Machine-Learning Image Classification and Hazard Identification of Dust and Fog in Next-Generation Geostationary Satellite Imagery

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Introduction

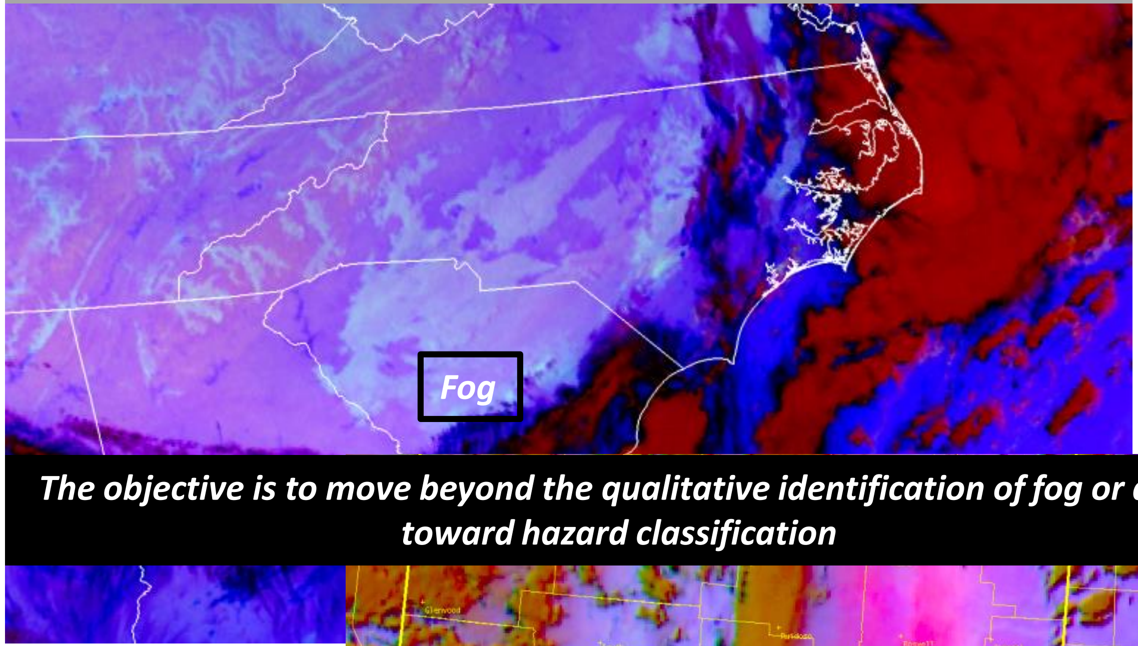
- NASA Short-term Prediction Research and Transition (SPoRT) has a long history of research, training, and applications related to multispectral (RGB) imagery derived from polar and geostationary imagers (Berndt et al. 2017)

- Many of the RGBs demonstrated in the JPSS/GOES-R Proving Ground have been transitioned to operations in the GOES-R era.

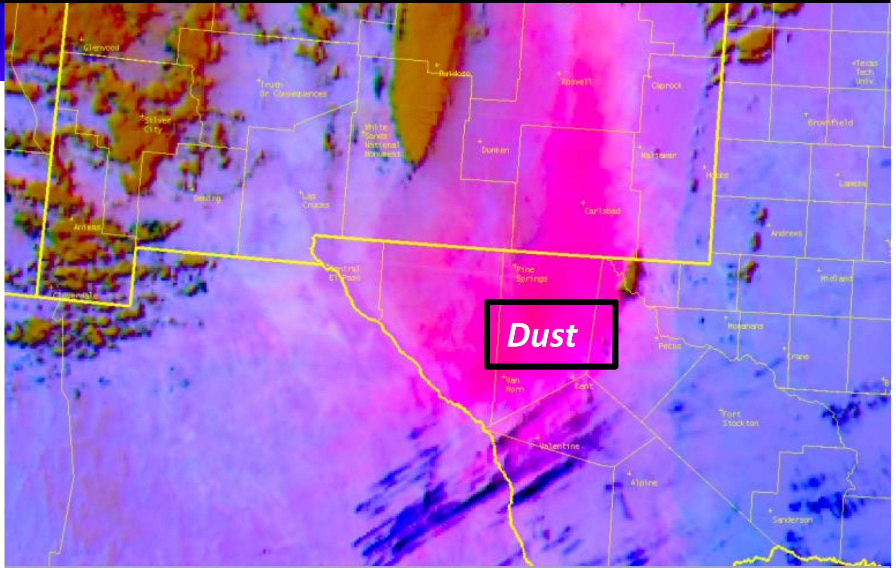
- SPoRT has documented impacts on the warning process for dust (Fuell et al. 2016) and continued efforts to improve reliability across multiple platforms (Elmer et. al 2016, Berndt et al. 2018, Elmer et al. 2019)

- This project explores the feasibility of machine learning approaches to pixel-level classifications of visibility hazards including blowing dust and low clouds or fog

