AN EFFICIENT APPROACH FOR TRACKING THE AEROSOL-CLOUD INTERACTIONS FORMED BY SHIP EMISSIONS USING GOES-R SATELLITE IMAGERY AND AIS SHIP TRACKING INFORMATION

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Lyndsay Shand*  
Sandia National Laboratories  
Albuquerque, NM

Kelsie Larson  
Sandia National Laboratories  
Albuquerque, NM

Andrea Staid  
Sandia National Laboratories  
Albuquerque, NM

Skyler Gray  
Sandia National Laboratories  
Albuquerque, NM

Erika L. Roesler  
Sandia National Laboratories  
Albuquerque, NM

Don Lyons  
Sandia National Laboratories  
Albuquerque, NM

Brigham Young University  
Provo, UT

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ABSTRACT

Ship emissions can form linear cloud features, or ship tracks, when atmospheric water vapor condenses on aerosols in the ship exhaust. These features are of interest because they are observable and traceable examples of marine cloud brightening, a mechanism that has been studied as a potential approach for solar climate intervention. Ship tracks can be observed throughout the diurnal cycle via space-borne assets like the Advanced Baseline Imagers on the National Oceanic and Atmospheric Administration Geostationary Operational Environmental Satellites, the GOES-R series. Due to complex atmospheric dynamics, it can be difficult to track these aerosol perturbations over space and time to precisely characterize how long a single emission source can significantly contribute to indirect radiative forcing. We combine GOES-17 satellite imagery with ship location information to demonstrate two feasible methods of tracing the trajectories of ship-emitted aerosols after they begin mixing with low boundary layer clouds in three test cases. The first method uses the parcel trajectory model HYSPLIT, which was driven by well-studied physical processes but often could not follow the ship track beyond 8 hours. The second method uses the image processing technique, optical flow, which could follow the track throughout its lifetime, but requires high contrast features for best performance. These approaches show that ship tracks persist as visible, linear features beyond 9 hr and sometimes longer than 24 hr. This research sets the stage for a more thorough exploration of the atmospheric conditions and exhaust compositions that produce ship tracks and factors that determine track persistence.

Keywords: ship tracks · optical flow · HYSPLIT · cloud-aerosol interactions

1 INTRODUCTION

It is well documented that aerosols from anthropogenic sources can apply direct radiative forcing by reflecting or absorbing sunlight, as well as apply indirect radiative forcing by altering the radiative properties of low-lying clouds [Twomey, 1974; Albrecht, 1989; Seinfeld et al., 2016; Christensen et al., 2020]. Natural aerosols can increase the concentration of cloud condensation nuclei (CCN) and lead to more, but smaller, cloud droplets for a fixed liquid water content. This, in turn, can cause changes in cloud albedo resulting in changes to a cloud’s radiative properties [Myhre
The magnitude of the impact of aerosols on a cloud’s radiative properties can vary greatly depending on the properties of the aerosol and the surrounding atmosphere [e.g., Chen et al., 2014]. Most often, anthropogenic aerosols increase the amount of radiation reflected by clouds, but in some cases, they have been known to reduce a cloud’s albedo [Chen et al., 2012].

Aerosols can directly and indirectly exert positive and negative radiative forcing on local and global climates [Seinfeld et al., 2016 and references therein]. Direct radiative forcing occurs when aerosols scatter or absorb solar radiation to the surrounding air, either locally warming or cooling the atmosphere. Indirect radiative forcing by aerosols occurs when the aerosols interact with clouds and precipitation, impacting the clouds’ lifetime, albedo, precipitation, and micro- and macro-physical properties [Penner et al., 2001, IPCC, 2007]. Currently, indirect radiative forcing is the largest documented source of uncertainty when it comes to overall radiative forcing in climate modeling [Carslaw et al., 2013, Myhre et al., 2013b, Wang et al., 2020]. This large uncertainty is due in part to the complexity of cloud dynamics, making it difficult to clearly separate the aerosol’s radiative effect from that of the surrounding clouds [Stevens and Feingold, 2009]. Improving our understanding of aerosol-cloud interactions is necessary to reduce this uncertainty in climate models.

Increasing the reflectivity of all clouds has the potential to reduce positive radiative heating through targeted “climate cooling,” the central concept in solar climate intervention. Marine cloud brightening (MCB) and other intervention approaches have been proposed to intentionally increase the reflectivity of low altitude, boundary-layer clouds [e.g., Latham, 1990, National Research Council, 2015, Myhre et al., 2013b] through the intentional increase of CCN via targeted aerosol injections in marine stratocumulus clouds. Low-lying marine clouds are most predisposed to albedo changes due to low densities of CCN, making this a promising approach to reducing global warming [Bickel and Lane, 2018].

