Performance evaluation of deep segmentation models on Landsat-8 imagery

Akshat Bhandari Sanchit Singhal* Sriya Rallabandi* Aditya Kasliwal*
Pratinav Seth

Manipal Institute of Technology
Manipal Academy of Higher Education

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*=Equal Contribution

Introduction and Motivation

- Contrails, or vapor trails, usually form when water vapor from the exhaust of aircrafts combines with the low ambient temperatures in high-altitude regions

- These contrails increase the heat trapping effect that directly contributes to Global Warming

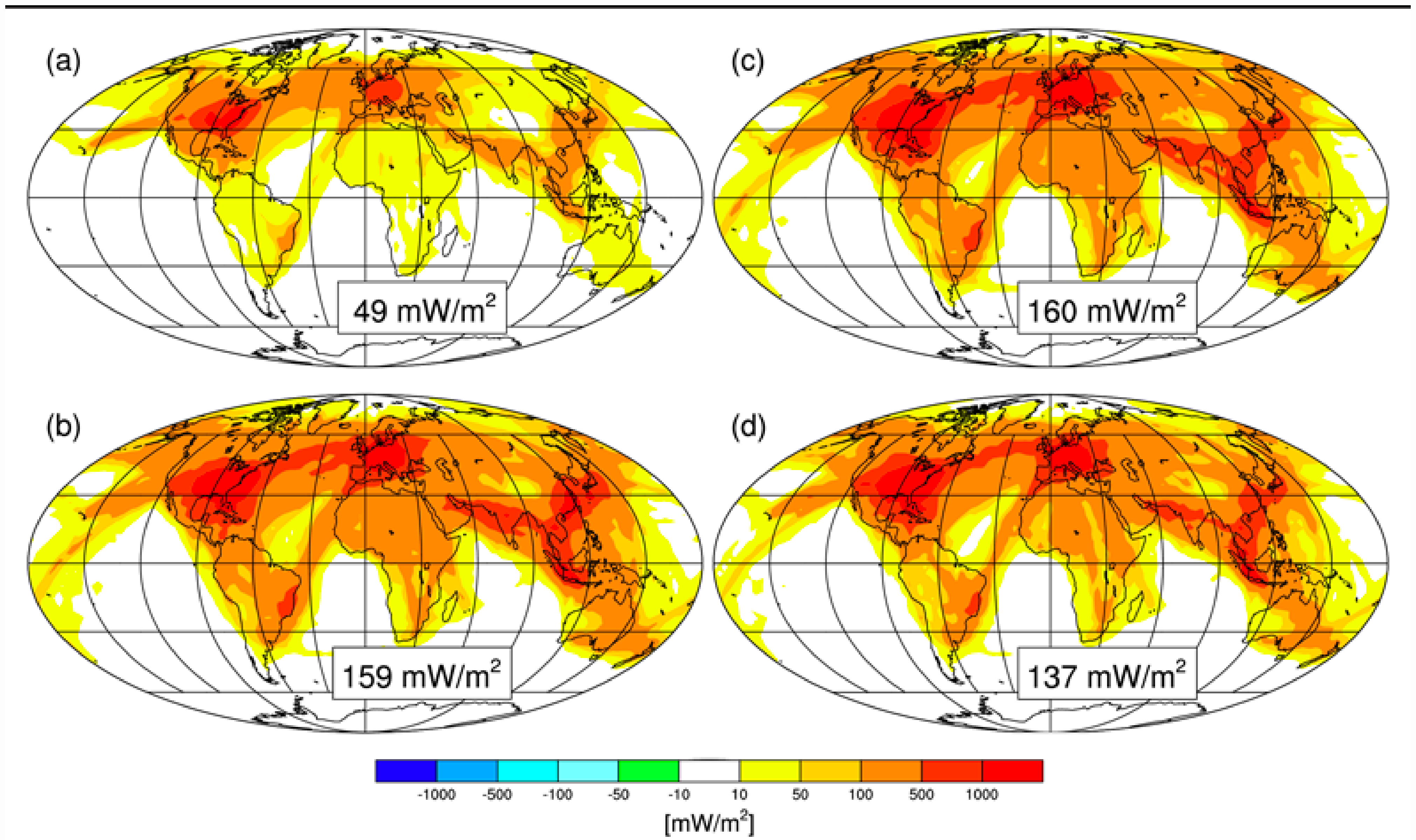
- As a result, contrails have become a new cause of alarm for climate change as they have become one of the most significant contributors to global warming caused by the aviation industry

Introduction and Motivation

- Contrails left behind by aircraft account to about 57% of the global warming caused by aviation industry
- Global radiative forcing from contrail cirrus clouds is estimated to increase threefold by 2050. This increase is primarily due to the rise in air traffic and not the different climate conditions in the future.
- Airspace with the densest air traffic, including southeast Asia, western Europe, and the eastern United States, will be the most heavily affected.

