Examining the Nexus of Environmental Policy, Climate Physics, and Maritime Shipping with Deep Learning Models and Space-borne Data

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Abstract

Ship-tracks are produced by ship exhaust interacting with marine low clouds. They provide an ideal lab for constraining a critical climate forcing. However, no global survey of ship ship-tracks has been made since its discovery 55 years ago, which limits research progress. Here we present the first global map of ship-tracks produced by applying deep segmentation models to large satellite data. Our model generalizes well and is validated against independent data. Large-scale ship-track data are at the nexus of environmental policy, climate physics, and maritime shipping industry: they can be used to study aerosol-cloud interactions, the largest uncertainty source in climate forcing; to evaluate compliance and impacts of environmental policies; and to study the impact of significant socioeconomic events on maritime shipping. Based on twenty years of global data, we show cloud physics responses in ship-tracks strongly depend on the cloud regime. Inter-annual fluctuation in ship-track frequency clearly reflects international trade/economic trends. Emission policies strongly affect the pattern of shipping routes and ship-track occurrence. The combination of stricter fuel standard and the COVID-19 pandemic pushed global ship-track frequency to the lowest level in the record. More applications of our technique and data are envisioned such as detecting illicit shipping activity and checking policy compliance of individual ships.

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Proceedings of the 38^{th} International Conference on Machine Learning, PMLR 139, 2021.

1. Introduction

Ship tracks appear as semi-linear features and were first identified as “anomalous cloud lines” in satellite images (Conover, 1966). They are frequently found within stratus /stratocumulus cloud fields that are capped by moderate to strong temperature and humidity inversions (Figure 1). Ship-tracks are produced by aerosols affecting cloud physics: particles formed from ship exhaust increase droplet concentration in clouds, resulting in smaller but more numerous cloud droplets, and increase total reflected sunlight. This effect is particularly evident for spectral bands in the shortwave and midwave infared spectral regions, such as 2.1 and 3.7 µm bands (Platnick, 2003). Ship tracks are also used to study the response of total cloud liquid water to aerosols. Both effects, more numerous droplets and more cloud liquid water, can lead to more reflected solar radiation back to space, producing a cooling effect on the climate.

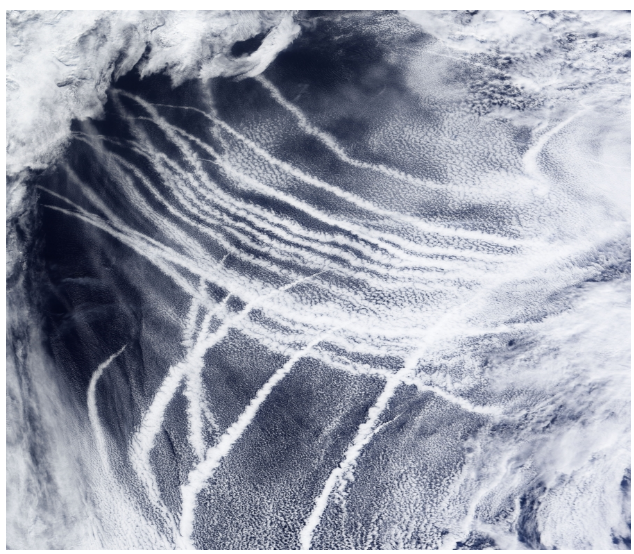

Figure 1. An example of a MODIS scene with multiple ship-tracks visible. It is in the Northern Pacific south of Alaska. In this example, ship-tracks are easily noted in the visible wavelength, which is not the case in general. This is for illustration purpose.

This cooling effect, known as aerosol indirect forcing, is a key climate driver. The aerosol indirect forcing is a result of anthropogenic pollution in general affecting cloud properties and changing reflected solar radiation. It remains the most uncertain component of human-induced radiative forcing to the climate and predicted future warming depends sensitively on its magnitude (Stocker & et al., 2013). Ship tracks provide ideal settings to study aerosol indirect effects because of the clear separation between dynamics and aerosol effects and between control and perturbed clouds. Cloud responses to aerosols from ship exhaust provide important observational constraints for estimating aerosol indirect forcing.

Manual segmentation of ship-tracks is expensive and the amount of data to process is large. A consequence is limited ship-track samples for analysis while the aerosol indirect effects depend sensitively on background conditions, which requires large samples. For example, it has been 55 years since the discovery of ship-tracks and no global maps of ship-tracks have been produced. Research progress is thus slowed.

