Pixel Based Model For High Latitude Dust Detection

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1. Introduction

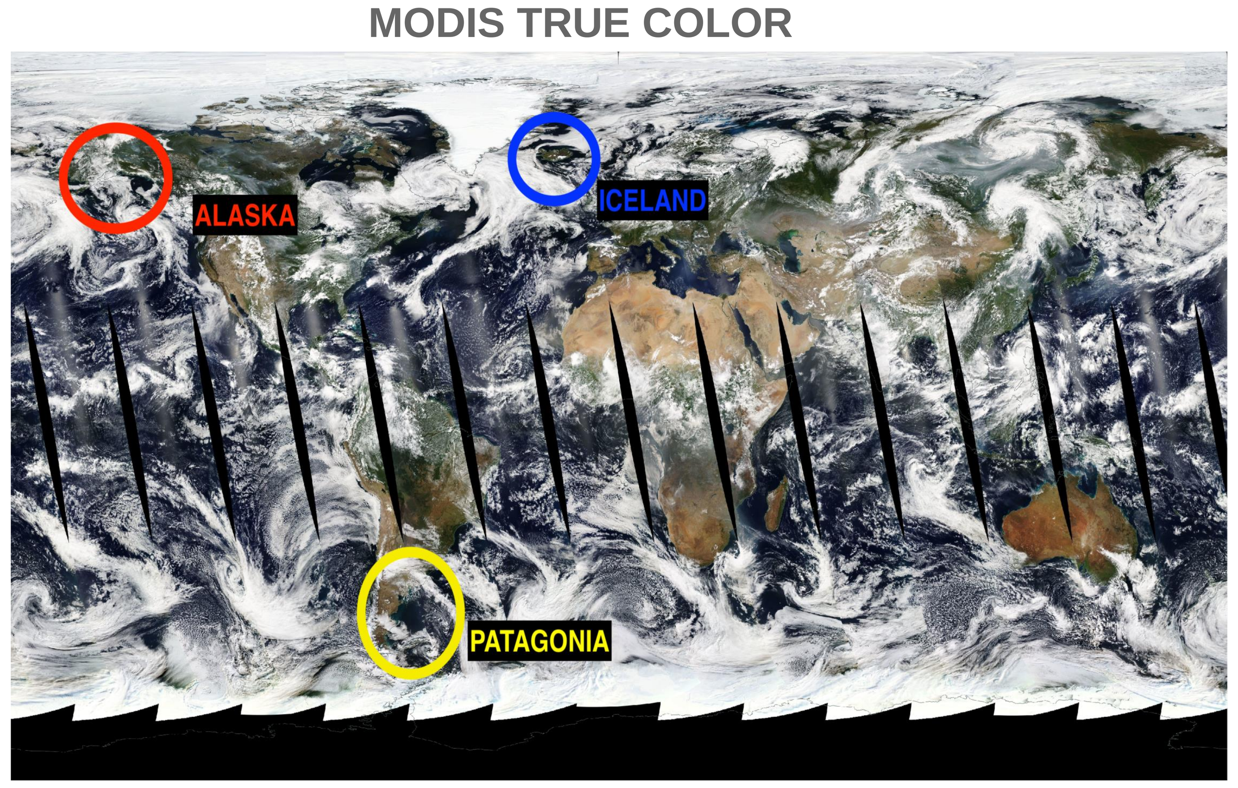
High Latitude Dust (HLD, $\geq 50°N$ and $\geq 40°S$) load has implications on the energy budget, ocean biodiversity and economy on a regional and global scale [1]. Current methods of dust detection rely on spectral sensitivity at visible (RGB) and infrared wavelengths. The characteristics of HLD vary according to the sediments and sedimentary processes operating on the land surface that are the source of the dust particles [2]. Leveraging machine learning (ML) methods, we propose a new detection method based on convolutional neural network (CNN) using true color images.