Images of Contrails left behind the Aircraft



Simulated global radiative forcing levels from contrail cirrus clouds from (a) current climate and current airplane traffic, (b) current climate and expected 2050 airplane traffic, (c) predicted 2050 climate and expected 2050 airplane traffic, and (d) predicted 2050 climate, expected 2050 airplane traffic, and improved fuel efficiency and emission standards.

Introduction and Motivation

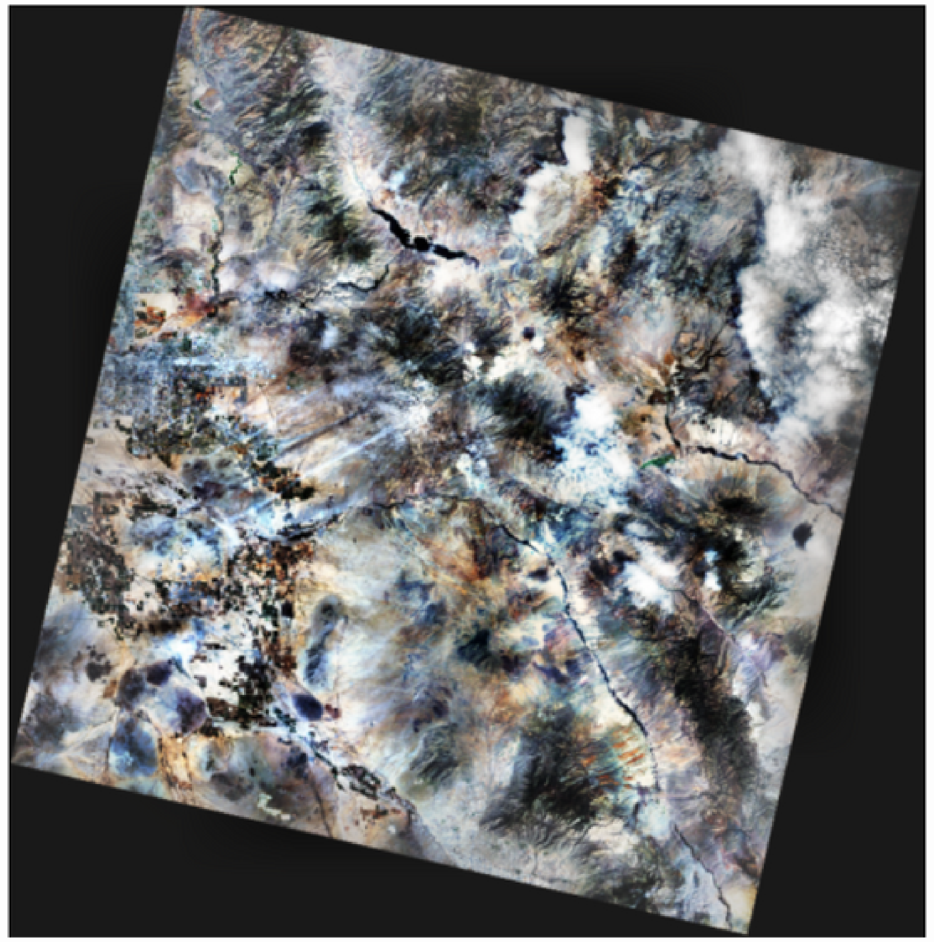
- Detection of contrails can help us adjust flight routes and to reduce the air traffic in regions of atmosphere which are cold and humid enough to create contrails
- Our work explores the potential of 'deep convolutional nets' to identify and segment contrails in satellite imagery
- For this purpose, we use popular semantic segmentation models with different combinations of loss functions and encoders to adjust it accordingly to capture the intricacies of contrails and achieve a more generalized result

Dataset-A human-labeled Landsat-8 contrails dataset.

