Physically-Based Machine Learning Approach to Dust Detection in NASA/NOAA Geostationary Satellite Imagery

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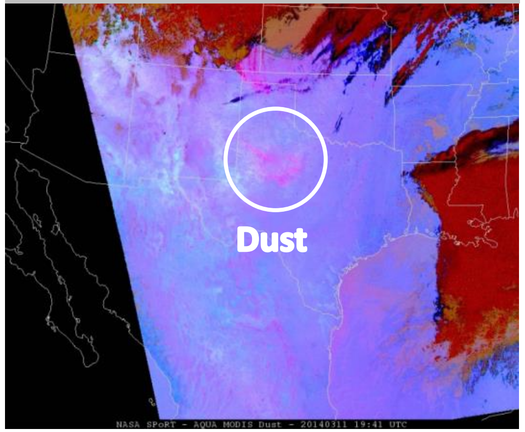
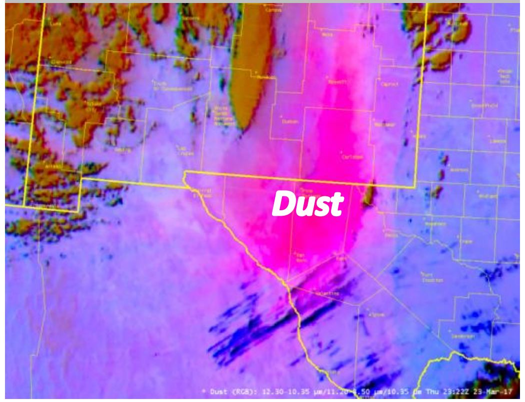
Motivation

Since 2013 NASA SPoRT refined and experimentally transitioned multispectral composites to NOAA NWS partners

NASA AQUA MODIS Dust RGB



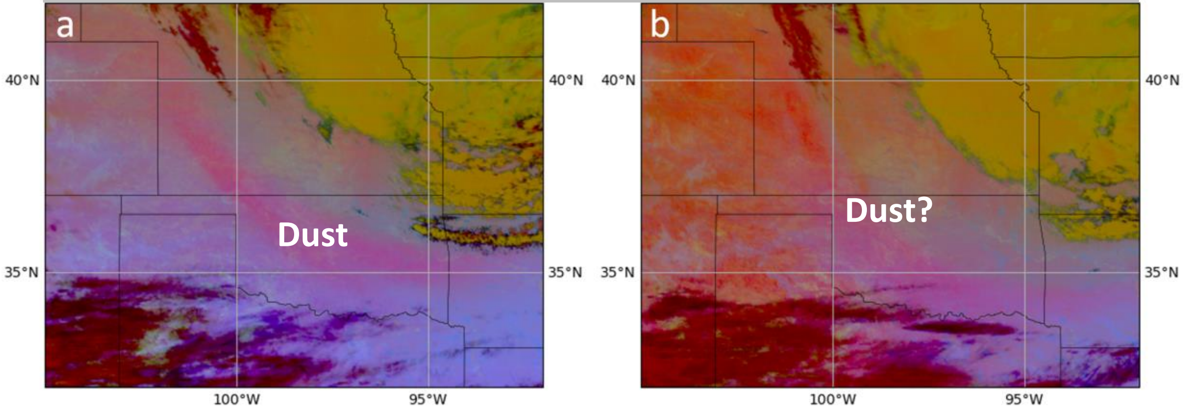
NASA/NOAA GOES-16 ABI Dust RGB



Airborne dust has broad adverse effects

Night-time dust detection at night is limited as the ground surface cools, making it difficult to distinguish dust from the surface

NASA/NOAA GOES-16 ABI
Dust RGB 7 March 2017 (a) 0002 UTC (b) 0102 UTC



This study applies machine learning to the problem of night-time dust detection with a physically-based simple random forest model using NASA/NOAA Geostationary Operational Environmental Satellite-16 (GOES-16) Advanced Baseline Imager (ABI) infrared imagery as inputs to the model.

