Research Summary
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Analysis of Offshore Wind Farm Wakes from Satellite SAR

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1. Introduction

Using satellite data to study offshore wind energy is a powerful and efficient approach since it provides spatial information that isn't available from standard meteorological methods. Early in this project, I began by evaluating all publicly accessible satellite datasets and categorizing them based on type of data they collect and potential applications, which is summarized in Figure 1 below (link to original presentation).

Figure 1:

EM			**Other**	
SAR	Optical/Multispectral	Hyperspectral	Gravitational	Oceanographic/Climate
- **Sentinel-1** (European Space Agency) - **RADARSAT** (Canadian Space Agency) - **TerraSAR-X** (German Aerospace Center)	- **Landsat** (NASA and USGS) - **Sentinel-2** (European Space Agency) - **MODIS** (NASA) - **Pleiades** (French Space Agency)	- **Hyperion** (NASA) - **EnMAP** (German Aerospace Center)	- Gravity Recovery and Climate Experiment (**GRACE**) (NASA and German Research Centre for Geosciences)	- **Sea Surface Temperature** (SST) data from satellites like **MODIS**, **AVHRR, GOES** - **Ocean Color data** from satellites like **MODIS** and **SeaWiFS** - **Wind Speed/Direction** data from satellites like **ASCAT and QuikSCAT**
- Pulse radar (all day?) - Penetrates clouds (good for any weather) - Sees wake patterns - Sees ice	- Reflected sunlight (only daytime) - Land/vegetation/water quality	- Seems good to assess hydrodynamic structures? - underwater vegetation, seabed compositions, and marine ecosystems	- Mass distribution - Water storage, ice melt, and sea level rise	- In-situ - Sea surface temperature, ocean color (chlorophyll-a concentration), and wind speed/direction

We eventually decided to use Satellite Aperture Radar (SAR) data, which has been used since the early 2000s to calculate ocean wind fields. In the context of offshore wind farms, SAR data has been used to characterize the spatial extent and behavior of wakes, which are critical for optimizing wind farm efficiency and mitigating environmental impacts. More specifically, SAR is preferred for mapping ocean wind fields because its radio waves (wavelength around 5 cm) can penetrate cloud cover and operate independently of sunlight, unlike sensors relying on visible light. Although this means we can't directly "see" the atmospheric turbulence created by wakes, instead, this can be inferred by looking far enough behind the turbine to the region where the wake begins to interact with the surface of the water. Offshore areas have gravity-capillary waves on the scale of centimeters, which react instantaneously (<1 second) to wind changes such as those from wakes, creating characteristic wave patterns which radar is well-suited to detect.

We opted to use ESA's Sentinel-1 SAR data since it's particularly advantageous for studying offshore wind farms due to high spatial resolution, frequent revisit times, and dual-polarization capabilities. This would enable more precise and consistent monitoring of wind patterns and wake dynamics.

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2. Approach 1: Sentinel-1 OCN Data

2.1. Methods

Rather than start with the raw SAR backscatter data, we began by working with the "derived" datasets provided by ESA which have been pre-processed from SAR into ready-to-use, intuitive quantities such as wind speed and direction.

These conversions come at the cost of some spatial resolution — the original radar data has resolution down to 10 meters by 10 meters per pixel, but the derived wind field data are reduced to 1 km by 1 km per pixel. Theoretically, this should have been enough to observe wakes since prior works have found that wakes are detectable by SAR starting at a downwind distance of about five times the rotor diameter (about 2-3 km in the farms we study), and continue for up to 20 km [2]. As such, our goal at this point was to determine if we can see/quantify wakes at this resolution, or if we'd have to upgrade to the raw SAR data. At the same time, I'd be able to develop familiarity and personal programming tools to work with geospatial data.