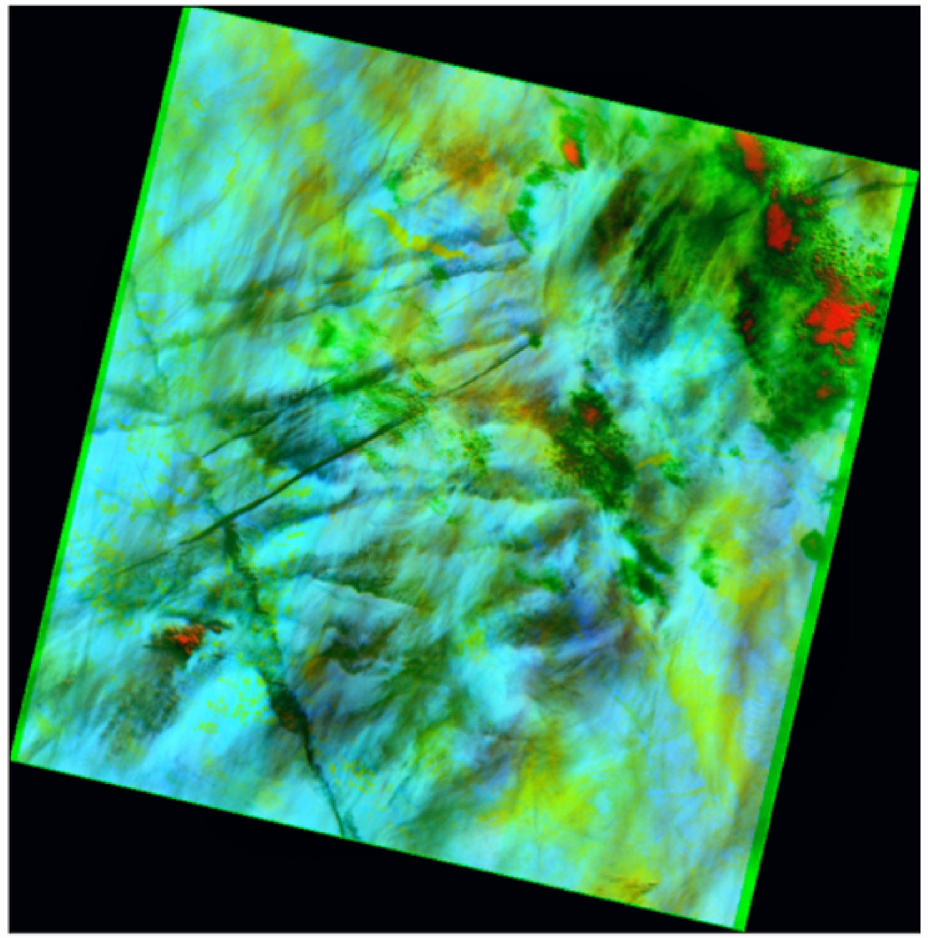
- The dataset includes Landsat-8 scenes (primarily from 2018 and inside the viewable extent of the GOES-16 satellite).
- Reviewed by human labellers taught to identify and mark the bounding polygon of each contrail in the scene.
- 4289 scenes primarily from 2018 of the Landsat-8 satellite, out of which 47% of scenes have at least one contrail.
- Each scene has a true-color RGB image, a false color image, and labeled contrail points.

False Color Images

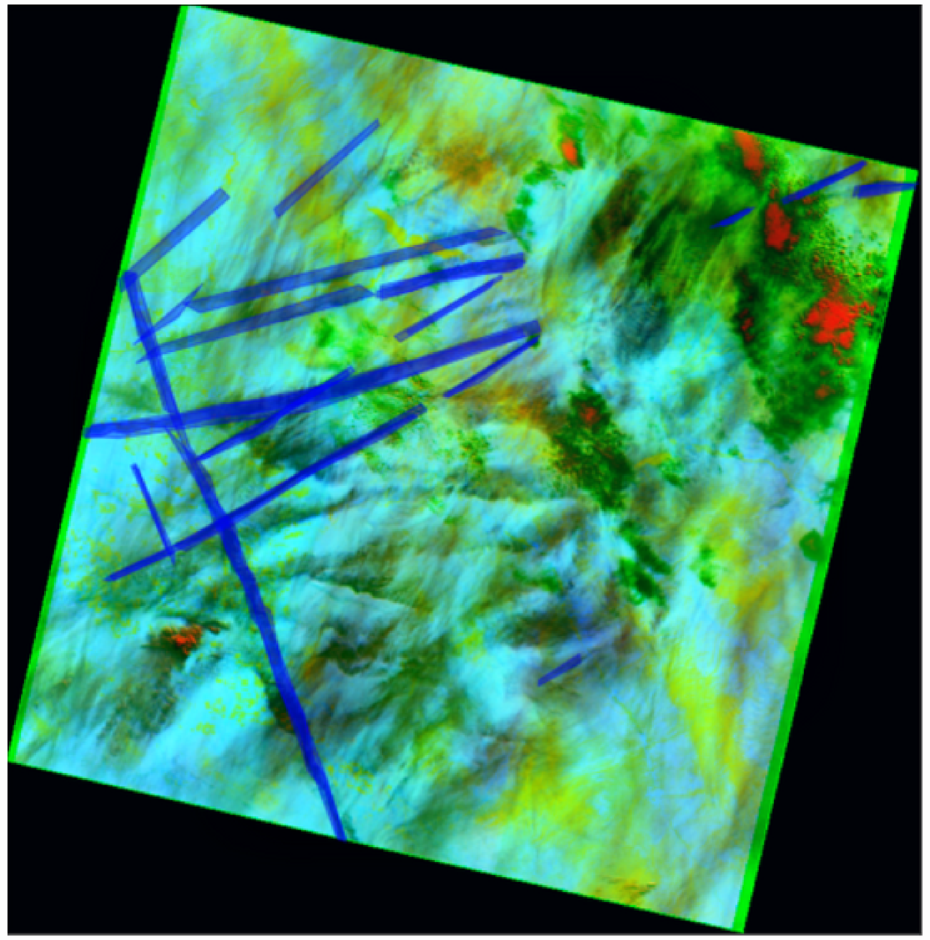
- The images are generated by extracting the following:
  - The brightness temperature difference or red channel between the 12 μm and 11 μm bands
  - The 1.37 μm cirrus cloud reflectance band, or the green channel which is omitted for nighttime images to avoid confusion
  - The 12 μm brightness temperature blue channel.
- The contrails in these images appear as black linear clouds, making it easier for the models to differentiate between cirrus clouds and contrails than RGB images for segmentation.