[More information at Berndt et al. 2021]

[NASA ESDS Article "Dust in the Machine"]

Methodology

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Initial Development of a Day-time Dust Machine Learning Model

- Collect training dataset
- Train/test classification models (e.g., Random Forest, Logistic Regression, Naïve Bayes)
- Evaluate model output (*Berndt et al. 2019*)

Focus on refining the training for Night-time dust detection

- Collect night-time training dataset
- Classify false surface and smoke detections

Evaluate Training, Model Inputs, and Performance

- Loss functions/Jaccard score
- Confusion matrix
- Individual conditional exception plots
- Partial dependance plots
- Dendrogram / Spearman rank correlation
- Permutation Importance
- ROC/AUC

Revisit Day-time Dust Model development and validation

- Collect training and other regions
- Consider additional satellite datasets that would add value

Forecaster Evaluation

- Compile case study
- Develop a feedback survey
- Summarize feedback
- *Is the model output useful?*

Training Dataset

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- GOES-16 ABI imagery for events in the southwest U.S. from Jan 2018-Jun 2020
- 28 cases, 83 distinct images a total of 790,921 dust pixels and 37,698,467 null pixels
- Cases randomly split into training (60%), testing (20%), and validation (20%)

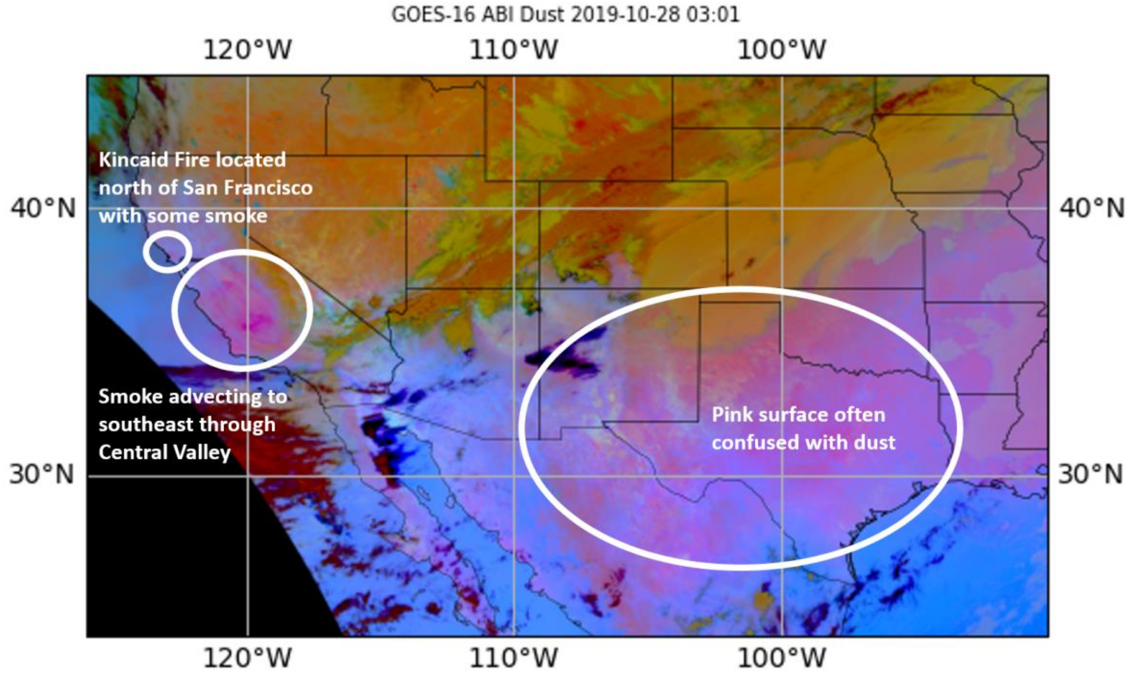
Training Variable	Physical Importance
7.3 µm	dust typically associated with a dry low-level environment
10.35 µm and 11.2 µm	provide estimates of temperature for the pixel
12.3 µm	used within the split window technique to identify optically thick clouds or dust
13.3 µm	despite CO_2 and water vapor absorption, can give an idea of the mean tropospheric temperature.
12.3-10.35 µm Difference	dust absorbs more of the 10.35 µm radiation, yielding a positive temperature difference
11.2-8.4 µm Difference	in thick dust, the particles absorb the radiation in both wavelengths equally, resulting in small differences
RGB Image Red Color Intensity	cloud optical depth/thickness to distinguish thick cloud or dust
RGB Image Green Color Intensity	cloud particle phase to distinguish water particles/thin cirrus from dust
RGB Image Blue Color Intensity	identification of warm surface or cloud top temperatures