Here we develop ensemble deep segmentation models to detect ship-tracks automatically and demonstrate a connection among environmental policy, climate physics and maritime shipping activity through ship-tracks. In section 2, we discuss the data and method used to detect ship-tracks as well as data for validation, environmental policy and maritime shipping. In section 3, we present insights from analyzing large amount of data. We conclude in section 4.

2. Data and Model

2.1. Data

We use radiance data measured by NASA's Moderate Resolution Imaging Spectrometer(MODIS) as well as retried cloud physics parameters such as cloud droplet size, cloud optical depth and cloud fraction. The $2.1\mu m$ reflectance data are the input for the segmentation model because they are most sensitive to perturbations in cloud droplet sizes due to ship exhaust and they are not affected by emissions from clouds themselves. We choose not to directly use cloud droplet size retrievals because they are not available everywhere. Three visible channels in red ($0.65\mu m$), green ($0.55\mu m$), and blue ($0.46\mu m$) are used to classify individual 128pixel X128pixel MODIS scenes into different cloud regimes (Yuan et al., 2020). The reflectance data are already normalized to between 0 and 1.

Retrievals of cloud variables such as cloud droplet size and cloud optical depth are used to analyze the cloud physics changes in ship-tracks. Derived variables such as cloud total liquid water and cloud top height as well as cloud fraction are also used.

The ground truth for ship tracks is hard to find for satellite data-based detection since in-situ measurements are extremely rare. We can only rely on human inspection of the original reflectance data, which is still not direct validation (Coakley & Walsh, 2002). Here we will use Automatic Identification System (AIS) data collected by the US Coast Guard to validate our detections. AIS data report real-time data such as location and speed every 6 minutes and are publicly available (https://marinecadastre.gov/ais/) for ships near US coastal regions. They also have information such as vessels size, draft, ship and cargo types.

We fine-tune the DeepLabV3 model with a ResNet50 backbone to train segmentation models. We explore different loss functions and adopt an ensemble average of two models as our final segmentation model (Chen et al., 2018). We average predictions of two models that use BCE loss and FocalLoss because they have complementary strengths and weaknesses.

We build a training set by manually labeling MODIS data with a quality control strategy. First, a new labeler learns to find ship-tracks and label a small set of scenes. A supervisor review the labels with the labeler and correct potential mistakes. The process iterates until the supervisor finds few mistakes in gradually increasing sizes of batches and the labeler then creates samples without supervision. We sample different climate regimes and locations so that the model can generalize. The quality of training data is critical as evidenced by the poor performance of our initial model when it was trained on a training data mixed with low quality labels.

We developed a forward trajectory model to facilitate validating detected ship-tracks. The forward trajectory model uses near-surface wind to advect ship exhaust based on AIS data. The 1-hourly averaged 50-meter U and V wind components are used. The 6-minute AIS ship location data are down-sampled to the half-hourly. Each ship releases a virtual exhaust parcel at every time step and the forward trajectory model predicts their locations at a future time. We then obtain an expected ship exhaust track at the MODIS overpass time by connecting predicted locations of each virtual parcel. These expected tracks is compared with the model detected ship tracks for validation.

An example is shown in Figure 2. The AIS ship locations are blue lines. Using the forward trajectory model we produce 'expected' ship exhaust tracks (red). The actual ship-tracks detected by the segmentation model is shown in green. For most ship-tracks, there are exhaust tracks that closely match them, except track 7. There is some mismatch between track 7 and the green ship-track, which may be due to imperfect model winds. Nonetheless, many cases like this provide strong validation for our model results.

Our model also generalize quite well. We give a few examples in Figure 3. In the first row, the manual ship track

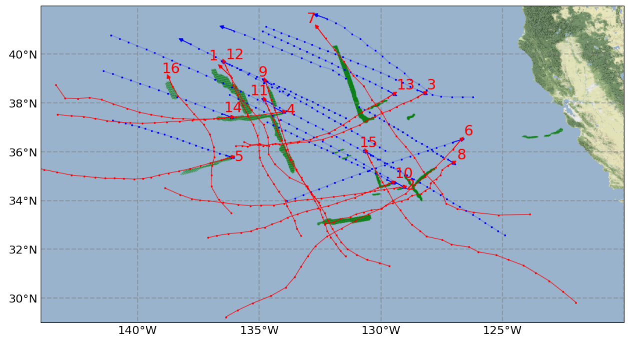

Figure 2. Model detected ship-tracks(green lines), actual AIS-based ship trajectories (blue), and tracks of ship exhaust from our trajectory model (red). Detected ship-tracks overlap with projected ship exhaust tracks quite well, validating our deep learning model results. Note that not all tracks of ship exhaust become ship-tracks since the region may not be cloudy or covered by the right kind of clouds. Also, not all ships are capable of producing ship-tracks even the cloud conditions are right.