Ship tracks have been unintentional, natural examples of MCB for decades. For more than fifty years, satellite imagery has detected these bright linear features produced when the engine exhaust from large ocean-traversing ships mixes with low-lying marine clouds within 2 km of the earth’s surface. Ship emissions have provided researchers with observable and traceable examples of aerosol-cloud interactions, which have been the focus of many studies to better understand the potential impacts of MCB [Hobbs et al., 2000, Glassmeier et al., 2021]. The Monterey Area Ship Track experiment off the coast of California [Durkee et al., 2000] was one of the largest aircraft campaigns to study the formation of ship tracks. Conover [1966] and Twomey et al. [1968] were the first to document their observations of this phenomenon in visible-wavelength images taken from the Television Infrared Observational Satellites (TIROSs). Possner et al. [2018] found that ship tracks can impact the radiative properties of clouds long after they are visible. Although not all atmospheric conditions and ship exhaust have the potential to produce ship tracks [Noone et al., 2000], these features are more abundant than previously thought [Yuan et al., 2019]. However, key questions remain regarding how long these tracks persist and what local impact they have on cloud radiative properties after the source of emissions has passed.

A lack of high resolution data, as well as difficulties isolating and tracing observed aerosol-cloud interactions over time, have been limiting factors in studying the longevity and long-term effects of ship tracks. Costly air campaigns have been the most reliable method of tracking the behavior of aerosols from a known source. Recently, due to the vast improvements in satellite imaging technology, more has become possible. For example, Zhao et al. [2018] used the Advanced Very High Resolution Radiometer (AVHRR) from the NOAA satellites to study the global long-term indirect effects of aerosols. Yuan et al. [2019] used machine learning to automatically label ship tracks in images from the MODerate resolution Imaging Spectroradiometer (MODIS) aboard both the Aqua and Terra satellites. Gryspeerdt et al. [2019] combined MODIS imagery and retrievals of cloud droplet number concentration (N_d) with known ship positions and properties to demonstrate a positive effect of emission sulfate concentration on the likelihood of ship track formation and a decrease in ship track observations due to fuel sulfur content restrictions set by the International Maritime Organization (IMO). More recently, Diamond et al. [2020] applied spatial kriging methods to cloud property data retrieved from MODIS and reanalysis from the Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2), to infer negative impacts on radiative forcing from emissions along a major shipping lane in the southeast Atlantic. New satellite observations of aerosol-cloud interactions have been a large source of untapped information since it is very difficult to infer the radiative impact of ship emissions from observational data collected from earlier generations of satellites [Falkowski et al., 1992, Kim and Cess, 1993, Han et al., 1994].

Historically, our understanding of the interactions between anthropogenic aerosols and clouds has been primarily limited to simulations. In atmospheric computational fluid dynamic numerical models, aerosol injections are initiated in the model at known, precise locations in fully defined environments that are easily traceable [e.g., Wang et al., 2011, Berner et al., 2015, Possner et al., 2018, Bossey et al., 2018]. Unlike simulated case studies, satellite observations of ship tracks have many uncertainties including, for example, the size, composition, and concentration of the emitted aerosols and properties of the atmosphere, including temperature, wind, pressure, water content, and previous aerosol
concentration. Real, observed ship tracks are initiated from an unknown source and form in a dynamic and only partially known environment, making it challenging to trace and fully characterize their behavior. In the research we present herein, we show how high-resolution spatial and temporal observations from the National Oceanic and Atmospheric Administration’s (NOAA) GOES-17 Advanced Baseline Imager (ABI) data can resolve ship tracks year-round.

In this paper, we present two methods of effectively following the behavior and persistence of ship tracks and demonstrate these tools in determining how long ship tracks persist in a maritime environment. These methods could be used as a means to record ship track impact on climate. The first method relies on the NOAA HYSPLIT trajectory model [Stein et al., 2015], an atmospheric transport and dispersion model widely used by atmospheric scientists to estimate and study the trajectories of air parcels forward and backward in time. The second method relies on the image registration technique of Lucas and Kanade [1981], which is a purely image-based approach to local feature tracking. Both methods rely on radiance spectra collected from the GOES-17 ABI sensor [GOES-R Calibration Working Group and GOES-R Series Program, 2017] and provide an efficient approach to accurately and systematically characterize ship track persistence.

This research sets the stage for a more thorough exploration of the atmospheric conditions and exhaust compositions that produce ship tracks and factors that determine whether a track persists for 3, 9, or more than 24 hr. Many of these tracks have persisted as detectable linear cloud features for as long as 12 to 24 hr, much longer than the 6–8 hr typically assumed in climate simulation studies in pristine environments [e.g., Berner et al., 2015]. The remainder of this paper is organized as follows; Section 2 outlines our data sources; Section 3 outlines our HYSPLIT approach; and Section 4 describes our optical flow approach. Section 5 compares both approaches, discusses how they might be used in practice, and recommends follow-on work.