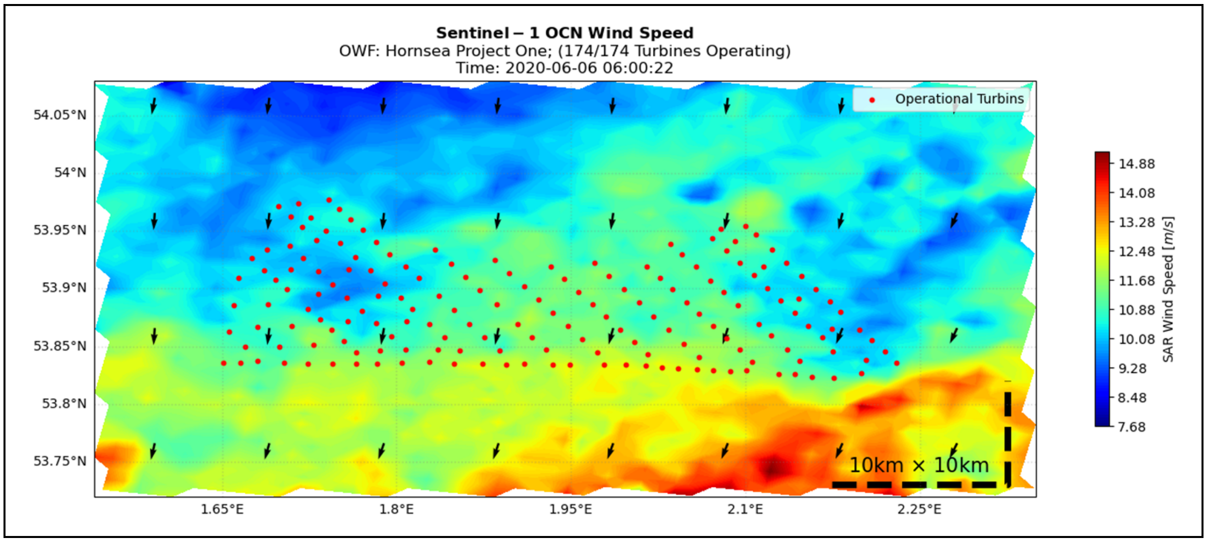
For the analysis, we arbitrarily chose the largest wind farm currently operating, "Hornsea Project One" in the North Sea off the coast of England. However, our code is structured/abstracted/modularized to work with any other wind farm as long as it's given basic information like bounding coordinates.

We wrote code to download the data (the Alaska Satellite Facility provides a nice Python package for this called `asf_search`), get turbine coordinates based on location and time (a 2022 paper provides turbine coordinates for every quarter since 2016, which are identified from Sentinel-1 SAR data using machine learning techniques [1]), and then generate geospatial visualizations over time.

2.2. Results

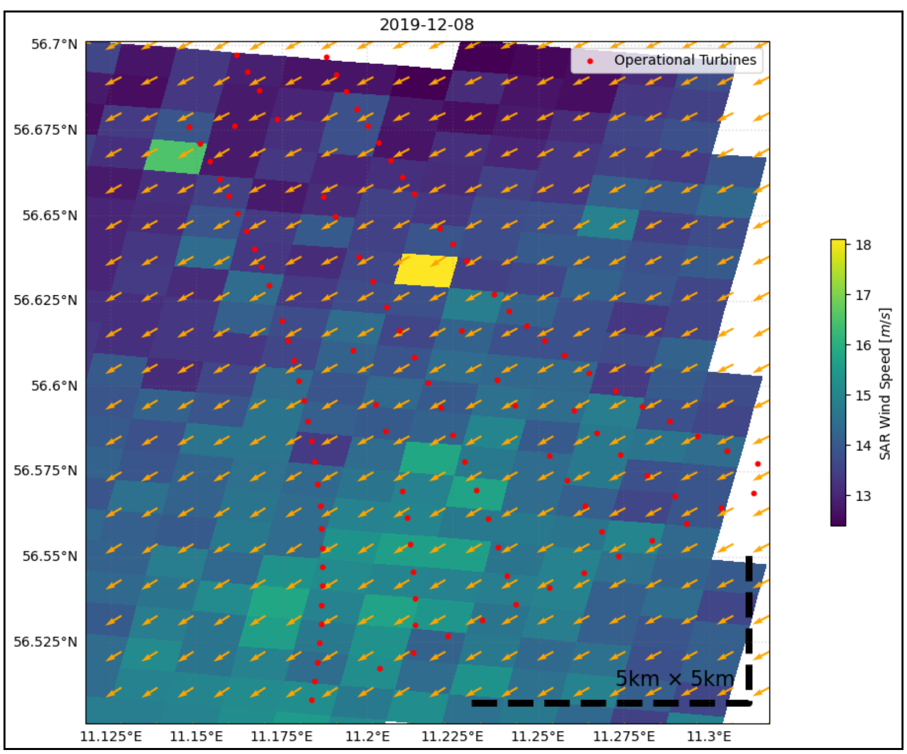
We produced a set of 604 plots from 2020 to present, each spaced roughly 7 days apart, representing the wind field over Hornsea Project One. One example of these images is shown in Figure 2 below. All plots can be downloaded here.