True-Color RGB



False Color Image



Labelled Contrails

Models and Backbones

Models- State of the Art

- U-Net: Encoder-Decoder-based standard network
- PSP Net: Pyramid pooling module-based network
- DeepLabV3: Combination of both encoder-decoder and pyramid pooling-based module
- DeepLabV3+: Combination of both encoder-decoder and pyramid pooling-based module

Backbones

- Resnet101
- ResNeXt101-32x4d
- Xception71

Pretrained weights- ImageNet

Loss Function

- Combination of Dice and Focal-Tversky loss
- Reasoning-
  - Over-suppression of the Focal-Tversky observed when the class accuracy is high, as the model is close to convergence,
  - Dice loss is very unstable as the model goes closer to converging and hence doesn’t converge well.
  - Combining the two helps combat the issue

Loss Function

$$\mathrm{TotalLoss} = \sum_c \left(\delta \left(1 - \frac{\sum_{i=1}^{N} p_{ic} g_{ic} + \epsilon}{\sum_{i=1}^{N} p_{ic} + g_{ic} + \epsilon}\right) + (1-\delta)\left(1 - \frac{\sum_{i=1}^{N} p_{ic} g_{ic} + \epsilon}{\sum_{i=1}^{N} p_{ic} g_{ic} + \alpha \sum_{i=1}^{N} p_{i\bar{c}} g_{ic} + \beta \sum_{i=1}^{N} p_{ic} g_{i\bar{c}} + \epsilon}\right)^{1/\gamma}\right)$$

N: total number of pixels in an image

g_{ic} and p_{ic} represent the per pixel ground truth and predicted probability, respectively, for contrail class c

g_{ic} and p_{ic} represent the non-contrail class $\bar{c}$

α, β, and γ are hyper-parameters for Focal-Tversky loss that can be tuned.

δ is a hyper-parameter that decides the percentage of contribution of both Focal-Tversky and Dice loss towards the final loss calculated

