICATIONS

1. **O'Driscoll, O.**, Mouche, A., Chapron, B., Kleinherenbrink, M., & López-Dekker, P. (2023). *Obukhov length estimation from spaceborne radars*. [Geophysical Research Letters](#), 50(15), e2023GL104228.
2. **O'Driscoll, O.**, López-Dekker, P., & Payez, A. (2025). *Phantom motion of the ocean: leakage of geometrical Doppler into geophysical motions observed with Doppler scatterometers*. [IEEE Transactions on Geoscience and Remote Sensing](#).
3. **O'Driscoll, O.**, López-Dekker, P., & Chapron, B. (2025). *Disentangling Currents and Waves: Exploitation of Polarization Diversity for Wave-Doppler Estimation*. [IEEE Transactions on Geoscience and Remote Sensing](#).
4. Klocke, D., Wing, A. A., Segura, H., Dengler, M., Bell, M. M., Ruppert Jr, J. H., ... **O'Driscoll, O.**, ..., Windmiller, J., (2026). *40 days and nights in the Rains: The inner life of the Atlantic ITCZ during BOWTIE*. [Bulletin of the American Meteorological Society, BAMS-D](#).
5. **O'Driscoll, O.**, López-Dekker, P., Chapron, B., Mouche, A., & Chapman, C. *Organized Ocean Surface Roughness Textures Uniquely Trace Air-Sea Heat Fluxes*. Rejected by Communications Earth & Environment. *Submitted in 2026*.