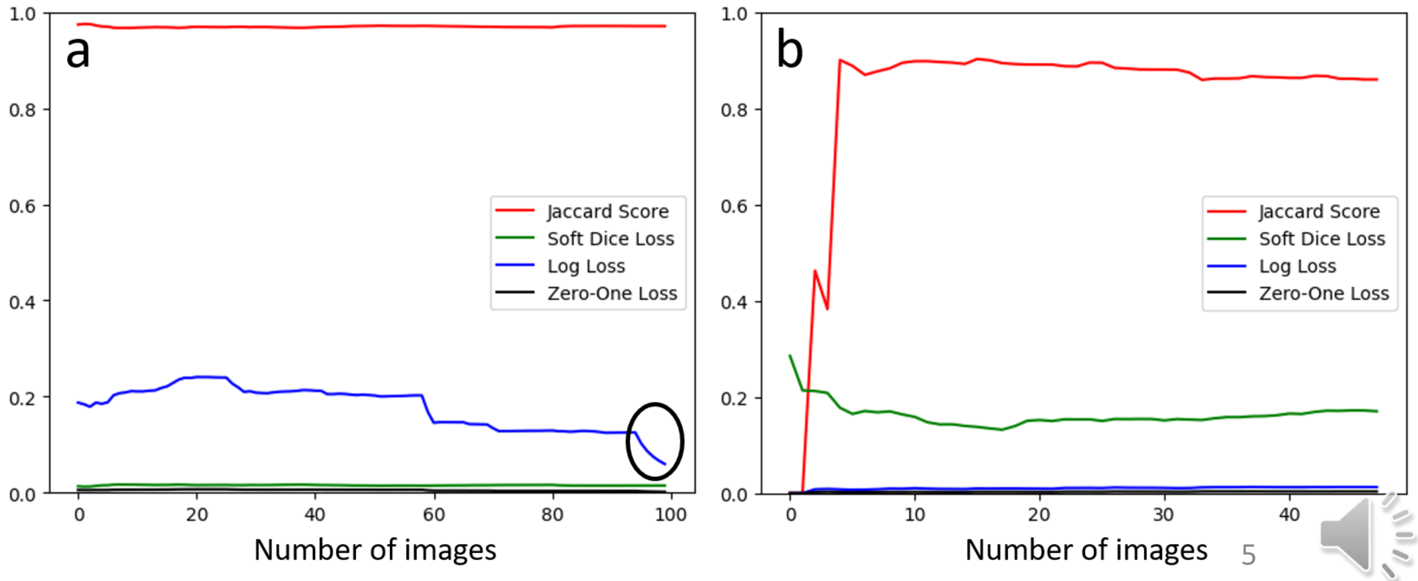
Random Forest Model

- Hyperparameters chosen based on loss functions and Jaccard Score to prevent over- or under-fitting

- Null cases important for diversifying training and reducing the log-loss

- Confusion matrices used to assess model performance on the training dataset
    - For images with dust present, the model correctly labels 85% of dust pixels and 99.96% of no-dust pixels.
    - Type 2 error (labeling dust as no dust) is reduced by 30.5% by expanding the training dataset to include a wider range of cases and null events.