is actually a false positive. In the second row, the models pick out most manual labels and leave out the questionable ones. Models and manual label agree well in the third row. In the last example, the labeler clearly missed several true positives while the models correctly detected them.

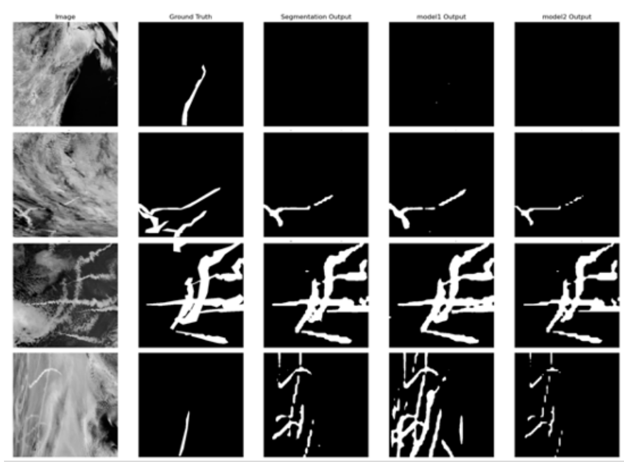

Figure 3. Four examples of (left)MODIS 2.1um images, (second to the left) manually labelled ship track masks (white pixels), (middle) ship track masks from the ensemble average, (right two) ship track masks from two models.

3. Results

3.1. The First Global Map

Figure 4 shows the first global map of ship-track distributions after we apply our ensemble model detection to one year of MODIS data (10Tb). We want to underscore that to form ship-tracks the right kind of low clouds need to

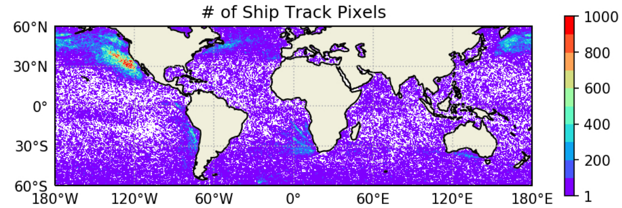

Figure 4. Number of ship-track pixels in 2010.

be present and no overlapping high clouds are observed. This explains the general lack of ship-tracks detected in the lower latitudes despite significant shipping activity in regions like tropical Indian Ocean and tropical Atlantic Ocean. It also explains the relatively fewer ship-tracks in the North Atlantic where high, storm clouds are frequently present. Several major shipping lanes are nevertheless clearly detected in our map: the busiest one connecting East Asia and North America; the one off west coast of South America; the North Atlantic shipping lane; several shipping routes emanating from Cape Town; one to the South of Australia. These regions all happen to be dominated by the right kind of low cloud during some months of the year. These shipping lanes agree with known shipping activities based on global commercial AIS data (raw data not available for us, only images).

3.2. Impact of Policy

International Maritime Organization set up four Emission Control Areas (ECAs) in 2011. One of them is along the west coast of Canada and US. Ships in ECAs have to obey stricter fuel standards to reduce the emission of pollutants such as sulfur oxides, nitrogen oxides, and volatile organic compounds. The standards started to be enforced in 2013 for the ECA in the west coast of North America (Figure 5). Starting 2013, the number of ship-tracks within the ECA decreased significantly. It went down further in 2019 when stricter emission standard was in effect. Not only the number, but also pattern of shipping changed. After 2013, the ship lane outside of the ECA 'consolidated' and contracted to form a tight 'line' instead of a more spread-out blob before that. Also, there is evidence of ships moving along the ECA edge and going straight towards major ports like Los Angeles, San Francisco, and Seattle/Vancouver (e.g. 2018), which minimizes their time spent in the ECA.