Figure 2:



By visual inspection of various plots, we immediately noticed that we failed to consistently observe wakes. We decided this may be an issue with the spatial resolution of this dataset, which seems more clear when we remove all interpolation and zoom in close enough to observe the relatively large "width" of the pixels, as shown in Figure 3 below (taken over a different wind farm, Anholt instead of Hornsea Project One, but the point still applies).

Figure 3:



Zain Kamal

Regardless, we decide to shelve this data product and try working directly with SAR data.

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3. Approach 2: Sentinel-1 SAR Data

3.1. Accessing Data (Google Earth Engine API)

The Sentinel-1 satellite passes over a given location about once per week, and the resulting SAR data file is about 8-12 GB. Direct downloading is unfeasible given the target scale of our analysis, so we use Google Earth Engine's API to remotely and efficiently access/process/visualize data which is hosted on Google's cloud servers.

3.2. SAR Data Parameters

At this point, it's important to carefully choose SAR data parameters to ensure meaningful analysis and substantiate our conclusions. Our parameter choices fall into three main categories:

(1) We selected Ground Range Detected (GRD) products, which, unlike Single Look Complex (SLC) products, are multi-looked and contain amplitude information. This choice was made as GRD products are more suitable for our analysis of wind fields due to their reduced speckle noise and enhanced image clarity, compared to the phase-preserving SLC format, which is more apt for interferometric applications [3].

(2) Interferometric Wide (IW) swath mode was chosen over other modes like Stripmap (SM) or Extra Wide (EW). IW mode offers a balance between spatial resolution (approximately 10 x 10 meters per pixel) and swath width (250 km), making it ideal for extensive offshore areas. SM, while offering higher resolution, has a narrower swath (50 km), limiting its coverage, and EW, although having the widest swath (400 km), sacrifices resolution, which is vital for detailed wake analysis [3].

(3) Lastly, the VV polarization was selected over VH, HH, or HV. The VV (vertical transmit, vertical receive) polarization is more sensitive to the surface roughness and geometric properties of the sea surface compared to cross-polarizations (like VH or HV), which is crucial for detecting changes in the ocean surface roughness caused by wind turbine wakes (see discussion of gravity-capillary waves in introduction). HH polarization was not considered as Sentinel-1 primarily operates in VV/VH polarization modes [3].

3.3. Data Accessing and Cleaning

Our analysis will be explained with respsects to a single SAR image chosen based on the previously described parameters (GRD-IW-VV), taken over over Hornsea Project One on January 4 2020 6:06.09 UTC, which is shown in Figure 4 below.

Figure 4:

The bright dots in the center of the image are the 174 turbines which were operational at the time of the image. The brightness of each pixel represents radar backscatter intensity in units of decibels. We can interpret the dark streaks as indication of two types of wakes, (1) small-scale individual wakes behind each turbine, which often intersect with another turbine downwind, and (2) large-scale wakes that emerge from the wind farm. It's important to note that although wakes are very clear in this image, not all SAR images are as clean and clear-cut. Further work is needed to better quantify how often these conditions are visible.

We import this data to Python in an optimized data structure — this step is largely glossed over, but no Python code is currently publicly available to access the Google Earth Engine API in this way, so at some point in the future, this can be wrapped in a Python package and published to the community or the Journal of Open Source Software (JOSS).