2 Data

This research uses ship location information combined with L1b radiances measured from the Advanced Baseline Imager (ABI) instrument on the GOES-17 geostationary weather satellite [GOES-R Calibration Working Group and GOES-R Series Program, 2017], which provides four times higher spatial and three times higher temporal resolutions than previous generations of GOES imagers. Higher resolutions in both space and time allow us to study fast-changing cloud features such as ship tracks with greater precision. We rely on the near-infrared “cloud particle size” band (C06) and the infrared “shortwave window” band (C07) with central wavelengths of 2.24 and 3.90 µm, respectively, to visualize ship tracks throughout the diurnal cycle. To seamlessly visualize ship tracks during day-night transitions, we transform the data for each time stamp by subtracting spectral band C07 from band C06 and apply the image processing technique of histogram equalization to systematically control the contrast of each image. Histogram equalization enhances the contrast of each image, making it easier to visualize and identify key ship track features that may otherwise be invisible to the naked eye. The spatial resolution of both bands (C06 and C07) is 2 km, and the temporal resolution is every five minutes for the GOES-17 CONUS imager.

For the first half of 2019, we relied upon both satellite and terrestrial-based Automatic Identification System (AIS) data provided by the SeaVision database [U.S. Department of Transportation, 2020], which has near real-time resolution as frequent as every 15 minutes. In accordance with “Regulation 19 of SOLAS Chapter V Carriage requirements for shipborne navigational systems and equipment” of the International Maritime Organization (IMO), all ships must have on-board transponders capable of automatically transmitting ship information to other ships and coastal authorities [IMO, 2003]. The AIS provides positional data (latitude and longitude) and attributes, such as vessel name, size, type, and speed. AIS data was used to (1) cross-reference observed track locations with nearby ship positions to confirm which ship produced the track emissions and (2) determine a precise location to initialize track trajectories via HYSPLIT, as described in Section 3.

We began by processing and plotting GOES-17 CONUS satellite imagery for a selection of dates in the first half of 2019 that coincided with available ship location information, which allowed us to identify a large number of dates with clearly visible ship tracks. We then selected three examples for further case study. These three examples consist of ship tracks in the Northern Pacific Ocean, often some distance off the western coast of the U.S. in February, April, and June 2019. Each example had a different composition of high and low clouds and thus exhibited different ship track behaviors (i.e., different feature formations and movements). While not a comprehensive study, these examples demonstrate the robustness of our approaches under different ship track conditions.

In the February 2019 example, we follow an intersection of two tracks, which is often easier to distinguish, and begin tracking on February 20, 2019, at 17:00 UTC at approximately 44.25° latitude, −139.45° longitude. We follow this intersection in a rotating cloud field until it dissipates and is no longer a distinguishable feature. In the April 2019 example, we follow a single track when it becomes clearly distinguishable and begin tracking on April 23, 2019, at 19:00 UTC at approximately 37.76° latitude, −131.37° longitude. This track quickly begins mixing with other nearby
ship tracks until they all become indistinguishable in a larger cloud field. In the June 2019 example, we again follow an intersection, which becomes visible just as one ship passes into a large cloud bank. We begin tracking on June 17, 2019, at 05:00 UTC at approximately 36.4° latitude, -135.65° longitude. This is likely the best example of the three because it remains clearly visible throughout the 24-hr period even as it begins to dissipate and dim. The following sections demonstrate our two proposed tracing methods across these three examples.

3 Validating track persistence with HYSPLIT

We demonstrate the feasibility of using NOAA’s HYSPLIT model [Stein et al., 2015] to predict ship track trajectories and assess track persistence, noting the model’s advantages as well as its limitations. The HYSPLIT trajectory model [Stein et al., 2015] estimates air parcel locations using forward and backward trajectory analyses to determine either the future locations or historical origins of air masses or sources. Our simulations used analysis data from the Global Data Assimilation System (GDAS) provided by the National Weather Service’s National Centers for Environmental Prediction. GDAS data is often used when gridded observational data is required, and the Air Resources Laboratory processes this data into HYSPLIT-useable formats. Until June 12, 2019, GDAS data had a spatial resolution of 0.5° grid cells (∼50 km), but it now has a resolution of 0.25° grid cells (∼25 km), and our simulations rely on data both before and after that date (both resolutions). For all trajectory analyses, the temporal resolution is hourly.

We used HYSPLIT to project the movements of pre-formed ship tracks forward in time. The “head” of a ship track is the position at which a new, visible cloud track is forming and is also referred to as the “initialization point” in this paper. We then constructed the forward trajectory of an air parcel using this position as the initial location for HYSPLIT and let the simulation run 24 hr forward in time. To quantify persistence, we visually verified whether the portion of the track we were following was still visible as a linear feature at the predicted locations.

We manually inspected satellite imagery to identify a ship track initialization point (e.g., intersection of ship tracks for easier feature matching), then matched the AIS location data to the feature of interest, and used the latitude and longitude values of the ship at the initialization point. We ran it forward in time for 24 hr, collecting the position data where the air parcels would have moved each hour. We then overlaid the HYSPLIT trajectory points onto the satellite imagery for these forward time points and visually assessed a) how well the air parcel projections estimated the observed ship track movement and b) whether there was still a clear remnant of the feature at each forward time step. Fig. 1 shows what this looks like for an initialization point (here, at the head of a track) from June 17, 2019.