2. Data Analysis

Previous research indicates that a combination of visible and infrared wavelengths has the highest performance in dust detection. The **MODIS** instrument, onboard Aqua and Terra satellites, provides high spectral (within 0.4μm to 14.4μm) and varying spatial resolution (250m, 500m, 1km), in a sun-synchronous orbit around the Earth. **True color images** over Alaska, Iceland and Patagonia (**A**) are obtained by a NASA web-based analysis tool, the Image Labeler (https://earthdata.nasa.gov/esds/impact) which incorporates Worldview and Global Imagery Browse Services (GIBS) and extracts analyzed event imagery.

A

MODIS TRUE COLOR



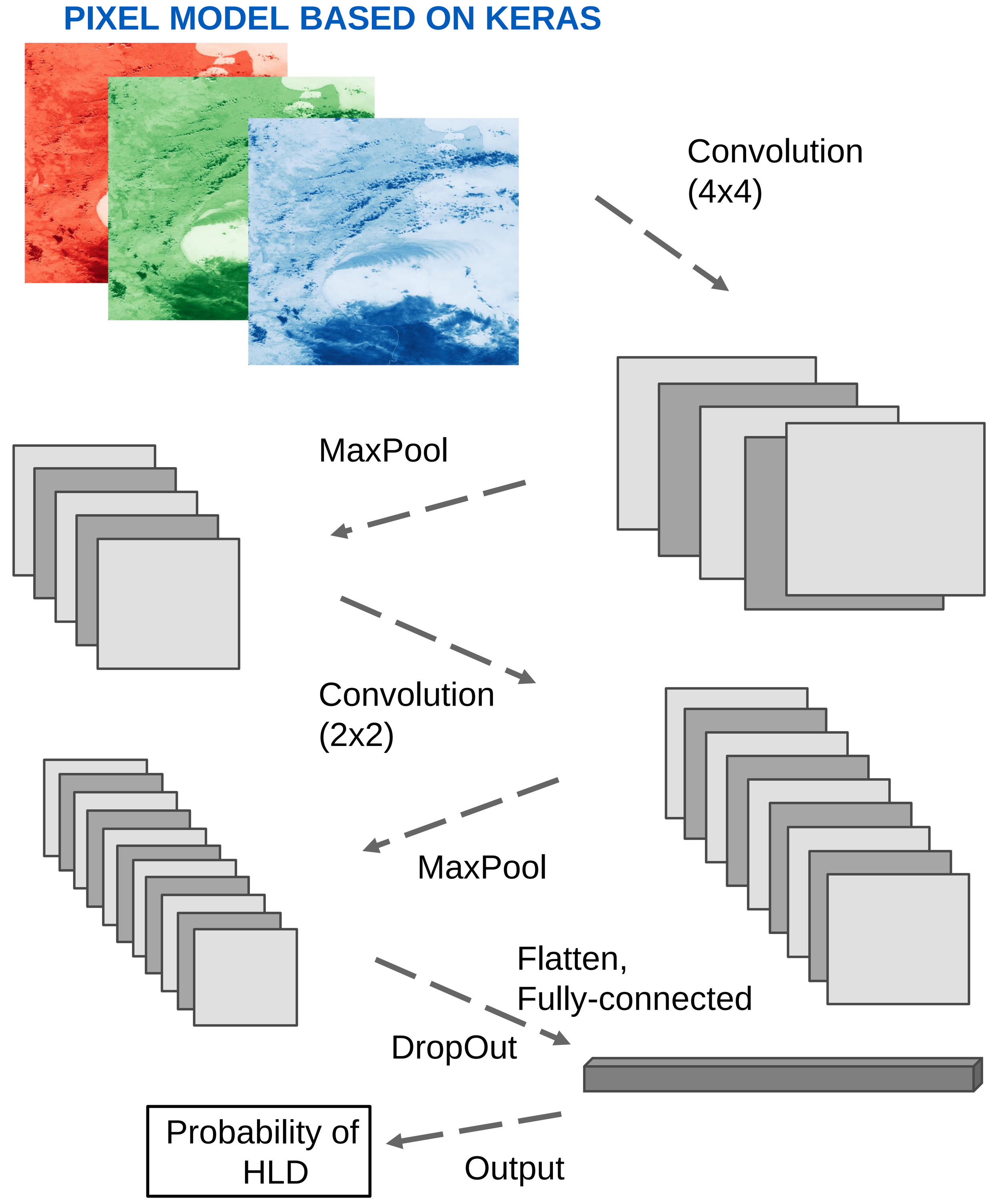
For more information, see the e-lightning (image labeler) talk at session ID:82541 in 551788.