Assessing Model Inputs

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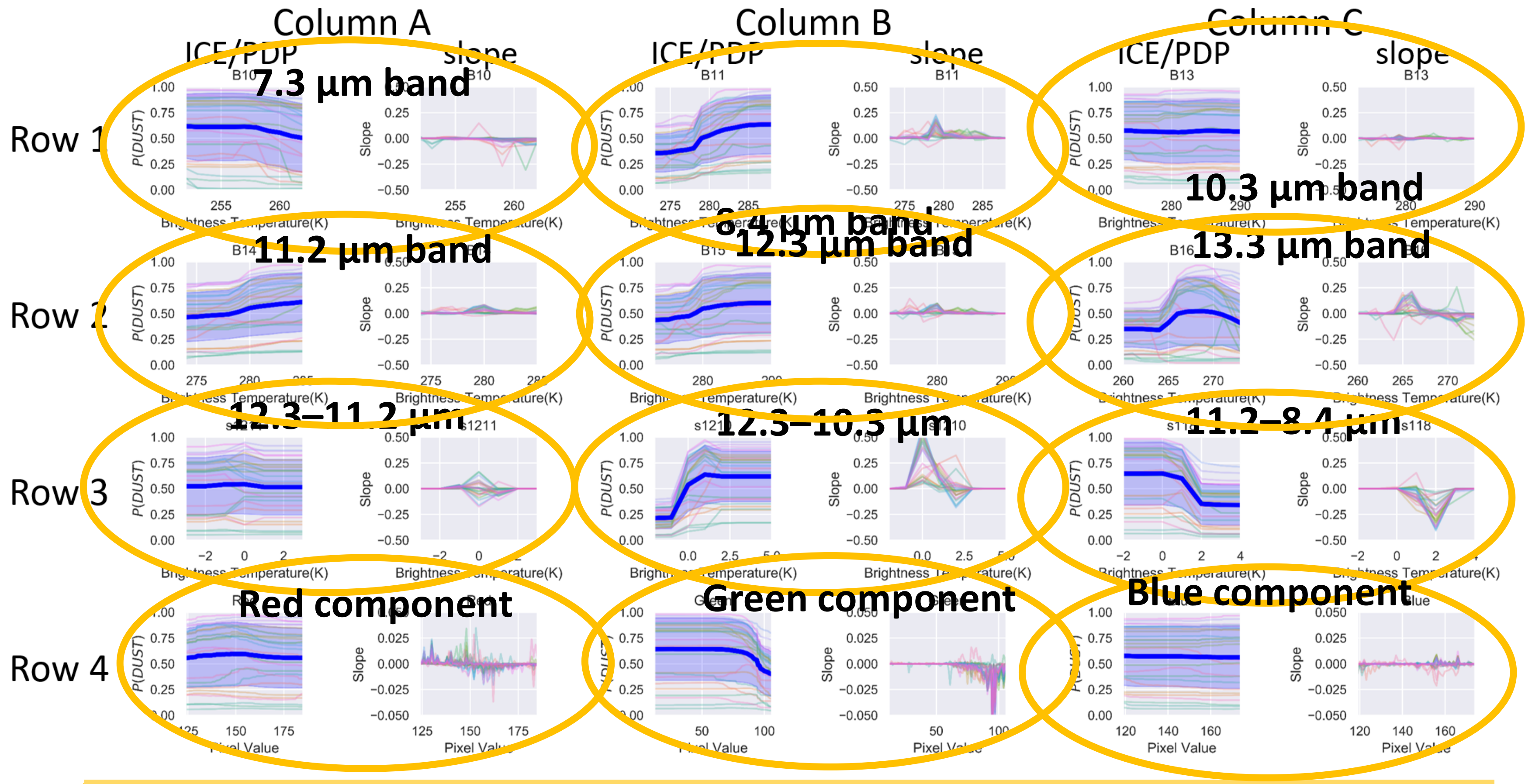
- Partial dependence plots assist in identifying which model inputs are utilized the most by the model in the classification process
- Individual conditional exception plots are a mechanism to determine the influence on the model input on the RF classification process
- Initial evaluation indicates the inputs align with physically based satellite interpretation and remote sensing principles.



The blue component of the RGB is constructed from the 10.3 µm band but stretched over a brightness temperature range ideal for the identification of dust. The greater changes in slope of the blue RGB component compared to the 10.3 µm band physically relates to the deliberate processing of the RGB component to identify dust.