Overall, the predicted HYSPLIT trajectories estimated the track feature movement reasonably well within the first 8 to 12 hr, although the model’s performance was noticeably sensitive to the height initialization values required by HYSPLIT. The height initialization value identifies the correct air parcel to follow, is the starting point of a forward trajectory, and is used to interpolate pressure level data that largely drives the trajectory estimates. Initial exploration of cloud top height data, collected from the GOES-17 ABI as an L2 product, revealed significant variations in cloud top height measurements. While certain time periods had stable height values in a region of interest, others had values ranging from hundreds to thousands of meters within a small grid cell. In the latter case, due to the low spatial resolution of the cloud top height product (10 km) compared to L1b radiance data (2 km for bands > 2 μm), it was difficult to identify an appropriate initialization height for an observed track. Given that ship-induced cloud tracks are likely to form at the boundary layer, height values greater than 1 km are unlikely and greater than 2 km are unreasonable [Lin et al., 2009]. However, there is still uncertainty about the best choice of initialization height for these HYSPLIT trajectory runs. Therefore, we initialized HYSPLIT at multiple height values (0, 200, 400, and 600 m), which provided some information about the sensitivity of trajectory analysis to height and allowed us to qualitatively assess the uncertainty in predicted trajectories.

Fig. 1 shows our best example of the HYSPLIT trajectory model accurately estimating the predicted trajectory of the ship track feature that was clearly visible for more than 20 hr in June 2019 (also shown in Fig. 3). For this case, we initialized simulations at a discernible head of a ship track. Initializing the height at zero meters (sea level) seemed to provide the best match, and trajectories initialized at 200, 400, and 600 m are not unreasonable up to 9 hr. HYSPLIT’s predictions of the underlying air parcel trajectory reasonably align with the observed movement of this cloud feature with minimal variability due to height initialization until about the 9-hr mark when the trajectory variability becomes more prominent. Although the track is still clearly visible at 12 hr, the HYSPLIT trajectories no longer seem to be centered on the track feature of interest and have become much more variable for different height initializations. HYSPLIT projections no longer match the movement of this feature past 12 hr as shown in Fig. 1. Two more examples of trajectory analysis for dates in February and April 2019 revealed similar trajectory variability due to height initialization, and misalignment to the observed track movements was much greater than for the June 2019 case. These trajectories are shown in supplementary Figs. A.2 and A.3.
In summary, HYSPLIT can be useful in predicting the trajectories of visible cloud-aerosol features up to approximately 8–12 hr depending on the case. However, due to the hourly time resolution, it can only provide a rough estimate of the length of time the track persists as a linear feature. For ship tracks that are less distinguishable from the surrounding clouds, it becomes difficult to confirm that HYSPLIT projections align with the same portion of the track where we initialized the forward trajectory. This is likely due to the fact that 1) HYSPLIT is initialized at a single location and then runs forward with no intermediate checks to see if it is still tracking the same (initial) feature, 2) HYSPLIT only projects at 25 km spatial and 1-hr increments (compared to the 0.5–2 km and 5–15 minute resolutions the GOES-17 imager collects) and might miss nonlinear movement within the hour, and 3) HYSPLIT predicts the locations of the emitted aerosols rather than the aerosol-cloud interactions that form ship tracks. However, an interesting application of this proposed HYSPLIT approach is to use it to infer the height at which the aerosol track resides. For example, if we initialize at several more height increments, the initialization height that best predicts the trajectory of the feature might be a more accurate estimate of the aerosol track height than the cloud top heights retrieved from the GOES-R L2+ products. Additionally, for improved predictions, we could re-initialize the starting point for trajectory analysis at each time step as long as the feature can still be clearly identified.

4 Tracking ship track features with optical flow

As discussed in Section 3, following a ship track feature using HYSPLIT can be challenging and has its limitations. In this section, we present a more precise “optical flow method” that relies on the Shi-Tomasi feature selection technique [Shi and Tomasi, 1994] and the Lucas-Kanade feature tracking technique [Lucas and Kanade, 1981]. These techniques are widely used in video processing to find and estimate motion of features between video frames. This approach relies on visual features alone and is thus unaffected by the meteorological errors and uncertainties to which HYSPLIT is
subjected. By augmenting the two techniques to fit a simple motion prediction framework, we are able to reliably follow ship track features well past the point where HYSPLIT projections do not agree with observations.