3.3. Enable Studying Cloud Physics

With the ship-track segmentation model, we can sample orders of magnitude more samples than before, which allows analyzing cloud responses to aerosol particles in a more nuanced way. Together with a cloud regime classification algorithm, we collocated space-borne lidar and radar data

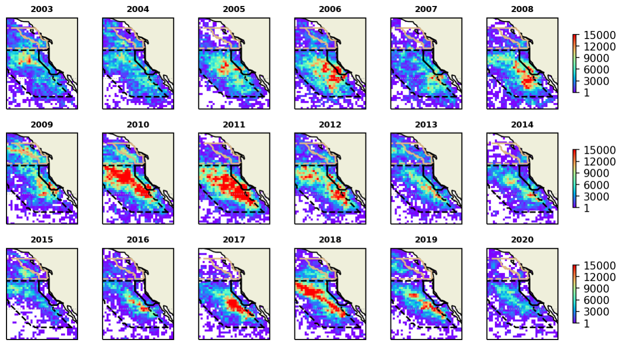

Figure 5. Ship-track numbers in the Northeast Pacific in June and July (peak season) between 2003-2020. The ECA is outlined in solid(both black and yellow) lines.

together with the ship-track segmentation and analyze how clouds respond under different cloud regimes. An example is given in Figure 6. An important take-away message from this analysis of the largest ship-track samples is that clouds responses are quite sensitive to the background cloud regime. For example, cloud fraction change is critical for aerosol indirect forcing and strong increases in cloud fraction, i.e. strong cooling effect, occur predominantly in three cloud regimes while in other regimes, cloud fraction change is minor. Same pattern occurs for the response of total liquid water. Such divergent responses will help us to narrow down uncertainties in aerosol indirect forcing studies. Our results also have direct implications for cloud seeding geoengineering ideas since they help to target the right kind of clouds for maximum efficiency.

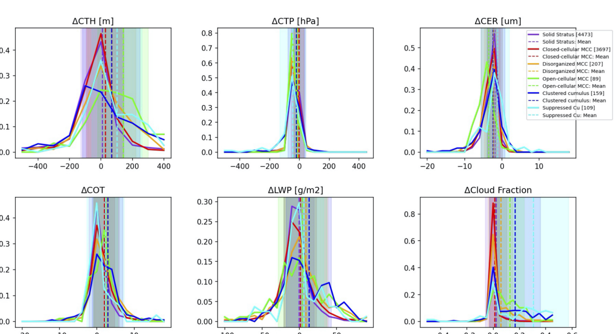

Figure 6. Responses of cloud height, optical depth, droplet size, total liquid water and cloud fraction to ship pollution under six different cloud regimes. The vertical lines are population means and shaded regions are standard deviation around the mean. The legends in the upper right corner indicate the cloud regimes and their sample sizes.

3.4. Socioeconomic Trends/Events

With almost two decades of global data, we can also use the ship-track data to gauge the impact of major socioeconomic

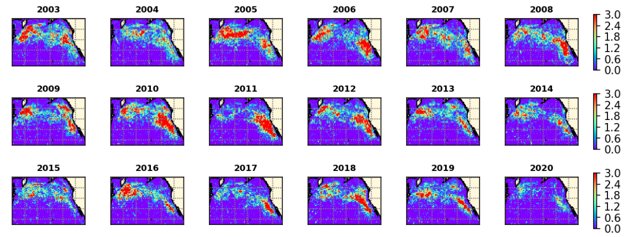

Figure 7. Percentage of low clouds that are affected by ship-tracks in the Northern Pacific.

trends or events on maritime shipping. The northern Pacific region is selected as an example here because it has the large samples of ship-tracks and connects several major markets. Examining the trend, it is noted that 2009/2009 financial crisis only had minor effects on the shipping. The strong increase in shipping from 2003 to about 2010 is mainly driven by economic activities in exporting countries in Asia. The 2015 local minimum is due to a severe downturn in China's economic growth and restriction of raw material import from the Americas to China. The shipping activity recovered after that quickly. The 2020 pandemic had a clear impact on the shipping activity across the Pacific. In fact, the 2020 is the global minimum during the whole record.

4. Conclusions

In this paper, we demonstrate the power of combining deep learning models with space-borne data. We produce the first global map of ship-tracks. Ship-track samples extracted by deep learning models can enable various research topics such as climate physics, impact of environmental policy, and socioeconomic events and trends. There are further application of our method in the future to explore. We show that our ensemble model average approach generalizes well. It is also worth noting that based on our experience the quality of training data is critical for success of AI application.

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