Permutation Importance

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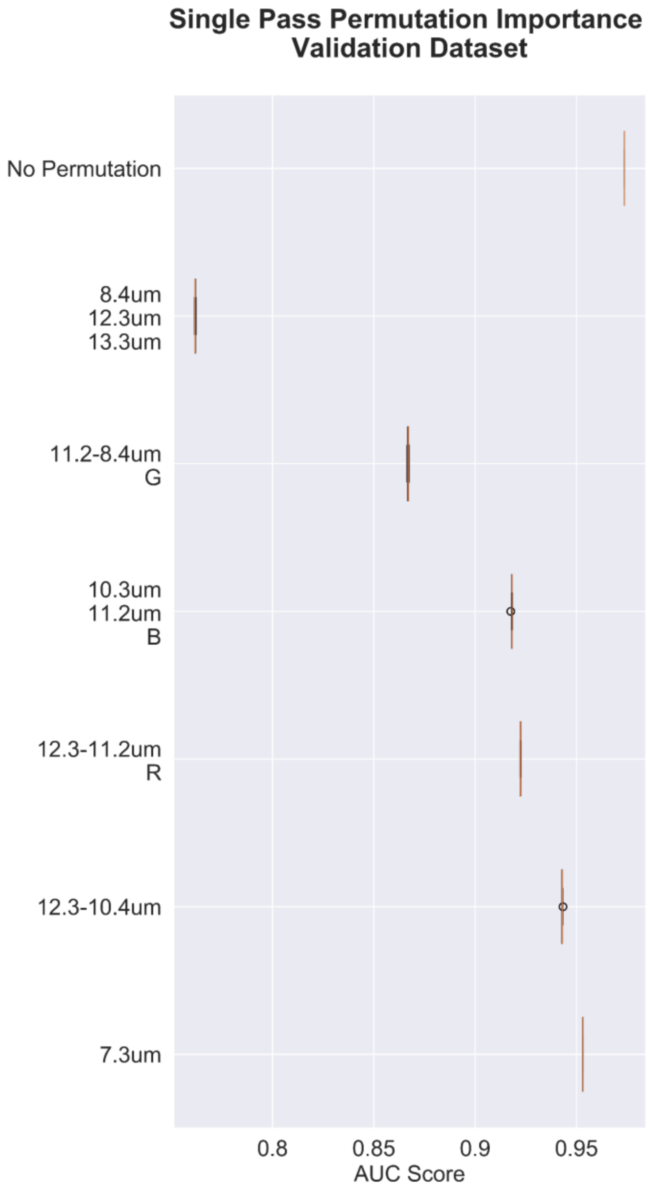
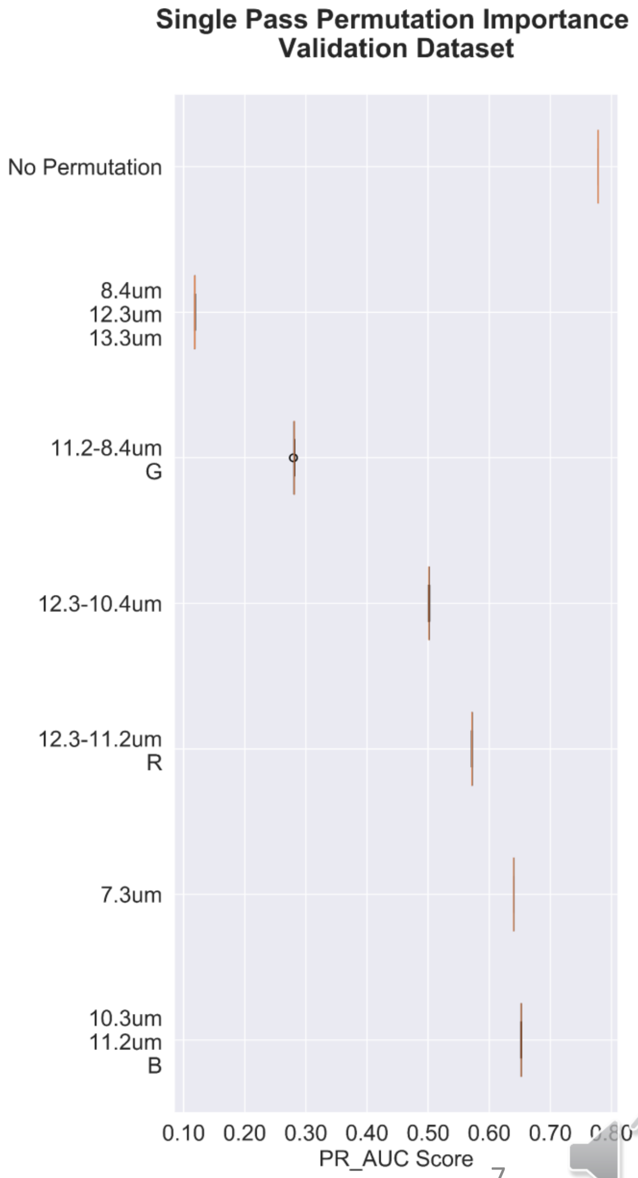
- Spearman correlation and a dendrogram were used to assess groupings of satellite bands and their importance.
- The groupings of correlated inputs were used to assess permutation importance based on the validation data.
- Permutation importance suggests which groups have the greatest impact on the RF model classification.
- The 8.4/12.3/13.3 µm bands ranked as the most important followed by the 11.2–8.4 µm difference and Green component of the Dust RGB.
- These results reflect some of the bands used in the Dust RGB recipe and are the same bands and differences known to be most sensitive to dust