Previously, the Lucas-Kanade algorithm was successfully used to estimate cloud motion in ground-based video feeds to forecast solar irradiance [Wood-Bradley et al., 2012] and in satellite image sequences to track individual cloud banks [Idder and Laachfoubi, 2016]. Shi and Tomasi [1994] showed that Lucas-Kanade is most successful with high-contrast textural features (specifically those with high contrast in both x and y directions), making it an appropriate choice for tracking features within the textured cloud regions where we observe ship tracks. The Shi-Tomasi algorithm was designed to detect the most distinguishable features within an image. Our method combines the Shi-Tomasi algorithm for feature detection with the Lucas-Kanade algorithm for tracking. This approach is strictly computational, relying only on image pixel values with no consideration of other atmospheric or meteorological data that might govern aerosol movement. Thus, it is an attractive method for tracking cloud features observed at any altitude, but it is sensitive to image data corruption and intensity variation between frames. The latter can be common between GOES-17 CONUS frames, especially when transitioning between nighttime and daytime images. As described later in this section, we make modifications to the Lucas-Kanade algorithm to allow continuous feature tracking for more than 24 hr.

Optical Flow Overview

The optical flow approach used here is a combination of the Shi-Tomasi and Lucas-Kanade algorithms. The Shi-Tomasi algorithm is used to determine the center pixel locations of high-contrast features within an image by assigning a quality value to each pixel in the image, where higher quality is associated with higher-contrast features. The quality q assigned to a pixel at location \((u_x, u_y)\) in the image \(I\) is the minimum eigenvalue of the associated structure tensor \(M\), which is computed over an \(n \times n\) neighborhood of pixels, i.e.,

\[
M(u_x, u_y) = \sum_{u_x-n}^{u_x+n} \sum_{u_y-n}^{u_y+n} \left( \frac{\partial I}{\partial x} \right)^2 \left( \frac{\partial I}{\partial y} \right)^2 + \left( \frac{\partial I}{\partial x} \frac{\partial I}{\partial y} \right)
\]

If \(\lambda_1\) and \(\lambda_2\) are the eigenvalues of \(M\), then \(q(u_x, u_y) = \min(\lambda_1, \lambda_2)\). When implementing the Shi-Tomasi algorithm in practice, all pixel locations with a quality less than a selected threshold \(t_q\) are first rejected. Further refinement is then performed by non-maximum suppression within an \(m \times m\) sliding window, and then all remaining pixel locations are selected as feature centers.

The Lucas-Kanade algorithm is then applied iteratively for each pair of frames in a sequence to estimate where features have moved from one frame to the next. A feature \(I_W(u_x, u_y)\) is the collection of pixel intensities in the neighborhood \(W\), about a feature center at location \((u_x, u_y)\) in frame \(I\). The width and height of neighborhood \(W\), are given by \(2\omega_x + 1\) and \(2\omega_y + 1\), respectively, where \(\omega_x\) and \(\omega_y\) are non-negative integers chosen by the user. Assuming that a given feature \(I_W(u_x, u_y)\) has moved between two consecutive frames, that same feature will be given by \(I_W(u_x+d_x, u_y+d_y)\) in consecutive frame \(J\), where \(d_x, d_y\in\mathbb{R}\) denote the distances (in pixels) the feature has moved between frames in the \(x\) and \(y\) directions, respectively. To identify \(J_W(u_x, u_y)\) the distance \(d^* = [d_x, d_y]^T\), also known as the optical flow, is estimated between \(I_W(u_x, u_y)\) and \(I_W(u_x+d_x, u_y+d_y)\) by minimizing the sum of squares between the feature neighborhood in frame \(I\) and the shifted neighborhoods in frame \(J\), i.e.,

\[
d^* = \arg\min_{(d_x, d_y)} \epsilon(d_x, d_y) \quad \text{and} \quad \epsilon(d_x, d_y) = \sum_{x=0}^{\omega_x} \sum_{y=0}^{\omega_y} [I(x, y) - J(x + d_x, y + d_y)]^2
\]

The Lucas-Kanade algorithm uses a Taylor approximation about \((d_x, d_y) = (0, 0)\) to estimate \(d^*\). This approach assumes minimal motion between consecutive frames, which is not a reasonable assumption for cloud features. To account for larger motion in practice, we apply Lucas-Kanade iteratively, such that \(d^*\) is estimated several times for each feature with each estimate updating the previous one, and use the pyramidal implementation described in Bouget [2001]. This implementation constructs a “pyramid” of image copies of various resolutions with each copy having half the resolution of the previous one.

Application to cloud feature tracking

We applied the optical flow tracking method to three ship track case studies in February 20, April 23, and June 17 of 2019 and compared its performance to that of the HYSPLIT approach described previously. Using the combination of
L1b radiances from GOES-17 ABI bands C06 and C07 described in Section 2, we implemented the optical flow method to identify and track features within a user-defined region of clouds surrounding a recently-formed ship track. This was accomplished using the OpenCV implementations of both the Shi-Tomasi and Lucas-Kanade algorithms [OpenCV, 2018]. The default values provided by OpenCV were used for any parameters not described here.