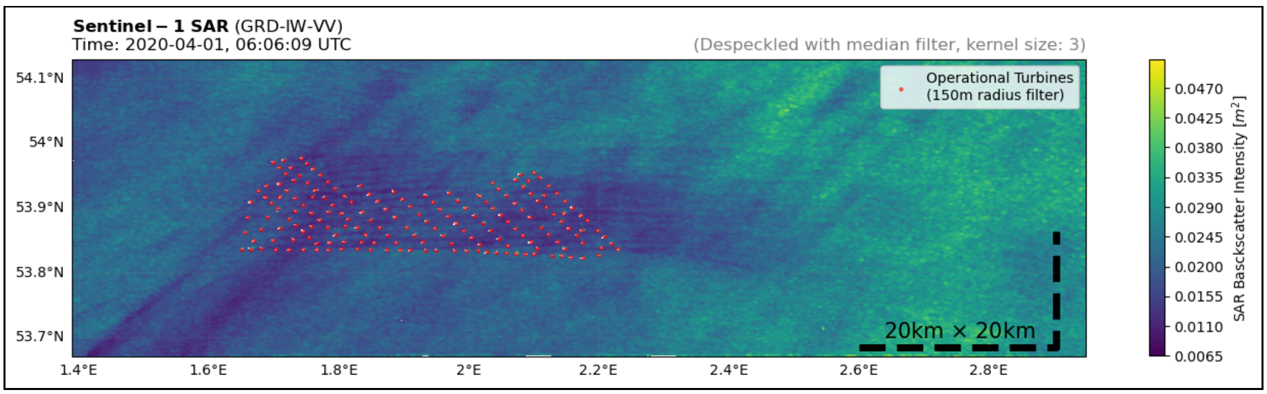
When analyzing SAR data in any context, a common challenge is dealing with inherent "speckle noise", which is a granular disturbance that can obscure critical details in SAR imagery. There are a range of sophistocated de-speckling techniques published in literature every year, including machine-learning approaches in recent years. We opted for a traditional and analytic/deterministic approach called a Lee filter, which tends to strike a good balance between feature preservation and despeckling [4]. Previous works suggest using a kernel size of 3, which is supported by our own experimental comparisons between various kernel sizes (see images here).

To put this in context of our full data cleaning process, our steps are:

1. Initially, we exclude all data within a 150 meter radius of each turbine. This step is critical as the proximity to the turbines often results in extremely high SAR values, which could potentially bias the effectiveness of the Lee filter.
2. We remove any pixels with a value greater than two standard deviations from the mean of the entire image. This step is designed to eliminate anomalously bright spots in the data, which are often due to boats rather than any type of natural turbine/wake-related process.
3. We apply the Lee filter with a kernel size of 3. This choice, as previously discussed, is based on both literature recommendations and our empirical observations, ensuring optimal noise reduction while preserving essential features in the data.
4. Finally, we repeat the exclusion of data within a 150 meter radius of the turbines. This step is necessary as the Lee filter can reintroduce data points in these areas, which could skew the analysis.

At this point, our SAR data can be visualized in Figure 5 below.

Figure 5:



3.4. Cross-Section Wake Analysis

At this point, we're ready to empirically quantify wake effects.

First, we sample many cross-sections parallel to the wind direction (in this case, horizontally left to right). As an illustrative example, a diagram in Figure 6 shows 10 evenly spaced horizontal cross-sections (represented as red dashed lines), each comprising 150 data points. For our actual computations, we significantly expanded this to 1,000 horizontal cross-sections, each containing 2,000 data points (resulting in a horizontal spacing of 41 meters). By averaging each of these 1,000 cross-sections, we obtained a representative profile of horizontal backscatter across the wind farm and its associated wake effects, which is shown in Figure 7 below.

Figure 6:

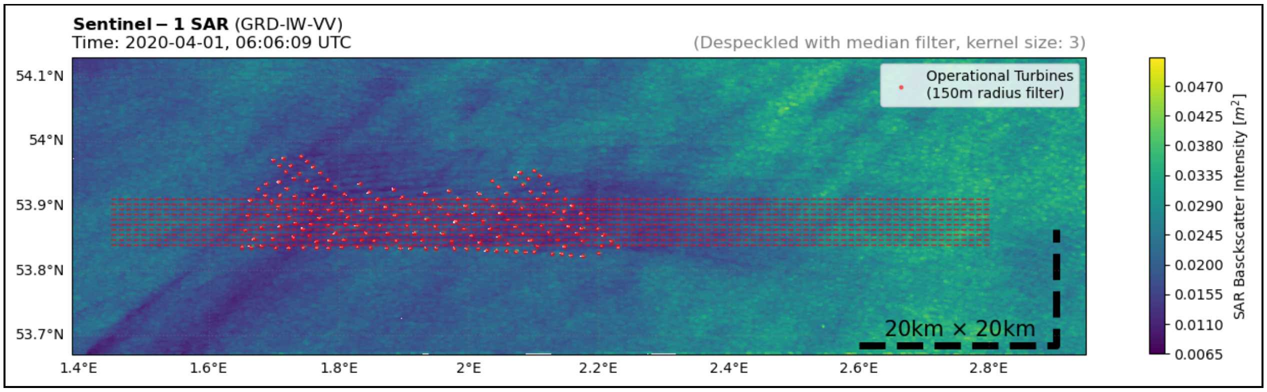
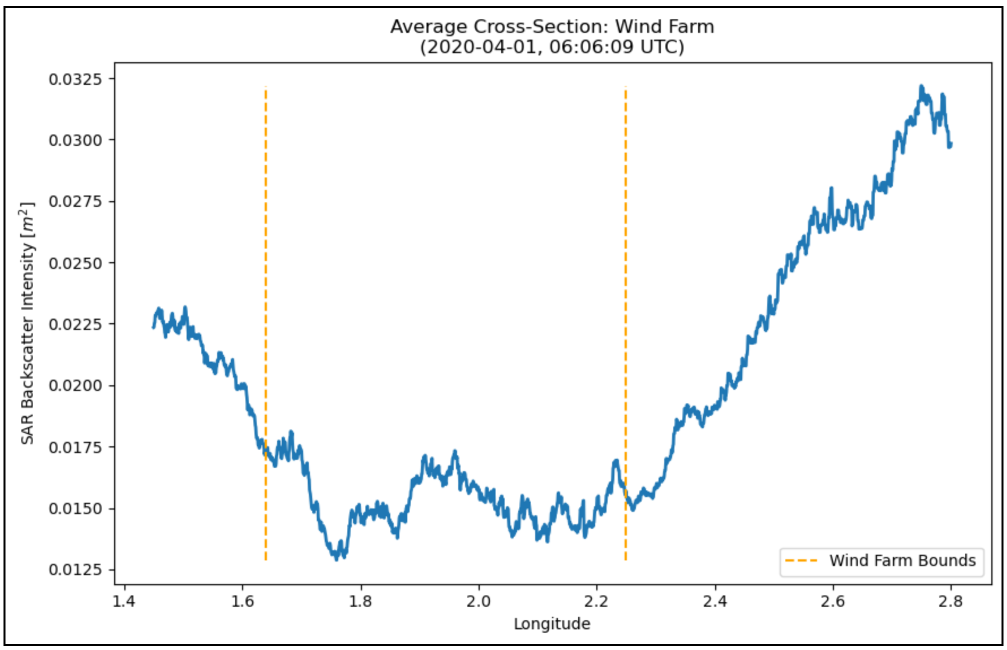


Figure 7:



However, we must use caution when interpreting these results due to potential large-scale biases in the SAR data, possibly caused by factors like wave patterns or wind structures. To address this, we identified an open sea area directly above the wind farm that seemed free of such biases, confirmed by examining a wider, zoomed-out image of the region shown in Figure 8. We applied the same cross-sectional sampling and averaging method to this area (an analagous illustrative example is shown in Figure 9, and the resulting averaged cross-section is shown in Figure 10), providing a nearby baseline open sea profile for comparison.

Figure 8:

Figure 9:

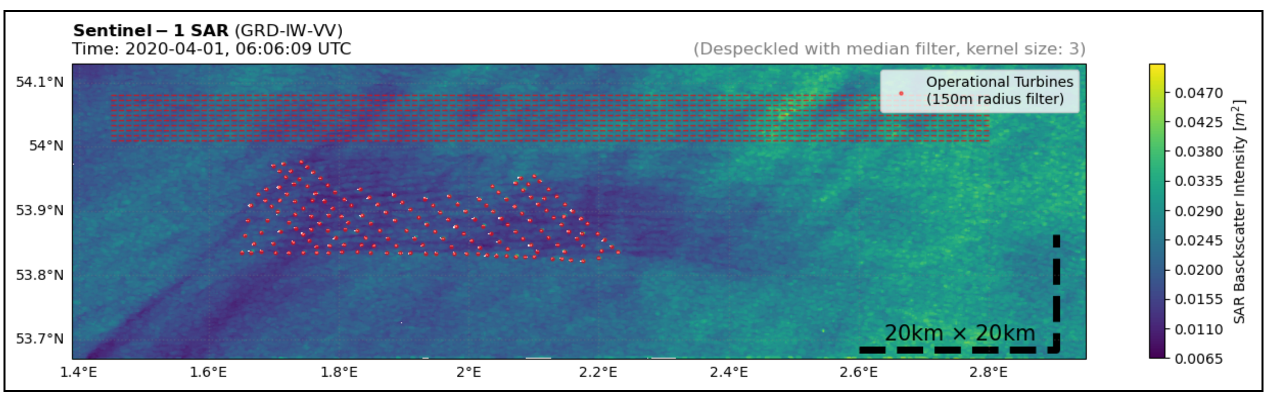
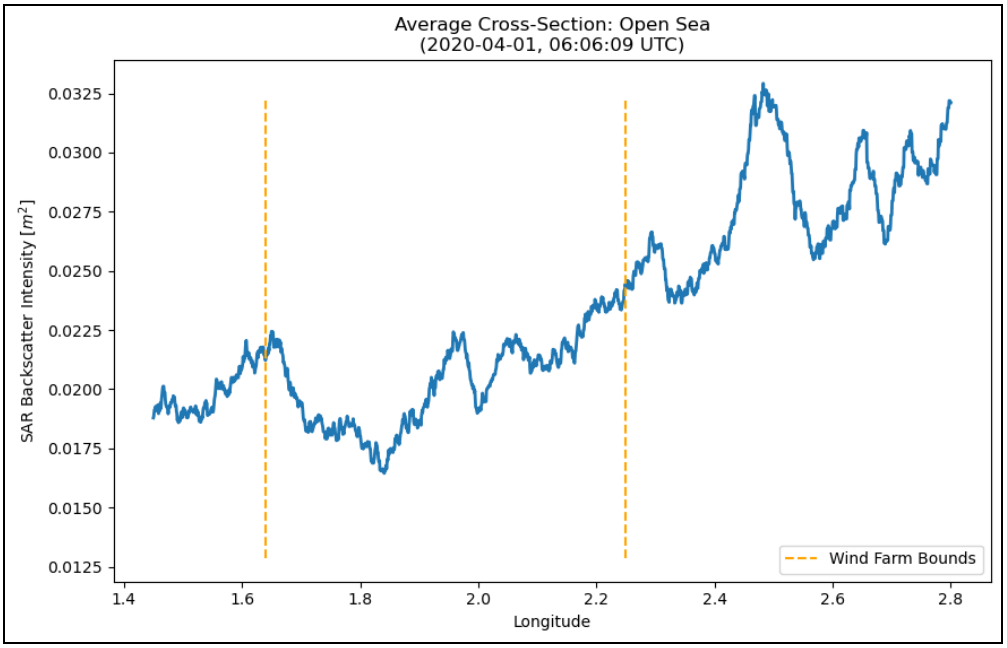
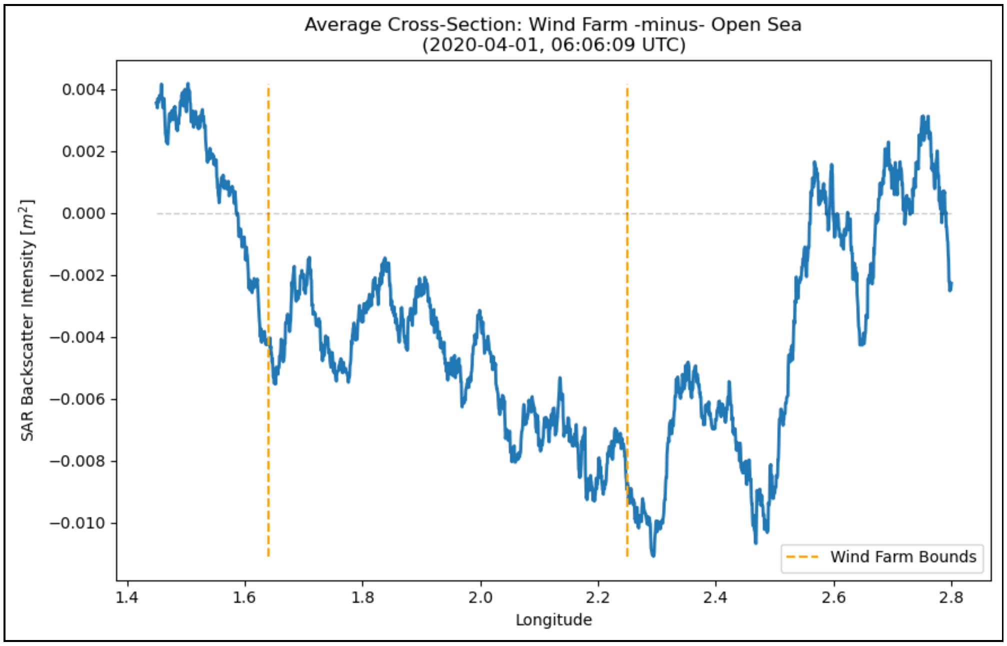


Figure 10:



Finally, we find the difference between the first average cross-section across the wind farm (Figure 7) from the average cross-section across the open sea (Figure 10), and plot the results in Figure 11 below. The intended goal of this is to isolate the SAR backscatter deficits attributable solely to the wind farm wakes. The analysis revealed a pattern consistent with turbine wakes: negligible backscatter differences before and after the wind farm (i.e. typical open sea conditions which hover around the zero line), spiky variations within the farm aligning with turbine rows, and most notably, a prolonged large-scale wake effect extending 18-22 km beyond the wind farm before normalizing to average open-sea conditions (i.e. zero). These findings present a clear, empirical demonstration of wake effects characteristic of offshore wind farms.