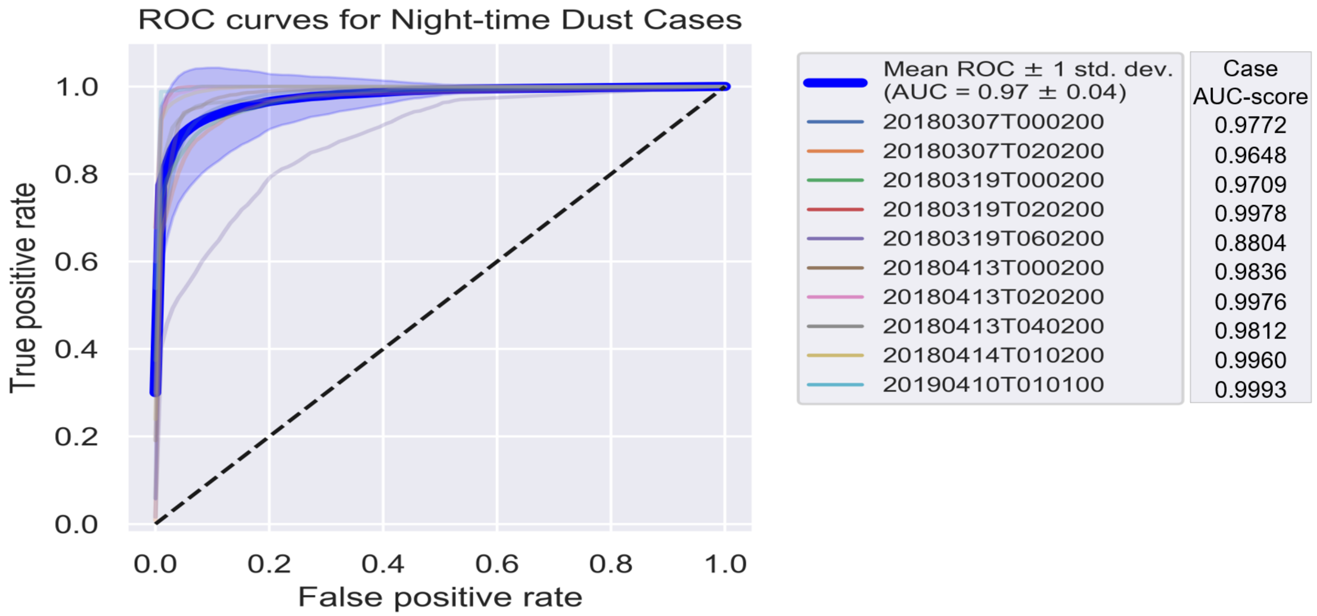




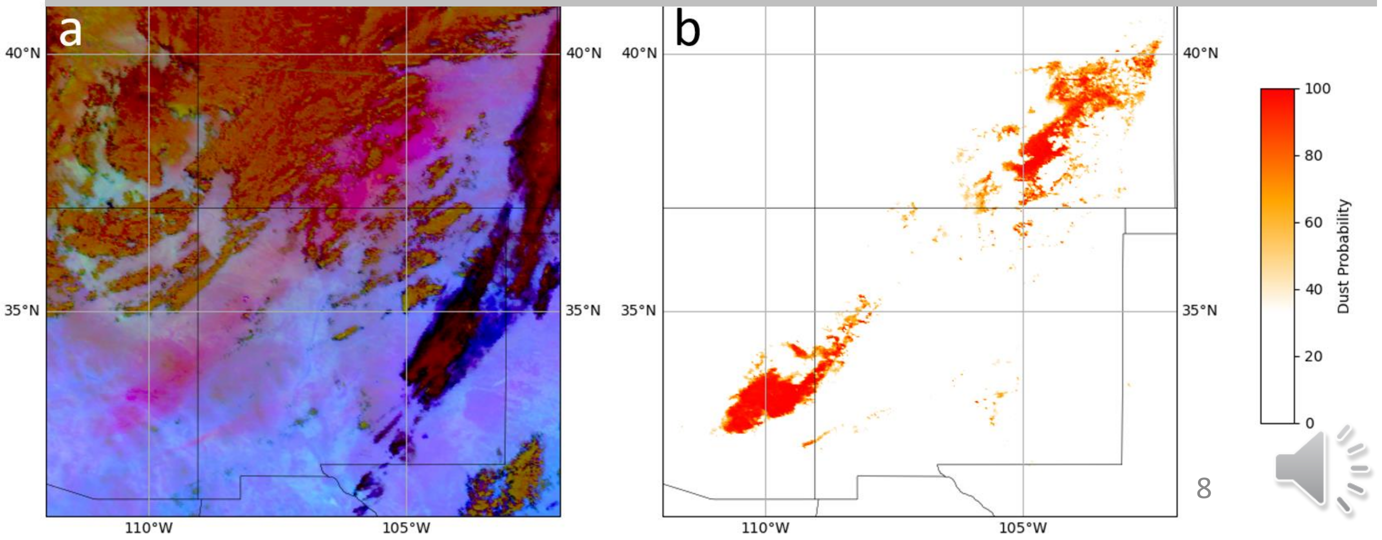
Results – Dust Events

- Model performed well on dust cases in the validation data set
  - Mean Area Under the Curve 0.97 with a standard deviation of 0.4
  - All but 1 case falls within 1 standard deviation

- 13 April 2018 case clear-cut for the model to identify dust and output confirms features in the Dust RGB imagery



(a) NASA/NOAA GOES-16 ABI Dust RGB 13 April 2019 and (b) random forest model dust probabilities



