Deep Learning Contrail Detection

1. Contrail Detection

1.1. Introduction

Contrail detection is an essential component towards understanding the impact and mitigation of contrails. Being able to detect contrails with high accuracy is a necessary capability in order to evaluate and compare contrail predictive models, to track contrails through their lifespan and measure the amount of heat that they trap, and ultimately to verify the effectiveness of flight path diversion efforts.

Remote sensing satellites, equipped with state-of-the-art sensors, such as the Advanced Baseline Imager (ABI) on the Geostationary Operational Environmental Satellites (GOES) [1] have allowed for reliable and consistent environmental observations. Compared to Polar-orbiting Operational Environmental Satellites (POES) such as the Suomi or Sentinel satellites, GOES maintains constant observation over a fixed area with relatively higher temporal resolution but at the cost of lower spatial resolution. With 2 kilometer spatial resolution in the infrared bands, GOES imagery in not sufficient to caputure the initial formation of young contrails, but is able to capture the more mature stages of contrails if they continue to spread out. GOES's coarser resolution narrows our focus on the contrails with the largest climate impact since persistent contrails that have expanded sufficiently to be observable at 2 kilometer resolution are associated with more significant warming effects [2, 3]. Additionally, the proposed contrail predictive model will be at 3 kilometer resolution, thus reducing the utility of higher resolution contrail detection.

1.2. Related Work

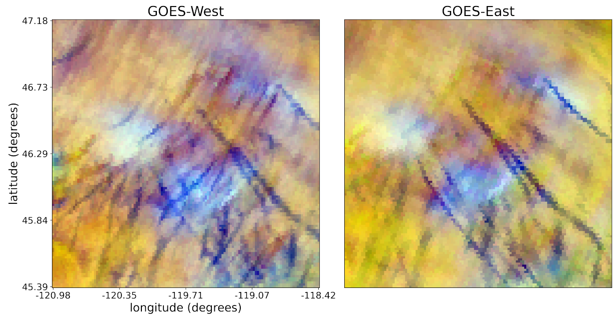
In the last 25 years, contrails have primarily been detected in POES imagery using image processing techniques such as the Mannstein et al algorithm [4] that applies a series of hand engineered convolution and thresholding operations to infrared imagery. More recently, a method for tracking the lifecycle of contrails that uses the aforementioned Mannstein et al algorithm on POES imagery for early stage detection and then uses a tracking algorithm on GOES imagery for later stage contrail evolution [5]. POES satellites are often contrained by a single pass per day over a given area of interest, limiting the ability to support contrail avoidance.

With the introduction of large human-labeled contrail datasets [6, 7], more recent studies have applied deep learning based contrail detection models [6, 8] with GOES imagery. While deep learning approaches have the potential to better support contrail avoidance preditions, there has not been a direct performance analysis between the Mannstein et al method and the deep learning models. Quantifying the effectiveness of contrail detection methods is crucial for accurate assessment of the cost and benefits of contrail predictive models. False positives of a high probability area for contrail formation would increase costs of fuel consumption for flights to take unecessary avoidance measures. False negatives, where a flight creates preventable contrail formations, would decrease the utility of implementing contrail predictive models.