First, we manually selected a cloud region of interest (approximately 50 × 50 pixels, or 100 km × 100 km) immediately surrounding an initialization point, i.e., the head of a ship track or the intersection of two ship tracks, as described in Section 3. The size of the region of interest was chosen such that at least five high-contrast features, as selected by the Shi-Tomasi algorithm, could be found within the region. The robustness of our approach for tracking a cloud region relies on the selection of more than one feature because the Lucas-Kanade algorithm may fail for some features over time. We applied the Shi-Tomasi feature detection algorithm within the cloud region to identify the locations of features for tracking with parameters \( n = 3 \), \( m = 3 \), and \( t_q \) as 20% of the maximum \( q(u_x, u_y) \) within the region. Next, these features were tracked in all the following frames using the Lucas-Kanade technique. We found that a neighborhood size of 15 pixels \( (\omega_x, \omega_y = 7) \) was appropriate for creating a unique set of features for effective tracking. We chose the neighborhood size such that some visible cloud texture was encompassed within each feature, though we expect the results to be robust for neighborhood sizes between 10 and 20 pixels for our studies. For each frame, we iterated using 3-level pyramids until either the estimated displacement was less than 0.03 pixels or 10 iterations were completed, whichever occurred first. The features were tracked in consecutive frames until the ship track was no longer recognizable in the frame.

Although best assessed in video format, we demonstrate tracking performance in this paper as a tracking box overlaid on the satellite imagery at 4 to 6-hr intervals. The tracking box is parameterized by the user-defined cloud region of the first frame and is updated in each frame to be roughly centered around the ship track cloud feature by adding it to the mean displacement of the features between the current and previous frames. Fig. 2 shows the performance of the optical flow approach on a cloud region on June 17, 2019. The tracking follows two distinct ship tracks over 18 hr, throughout which the tracks clearly persist. Fig. 3 shows the isolated user-defined cloud region of the same tracking result in 4-hr increments over a 28-hr period. We clearly observe ship tracks from the beginning of tracking at 05:02 UTC until at least 02:02 UTC the following day, accurately quantifying the duration of persistence as 20 hr. Using this approach, we can observe the persistence and dispersion of ship emissions in a cloud layer by tracking that region over several hours in increments of 5 min, the temporal resolution of the GOES-17 ABI CONUS scan.

Figs. 4 and 5 demonstrate the optical flow tracking technique for the two case studies in February and April 2019. Videos for all three examples can be found in the supplementary materials. We compare optical flow performance with HYSPLIT trajectory predictions in supplementary Figs. A.1, A.2, and A.3. Based on these comparisons and due to the high sensitivity of HYSPLIT to height initializations over time, we prefer the optical flow method over the HYSPLIT method to reliably predict the path of ship track features that persist beyond 8 hr.

**Limitations of optical flow**

Although we demonstrated the efficacy of the optical flow approach for these case studies, it is important to point out some of its limitations, as well as the modifications we made to track cloud features. A well-known source of error is abrupt changes in image brightness due to the algorithm’s dependence on pixel intensity values. These changes may occur if the data is corrupted, if there are large thermal changes in the atmosphere such as at sunrise and sunset, or if other artifacts cause large intensity disparities in one frame compared to others in the sequence. Errors due to data corruption are avoided by considering the data quality flag (DQF) field in the ABI data. For example, we chose to omit a frame of data from the optical flow computations if the percent of corrupt pixels, as specified by the DQF, surpassed 2%. This method was sufficient for the data we used because there were very few frames with corrupt pixels, but it could be improved by considering the DQF for nearby pixels.

Intensity changes in satellite images captured during sunrise and sunset nearly always cause the Lucas-Kanade technique to incorrectly identify features from one frame to the next; this is unavoidable when following features such as ship tracks because they persistently frequent for more than 8 hr. We were able to continuously follow a cloud region of interest across these boundaries by predicting the start and duration of these transitions and using observed trajectories rather than the Lucas-Kanade method to predict its trajectory.

We determined the starting and ending frames of a diurnal transition using calculated solar zenith angles at the right and left perimeter of our tracking box, respectively. These angles were calculated using the National Renewable Energy Laboratory’s Solar Position Algorithm [Reda and Andreas, 2008], which calculates the sun’s apparent altitude with a precision of about 0.0003 degrees given the date, time, and location. For a given frame, the minimum and maximum angles are used for both the right and left edges of the tracking box to determine the start and stop of a diurnal transition. Thresholds for the start and end of each transition were chosen empirically and conservatively to ensure the transition
At the start of a boundary, feature tracking is stopped, and the average motion of the region of interest is computed using the motion of the features across the six prior frames. The velocity of the region of interest is then assumed to be constant over the transition period, and the location of the region of interest at any point during this transition is predicted using this assumption. Over this short transition period, this augmentation has proved to work well for our cases. At the end of the transition boundary, new features are selected within the region of interest using the Shi-Tomasi algorithm and followed until the ship track is no longer visible in the region of interest. An equally appealing approach to overcoming large changes in intensities between images might be to correct for significant pixel intensity changes between images so that the Lucas-Kande method could be leveraged for the full 24 hr period. For example, Ganzetti et al. [2016] show a promising approach for correcting pixel inhomogeneities in magnetic resonance brain images. However, we found our approach to be sufficient and did not explore this route.