Results – Weak Dust Event

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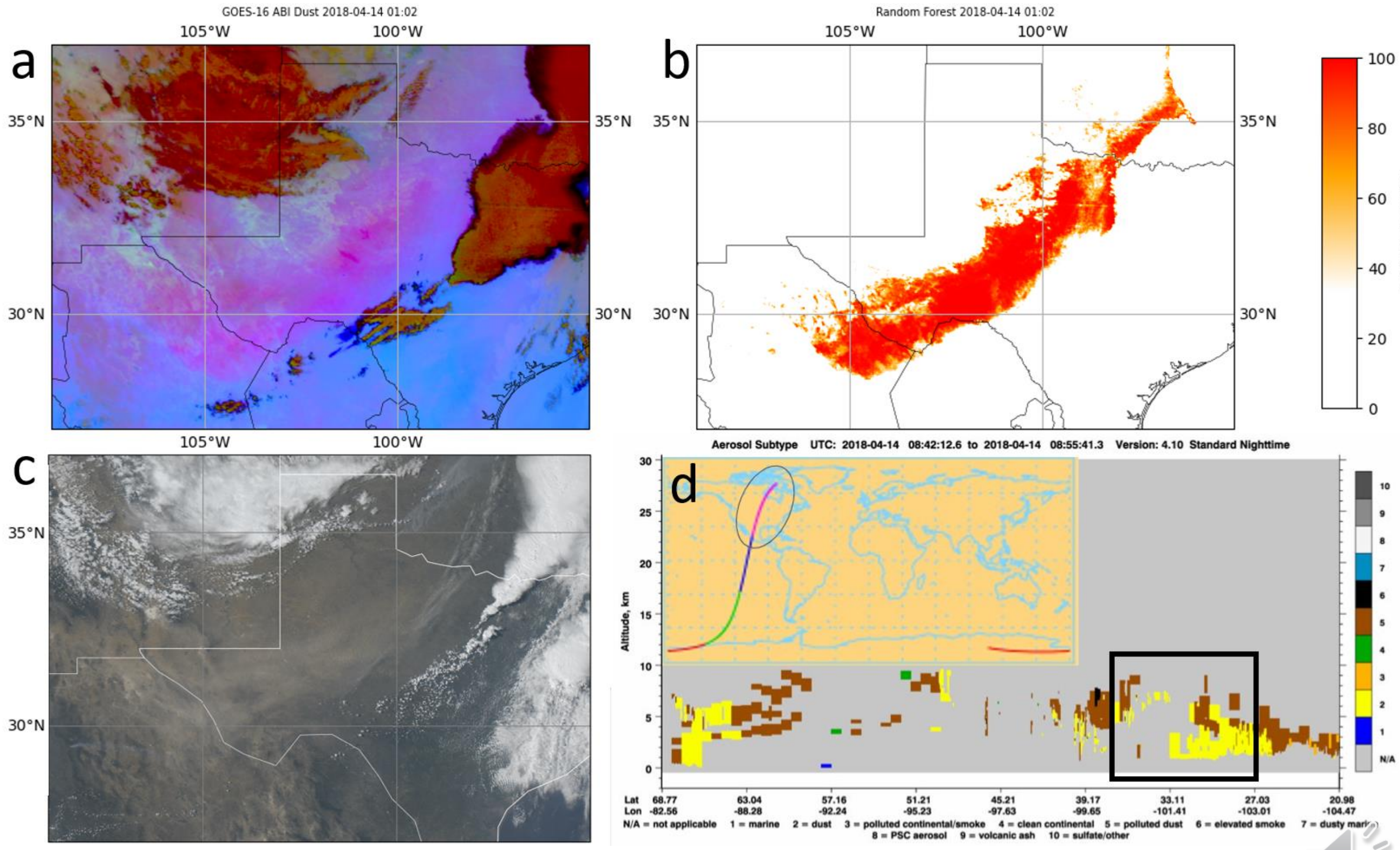
- 14 April 2018 weak dust case
  - Dust or false signature?
  - If dust what is the spatial extent?
- Dust model probabilities
  - Increase confidence dust is present
  - Clear delineation of the dust boundary
- Dust random forest model provides value in the transition from day to night when dust is difficult to visually identify in imagery

14 April 14 2018 0102 UTC (a) Dust Red-Green-Blue (RGB) and (b) Random Forest model output probabilities. (c) 2102 UTC April 13, 2018 True Color RGB and (d) 0842 UTC April 14, 2018 Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation aerosol classification cross-section (area corresponding to a–c is outlined in black) and overpass (section corresponding to the cross-section is colored in magenta and circled in black).