3. Methods

PRE-PROCESSING

- 163 tiles are explored for the presence of dust events and polygons are manually drawn along the perimeter of the dust plume via the image labeler web-based application.
- Pixels for true and false events are obtained for training (46.85 million pixels) and validation (18.51 million pixels).

PIXEL MODEL BASED ON KERAS



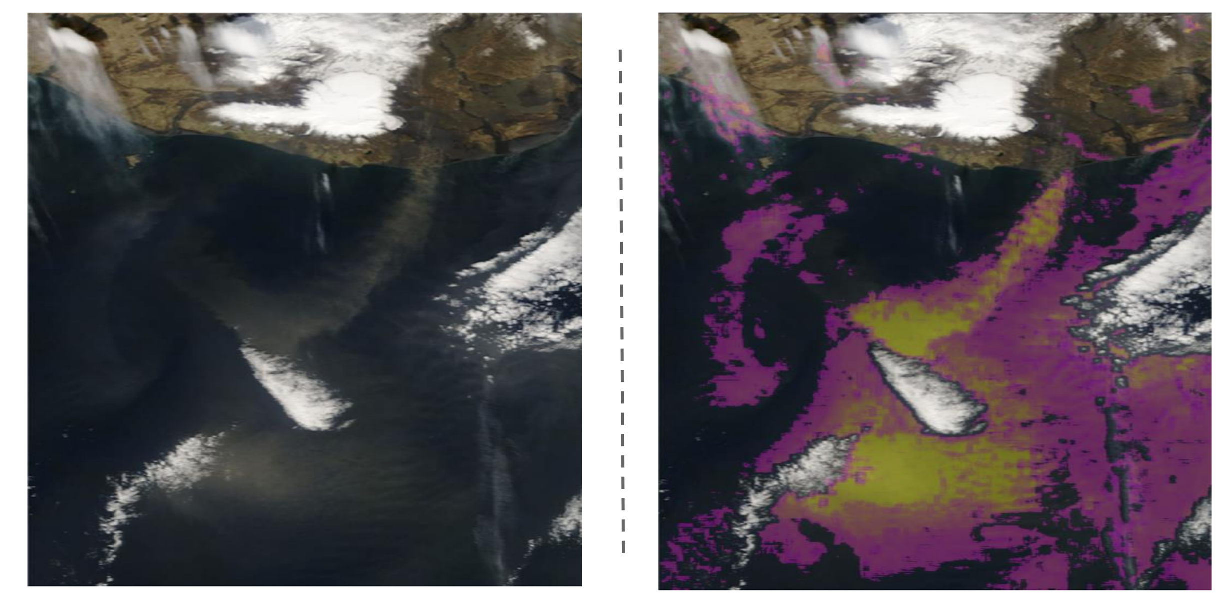
4. Results

I. Performance Metrics

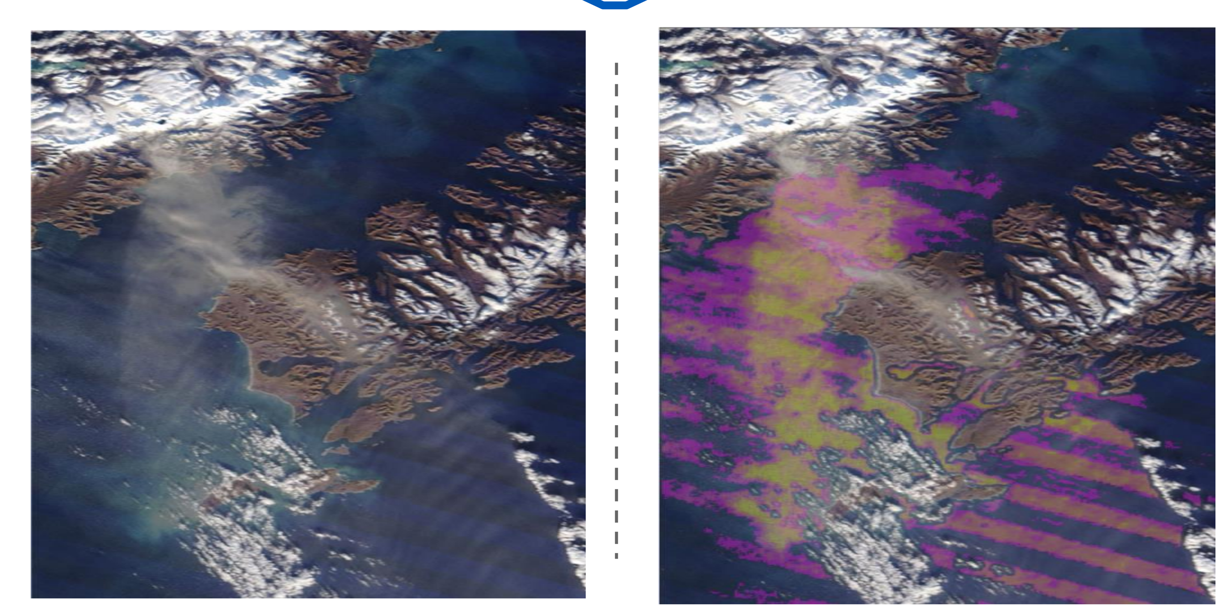
Accuracy	0.86
Precision	0.77
F1_score	0.70
Recall	0.65