In addition to changes in pixel intensity, the optical flow method is also sensitive to non-affine changes in the shapes of features. Common cloud motions can introduce warping, but the warping between two consecutive GOES-17 CONUS frames, measured 5 min apart, is minimal and does not affect tracking success. A larger temporal gap between frames may allow for a greater change in features and thus introduce notable tracking errors. Large temporal differences between frames can occur when data is absent from the database or the frames are rejected because they contain corrupt data. In our experience, a temporal gap of up to one hr between two frames is generally reasonable for successful feature tracking.

Other natural phenomena that can cause the Lucas-Kanade technique to fail include interference from high-altitude clouds passing over the region of interest, dispersion of the boundary cloud layer, and disappearance of texture from the cloud layer. In the first case, the features may be obscured or confused with similar features in the higher-altitude...
Fig. 3: These figures show the 110 px by 110 px image region centered on the tracking box of the optical flow method at each frame in 4-hr time intervals beginning on June 17, 2019, at 05:02 UTC. The box is removed from these images for better visualization. The remnants of the ship tracks are still visible up to 20 hr after they first appeared in clouds; in the latter two cases, the features disappear entirely and cannot be tracked further. Although the local feature tracker presented here has its disadvantages, we believe its advantages outweigh these challenges. Many of the obstacles described here could be circumvented by integrating known physical and/or meteorological factors that contribute to cloud feature movement. There is also the potential to integrate the HYSPLIT tracking approach described in Section 3 over short periods of time (<6 hr) when we expect the optical flow approach to fall short.

5 Conclusions and Discussion

We have presented two methods of systematically following ship track behavior observed in imagery from the GOES-17 geostationary weather satellite. We have demonstrated the cloud feature tracking capabilities of each and shown how they can be used to quantify track persistence using three case studies. HYSPLIT and optical flow have complementary advantages and disadvantages, and together they make a very efficient tracking method for aerosol-cloud interactions. This capability can be leveraged in the future to track and assess long-term local impacts of proposed solar climate intervention efforts such as MCB.
The first method we demonstrated relies on NOAA’s HYSPLIT trajectory model, and it accurately followed ship track behavior with some degree of uncertainty within the first ~8 hr before its tracking accuracy declined, which could be due a number of factors. Most notably, HYSPLIT results are sensitive to the reanalysis data it depends upon. It is likely that we could see improved results using reanalysis data from ERA-5 rather than the GDAS data we used here. Kazil et al. [2021], for example, find the meteorology data of the ECMWF atmospheric reanalysis [Hersbach et al., 2020, ERA5] work well to follow boundary layer trajectories within their Lagrangian large-eddy simulations over a 2-day period. Assuming ship tracks are a delayed response of the cloud to ship emissions, this time delay may also need to be taken into account to improve the accuracy. Additionally, the continual forward trajectory estimates of HYSPLIT have no intermediate checks to see if it is still tracking the initial feature, and the low hourly temporal resolution of HYSPLIT could also cause issues as any nonlinear movement that occurs within the hour will not be taken into account. Lastly, HYSPLIT is heavily dependent on atmospheric measurement retrievals and reanalysis products, which can have large associated measurement errors. An interesting observation in all three case studies is that HYSPLIT seems to follow the ship track reasonably well during the first 5 to 6 hr when initialized at a height of zero meters (sea level). Height is used by HYSPLIT to infer surface pressure for that location, which at sea level would be the highest vertically. Some of the NOAA higher resolution data files have five or more vertical levels in the boundary layer (<850 hPa), which could explain why we see so much variation between initialization height increments of only 200 m. Another potential use of the proposed HYSPLIT forward trajectory approach is to infer the height at which the aerosol track resides, which is difficult to infer from satellite measurements alone. Since we expect to see the first signs of track formation in boundary layer clouds, we can initiate HYSPLIT at varying altitudes and assess its tracking capability over the first few hours to potentially extract a boundary layer height estimate.

The second method we examined is a local feature tracking, or optical flow, approach that adapts the Lucas-Kanade algorithm for tracking ship track features and only requires radiance data from the GOES-17 ABI sensor. Note that we rely on spectral bands C06 and C07 to seamlessly observe the tracks throughout day-night transitions off the coast of California, but any method of feature visualization would work for this approach. We have shown that our
method can follow a ship track with high accuracy well past 12 hr and throughout day-night transitions, allowing more precise characterization of ship track feature persistence. However, due to its reliance on high-contrast features within the tracking window, it will not satisfactorily follow weak ship track features without further image preprocessing techniques, which can be tedious to perform over the many images a track can appear. In this case, using both the local feature tracking method (optical flow) combined with the HYPLIT approach can provide a complete picture of the ship track’s trajectory. Aside from following ship track features, there is the potential to use the optical flow approach to estimate the motion of the low-lying cloud bank where the ship track was last visible in an attempt to track its effect well beyond being a visible linear cloud feature. The algorithms used to produce the GOES-R ABI L2 product derived motion winds (DMW) [GOES-R Calibration Working Group and GOES-R Series Program, 2018] are promising approaches for following large high-cloud regions but are not suitable for local movement tracking needed to estimate motion at varying altitudes. This capability is currently being explored and is a topic for future discussion.