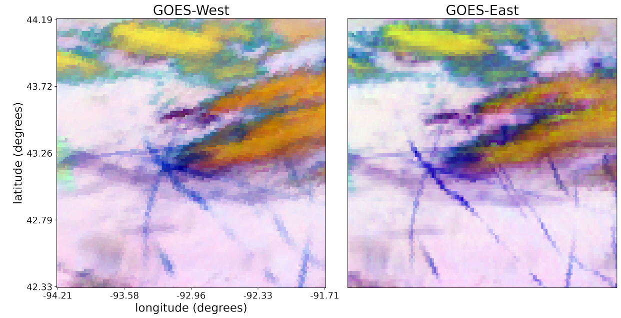
1.3. Proposed Work

1.3.1. GOES-East Deep Learning Detection Model

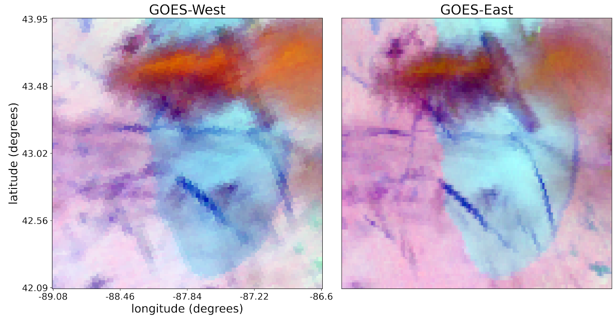
While the OpenContrail project has made their GOES-East dataset publically available, they have not shared the models they present in their paper [6]. The first step towards supporting contrail prediction models will be to train a deep learning contrail detection model using state-of-the-art



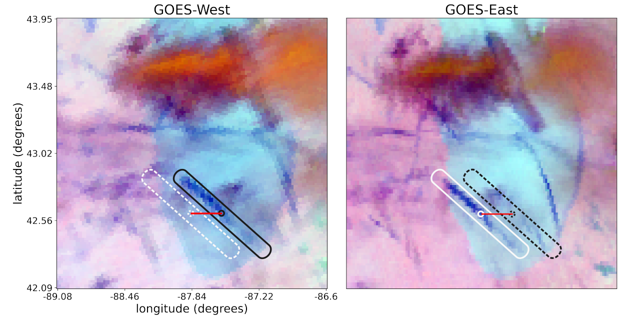
(a) GOES imagery from 2025/03/11 15:50 UTC.



(b) GOES imagery from 2025/02/28 13:30 UTC.



(c) GOES imagery from 2025/02/28 05:40 UTC with contrails over Lake Michigan to visualize the parallax difference between GOES-West and GOES-East.



(d) Same as figure 1c but with contrail labels from GOES-West (black) and GOES-East (white) with the parallax distance in red corresponding to a difference of 16 pixels or 32 km.

Figure 1. Side-by-side comparisons of GOES-West and GOES-East imagery that uses the ash composite that uses bands 11 (8.4μm), 13 (10.3μm), 14 (11.2μm) and 15 (12.3μm) to show cirrus as dark blue.

computer vision methods on the OpenContrails dataset. The input to the model will be GOES-East imagery for a given timewindow and the output will be a geospatial vector file with the geometry of detected contrails within that timewindow.

1.3.2. Analysis of Mannstein et al Algorithm

The OpenContrail dataset is human labeled, how does the Mannstein et al algorithm perform on this dataset? Given the importance of accurate contrail detection models, we propose to do a thorough analysis on how the dataset that trains the deep learning models compares to the trusted Mannstein et al algorithm. The algorithm was developed for the difference betweeen bands with a center wavelenth around 12μm and 10.8μm at 1km resolution [4]. We would need to perform minimal changes to get the algorithm compatable with bands 15 (12.3μm) and 13 (10.3μm) available on the GOES-ABI.

1.3.3.

1. A publicly available deep learning model trained on the GOES-East OpenContrail Dataset.
   1.1. OpenContrail did not release their models.
2. An analysis of the Mannstein et al algorithm on the OpenContrail dataset.
   2.1. Compare to prior deep learning studies and our GOES-East model.
   2.2. This can be used to validate the deep learning models.
3. A GOES-West specific contrail dataset derived from the OpenContrail dataset.

3.1. If we apply a parallax correction to the GOES-West satellite images, we should be able to use the same human-labeled contrails made for GOES-East.

4. A deep learning model trained on the new GOES-West contrail dataset.
   4.1. GOES-East does not cover Hawaii or Alaska.
   4.2. Preliminary plots (figure 1a) show that GOES-West can potentially show certain contrails missed by GOES-East.
   4.3. Can be used to validate the GOES-East model.
5. Altitude approximation directly from satellite imagery.
   5.1. Altitude is currently found by matching detected contrails to flight information. This is tedious and difficult to do correctly in high flight traffic areas.
   5.2. We will use cloud top temperature and parallax distance to approximate flight altitude.

References

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