δ = 0.5

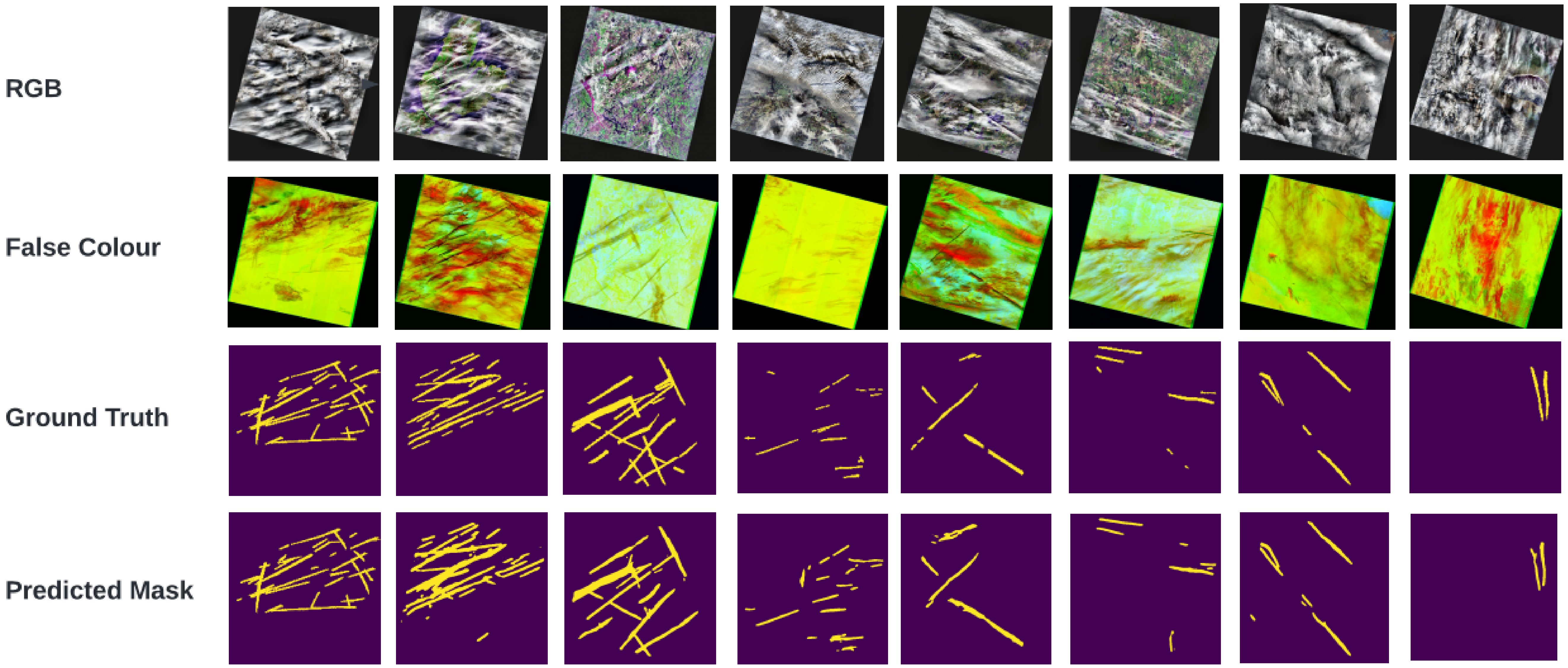
Results

Table 1: IoU scores of segmentation models with different backbones

		UNet	PSP Net	DeepLabV3	DeepLabV3+
ResNet 101	Training	0.6479	0.5032	0.4714	0.7048
	Test	0.3410	0.3788	0.4143	0.4015
ResNext 101-32x4d	Training	0.5411	0.6500	0.7211	0.6657
	Test	0.4224	**0.4044**	**0.4339**	**0.4266**
Xception 71	Training	0.6887	0.7272	0.7730	0.6290
	Test	**0.4395**	0.4027	0.4246	0.4230

Segmentation Examples

Figure 1: Comparison of RGB, false colour, ground truth, and predicted mask for test images



Limitations of the Dataset

- Even though the IoU was low, the model produced satisfactory contrail masks. We attribute this to the fact that the fundamental shape of the labels are thin and long hence the IoU calculation is affected drastically even if the prediction is a few pixels off.
- The dataset has several noisy labels because of manual labelling, due to which it suffers from large intra and inter-observer variability.
- Furthermore, numerous contrail labels in the dataset are broader than the corresponding visible contrail in the original image.

Limitations of the Dataset

- Severe class imbalance in the dataset was also a significant issue that limited the model’s ability.
- We have made use of Dice and Focal-Tversky to create our loss function as these are well known for dealing with class imbalance issue.
- We also chose to consider images with at least one contrail for training

Conclusion

- First to present a detailed work on Landsat-8 data and evaluation on benchmarking of different state-of-the-art models for semantic segmentation for contrail detection in low-orbit satellite imagery. (To the best of our knowledge)
- Achieved 0.4395 testing IoU using UNet architecture with Xception 71 backbone

Future Work

- Experiment with temperature-based color preprocessing
- Calculate uncertainty estimates under varying domains of satellite imagery to test the model's robustness
- Evaluate the model using a more suitable metric instead of IoU
- Contextual information incorporated based on publicly available datasets
- Using self-supervised and pseudo-labelling training techniques, attention-based models, and introduction of discriminator and vision transformers.

Contact Us!

Akshat Bhandari

akshatbhandari15@gmail.com

Sanchit Singhal

sanchitsinghal57@gmail.com

Sriya Rallabandi

sriyarallabandi@gmail.com

Aditya Kasliwal

kasliwaladitya17@gmail.com

Pratinav Seth

seth.pratinav@gmail.com

Github Link: https://github.com/Kasliwal17/Contrail_Segmentation