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Data Availability Statement  All data used is open source. GOES-17 ABI data can be found and downloaded at https://www.avl.class.noaa.gov and AIS data from SeaVision can be requested here: https://info.seavision.volpe.dot.gov/. We are currently working to make our optical flow algorithm open source as well and can be found here when available: https://github.com/lshand/CFTrack

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A Supplementary HYSPLIT Figures

Fig. A.1: Shown are the combined results of HYSPLIT trajectory analysis and optical flow approach for the June case study. Both HYSPLIT and optical flow were initialized on June 17, 2019, at 05:02 UTC, shown in (a), and snapshots are shown (b) 6, (c) 12, and (d) 18 hr later. The HYSPLIT analyses were initialized at four different altitudes for comparison. Though both methods agree with the motion of the ship tracks, some of the HYSPLIT projections appear to accumulate error over time. The ship tracks remain clearly visible 18 hr after initialization.
Fig. A.2: Shown are the combined results of HYSPLIT trajectory analysis and optical flow approach for the February case study. Both methods were initialized on February 20, 2019, at 17:02 UTC, shown in (a), and snapshots are shown (b) 4, (c) 8, and (d) 12 hr later. The HYSPLIT analyses were initialized at four different altitudes for comparison. Though both methods agree with the motion of the ship tracks, some of the HYSPLIT projections appear to accumulate error over time. The ship tracks remain visible 8 hr after initialization.
Fig. A.3: Shown are the combined results of HYSPLIT trajectory analysis and optical flow approach for the April case study. Both methods were initialized on April 24, 2019, at 19:02 UTC, shown in (a). GOES-R ABI data from 22:58 to midnight on April 24, 2019, is unavailable, so snapshots are shown (b) 5, (c) 9, and (d) 13 hr later. The HYSPLIT predictions were initialized at four different altitudes for comparison. The ship tracks remain clearly visible 9 hr after initialization.
B Details on sunset/sunrise transitions using solar zenith angle

We determined the starting and ending frames of a diurnal transition using calculated solar zenith angles at the right and left perimeter of our tracking box, respectively. These angles were calculated using the National Renewable Energy Laboratory’s Solar Position Algorithm [Reda and Andreas, 2008], which calculates the sun’s apparent altitude with a precision of about 0.0003 degrees given the date, time, and location. For a given frame, the minimum and maximum angles are used for both the right and left edges of the tracking box to determine the beginning and end of a diurnal transition. Thresholds for the start and end of each transition were chosen empirically and conservatively to ensure the transition periods are estimated accurately.

Specifically, let \( \alpha_r \) and \( \alpha_l \) be vectors of pixel solar zenith angles for the right and left half of the tracking box perimeter, respectively, and let \( c, d \in \mathbb{R} \) such that \( 0 < c < d \) be the thresholds for transition periods. Then a diurnal transition is occurring if the following condition is true:

\[
(\min(\alpha_r) < d \cap \max(\alpha_l) > c) \cup (\max(\alpha_r) > c \cap \min(\alpha_l) < d).
\]

The first set in the union describes a sunrise and the second describes a sunset. A demonstration of this condition is displayed in figure B.5, which shows the diurnal pattern of rising and falling slopes of \( \max(\alpha_l) \), \( \min(\alpha_r) \), \( \max(\alpha_r) \), and \( \min(\alpha_l) \) for the February case study. The sunrise boundary begins at the frame in which \( \min(\alpha_r) < d \) on a falling slope of \( \min(\alpha_r) \) values and ends at the frame where \( \max(\alpha_l) \leq c \). The sunset boundary begins at the frame in which \( \max(\alpha_r) > c \) on a rising slope of \( \max(\alpha_r) \) values and ends at the frame where \( \min(\alpha_l) \leq d \).

To determine empirical values for \( c \) and \( d \), we sampled a total of eight sunrise and nine sunset images from multiple dates. Using ten points manually selected from each image where sunrise or sunset significantly impacted cloud radiance, we derived a total of 160 solar zenith angles. Figures B.4(a) and (b) show an example of selected points along the start of a sunrise and sunset transition, respectively.

![Fig. B.4: Examples of selected observations (red points) for a sunrise (a) and sunset (b) transition on February 20th](image-url)
Fig. B.5: This figure demonstrates the diurnal cycle of the minimum and maximum solar zenith angles for the right and left side of the tracking box over a 25 hour period starting on February 20\textsuperscript{th} at 17:00 UTC and ending on February 21\textsuperscript{th} at 18:00 UTC. The top figure shows the behavior of \( \max(a_L) \min(a_R) \), which indicate the start and stop of a sunrise transition while the bottom figure shows the behavior of \( \max(a_R) \min(a_L) \), which indicate the start and stop of a sunset transition. The vertical grey boxes indicate the time period where the transition conditions are met and thus the time periods for a sunrise or sunset event.