Figure 11:



3.5. Limitation

For analysis of the chosen image, we took care to choose a SAR scene where the wakes are mostly parallel with either longitude or latitude lines, and the wind farm is mostly rectangular. However, these conditions don't always apply. Figure 12 shows Anholt wind farm with wakes (and cross-sections) going southeast. The resulting averaged cross-section is shown in Figure 13. In this case, I'm not exactly sure how to classify where the bounds of the wind farm begin and end. One potential solution is to only consider subsections of wind farms that approximate rectangles — in this case, only portions of the wind farm above 56.62°N latitude.

Figure 12:

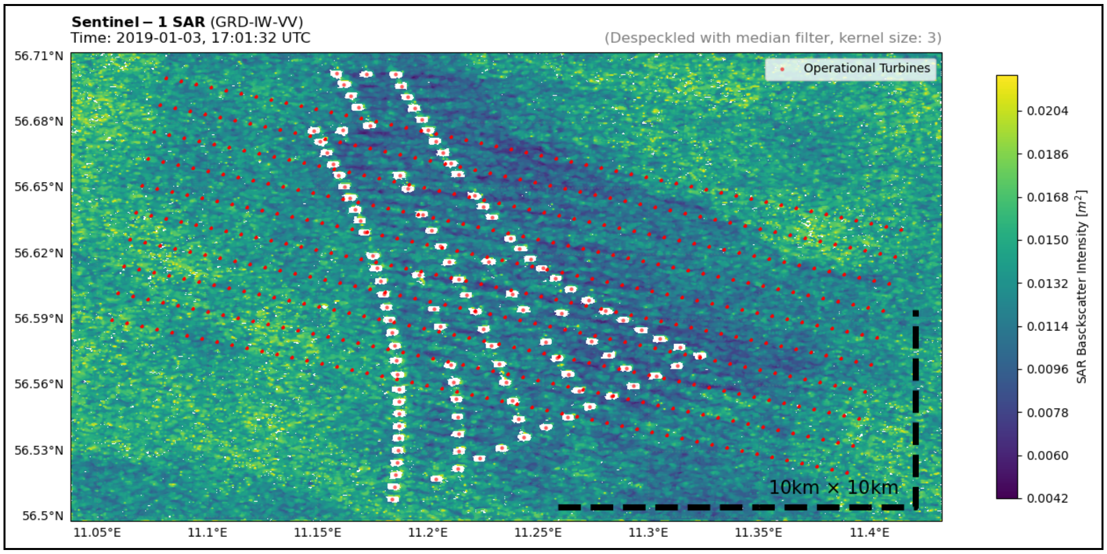
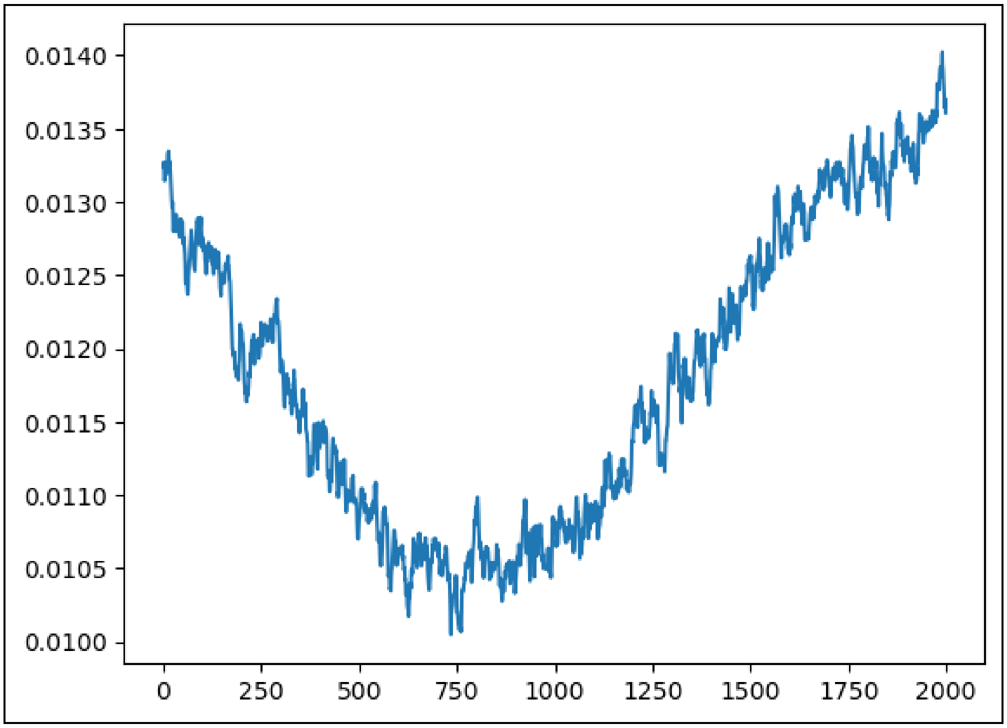