II. Visualizations

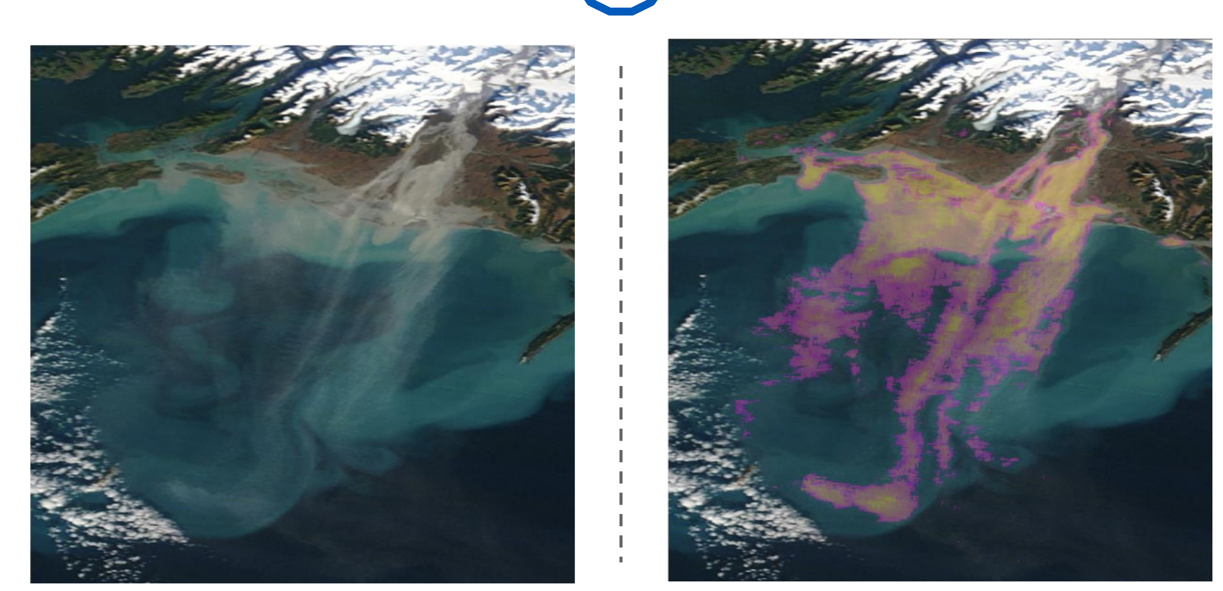
B



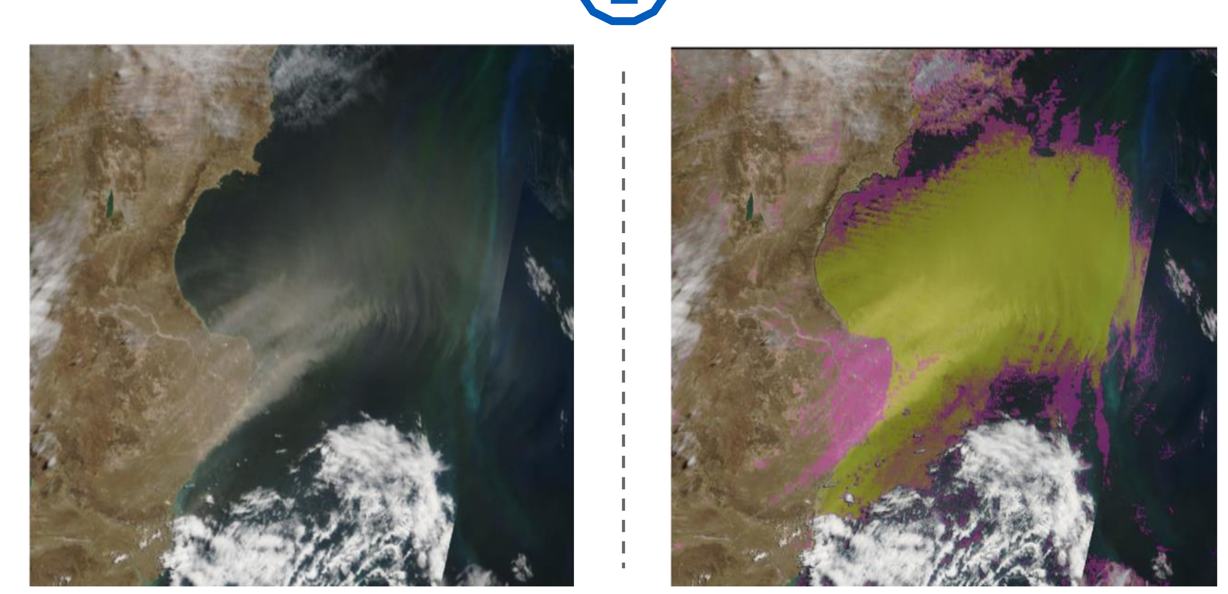
C



D



E



III. Summary

Strengths	Weaknesses
Detection of dust over the ocean (**B**)	Sedimentation near the coast leads to false detection (**D**)
Ability to distinguish between clouds and dust (**B**)	Over land, detection efficiency decreases (**E**)
The detection efficiency doesn't degrade over different areas	MODIS scanning effects enhances false detection (**C**)

5. Discussion

The detection of HLD events can be facilitated by leveraging deep learning techniques. The pixel based model has the following characteristics:

- Training data are obtained from different regions where HLD occurs to account for varying properties of the background scenes.
- CNN pixel classifier is consistent with other automated techniques for the detection of dust events.
  - False cases due to scan effects and sedimentation might reduce the robustness of the model.
  - Threshold method from Zhao et al. (2010) has a recall of 0.54.
- 86% of the validation data were correctly classified as dust/no-dust pixels.

References

1. Middleton, N. (2017), Desert dust hazards: A global review. Aeolian research, 24, 53–63.
2. Bullard, J.E., . . . others (2016), High-latitude dust in the earth system. Reviews of Geophysics, 54(2), 447–485.
3. Zhao et al. (2010), Dust and smoke detection for multi-channel imagers. Remote Sensing, 2, 2347-2368.

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