Stakeholder Feedback

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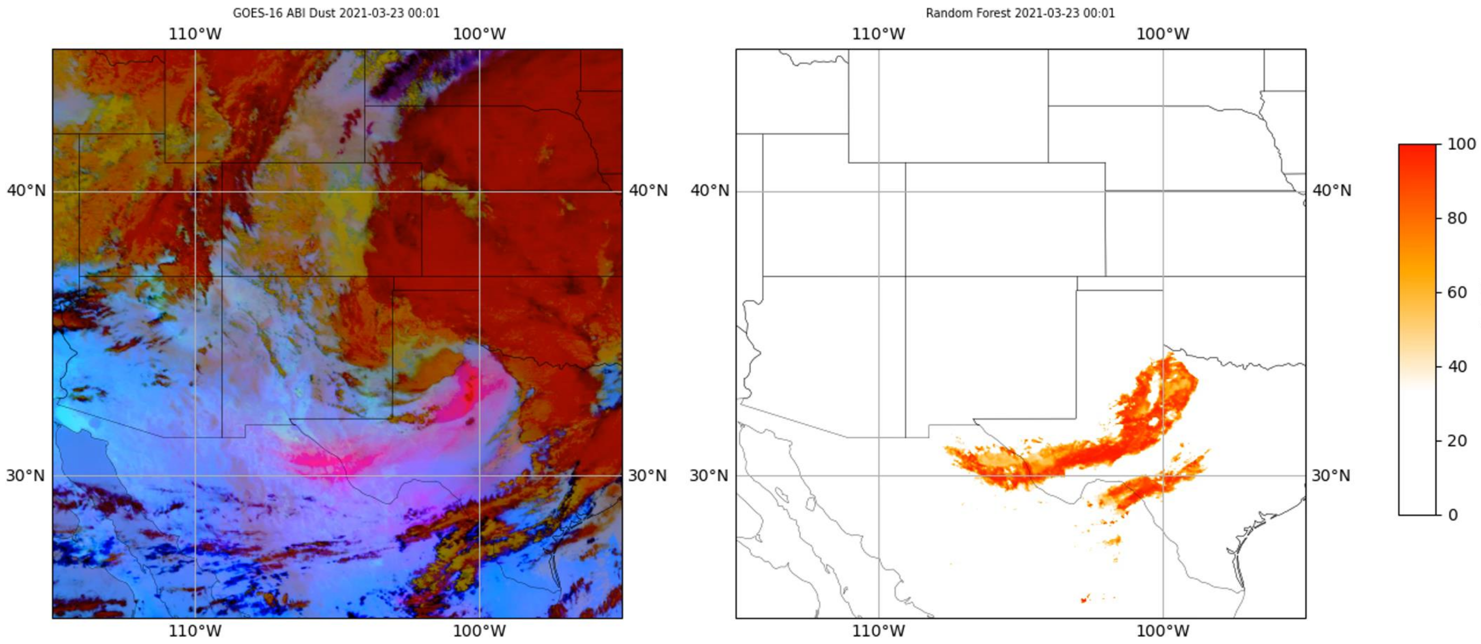
- 83% of the forecasters indicated the ML dust probabilities had a High/Very High impact on their confidence to identify the dust plume compared to satellite imagery alone

- All respondents indicated an improvement in the ability to track the dust longer into the night and 66% of respondents agreed identification of dust features improved

- Minor false alarm signatures in the ML dust probabilities were not an issue but an improvement beyond the typical false alarms in the Dust RGB at night

Dust on 23 March 2021 0000-0930 UTC evaluated by NWS forecasters to obtain operations to research feedback on the operational utility of ML-derived dust probabilities (Left) Dust RGB imagery and (Right) random forest model output probabilities.



Impact: NWS forecaster feedback indicated ML dust probabilities would be valuable for (1) complementing analysis with satellite imagery, (2) improving confidence in the location and extent of dust, with plume boundaries clearly distinguished, and (3) increasing the ability to track dust longer into the night

Summary

- Remote sensing principles were applied to develop a physically based machine learning approach for objective identification of dust to improve nighttime dust detection in NASA/NOAA GOES-16 satellite imagery.
- Validation of the model using statistical methods confirms the random forest classification is strongly based on the GOES-16 satellite inputs used in conventional dust detection and known to be most sensitive to airborne dust.
- For images with dust present, the model correctly labels 85% of dust pixels and 99.96% of no-dust pixels.
- Application of the machine learning model to a dust event on 13-14 April 2018 enhances identification of the dust plume during the nighttime hours, providing better discernment of the plume boundaries with minimal false detection.
- Preliminary NWS forecast feedback indicated machine learning dust probabilities would be valuable for (1) complementing analysis with satellite imagery, (2) improving confidence in the location and extent of dust, with plume boundaries clearly distinguished, and (3) increasing the ability to track dust longer into the night

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