Figure 13:



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4. Conclusions and Next Steps (Personal Thoughts and Reflections)

So far, we've been primarily focused on replicating existing analyses rather than investigating new hypotheses. However, we're definitely getting closer to doing novel work. Here are the next few steps in my mind:

1. Converting SAR Backscatter to Wind Speed: This type of calculation is typically done using a Geophysical Model Function (GMF). There are many models available for this, from traditional analytical methods to contemporary machine-learning approaches. With this, I can recreate Figure 11 with more physically intuitive units.
    - It's important to note that a potentially significant advantage of our cross-sectional methodology is its capacity to reduce uncertainty in this stage of the calculations. Typically, GMFs require a priori knowledge of either wind speed or direction, which is typically a source of uncertainty in prior works that try to derive large 2D swaths of ocean wind field maps. But in our method, by aligning cross-sections parallel to the wind/wake direction, we effectively have a fixed value for wind direction which makes wind speed calculation more straightforward.
2. Physical Analysis of Wind Speed: Once we have cross-sectional wind speed plots, our next step would involve computing the velocity deficit and turbulence intensity from the wind speed data.
    - The relevant equations for velocity deficit and turbulence intensity come from [2]:

$$\text{VD} = \frac{U_{\text{freestream}} - U_{\text{wake}}}{U_{\text{freestream}}} \cdot 100\%$$

$$I = \frac{\sigma_U}{U} \cdot 100\%$$

    - Again, our cross-section method helps us since the processing of averaging multiple cross-sectional slices also lets us calculate the standard deviation between slices, which allows us to calculate turbulence intensity.
3. Large-Scale Comparative Analysis: In my reading, previous studies on offshore wind farm wakes often seem to be limited by the small number of SAR images, low resolution, and the focus on only one or two wind farms. I believe we can leverage our generalized data accessing/processing/analysis pipeline (the entire thing is optimized to run in a few seconds), we can extend the previously described analysis to multiple offshore wind farms, enabling comparisons of variables such as average wake length relative to the wind farm's size, the influence of latitude on wake length, and the probability of wake presence among others.

Looking forward, I'd also like to continue evaluating the motivations and potential contribution of our work. Currently, my primary focus has been on data analysis and correlation identification.

- ~~One potential "bigger" idea is to apply these methods to the offshore wind turbines recently installed off the coast of New Jersey in October 2023. We're affiliated with both NJ's main university and the Economic Development Authority (EDA), so there's is an opportunity to access in-situ data like turbine power output which would significantly broaden the scope of our research by using data beyond Sentinel-1 SAR imagery. Let me know your thoughts :)~~

⟹ Nevermind, the NJ turbines were cancelled :(

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5. Citations

[1] T. Hoeser, S. Feuerstein, and C. Kuenzer, *DeepOWT: A Global Offshore Wind Turbine Data Set Derived with Deep Learning from Sentinel-1 Data*, Earth Syst. Sci. Data **14**, 4251 (2022).

[2] M. B. Christiansen and C. B. Hasager, *Wake Effects of Large Offshore Wind Farms Identified from Satellite SAR*, Remote Sensing of Environment **98**, 251 (2005).

[3] (ESA, 2023).

[4] V. K. Rana and T. M. V. Suryanarayana, *Evaluation of SAR Speckle Filter Technique for Inundation Mapping*, Remote Sensing Applications: Society and Environment **16**, 100271 (2019).