GOES-16 ABI Night-time Microphysics RGB



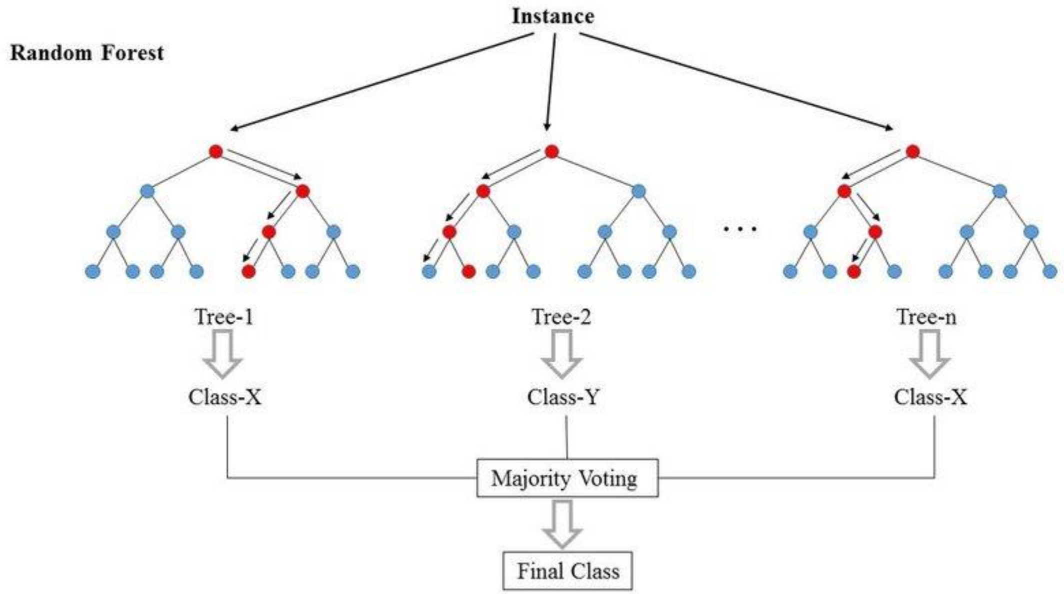
The objective is to move beyond the qualitative identification of fog or dust toward hazard classification



GOES-16 ABI Dust RGB

Methodology

1. **Identify cases**
   - Create dust RGB images to locate and examine dust events
2. **Training data collection**
   - Using ArcGIS, manually outline dust in RGB images with polygon shapefiles
   - Convert shapefiles to raster images which have the same grid and resolution as the source RGB image
   - Compile a large training database of dust imagery to be used as input into the different classification methods
3. **Train classification models**
   - Python's Scikit-Learn toolbox provides a robust number of classification methods. Random Forest, Logistic Regression, and Naïve Bayes classifications were chosen as they are able to output probability classifications.
4. **Evaluation**
   - Determine the method(s) that provide the most useful results
5. **Iterate**
   - Refine input training data and model parameters to create the best possible solution



From Dimitriadas and Liparas (2018)

Training Models

Random Forest

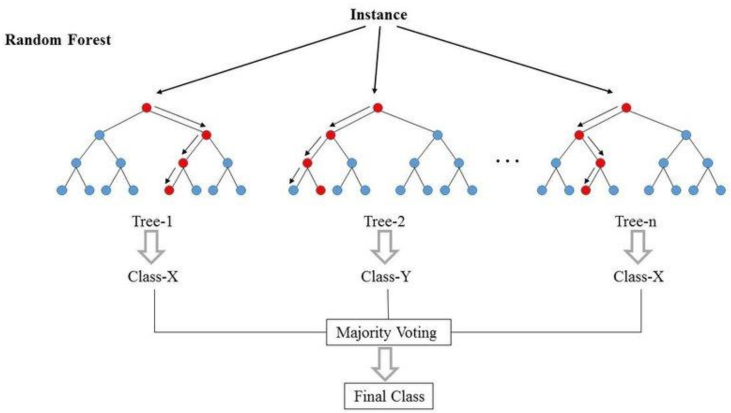
- Ensemble approach which constructs a multitude of decision trees
- Each decision tree has a random set of features (i.e., variables) and only has access to a random set of training data points
- Allows for the determination of feature importance, or how important is each variable is to the final decision.

Logistic Regression

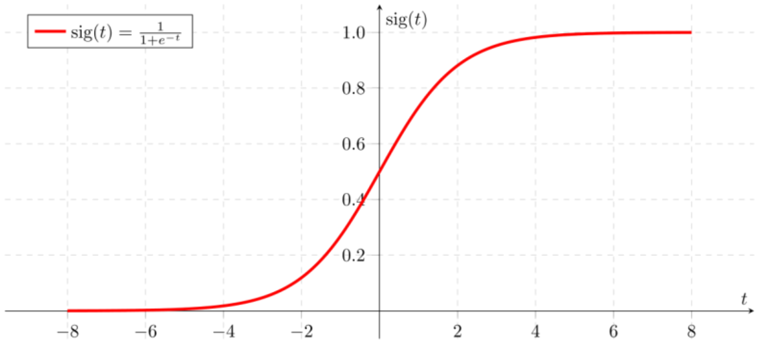
- Works well for binary (0 or 1) dependent variables (i.e., is a pixel dust?)
- Describes the linear relationship between the dependent variable and one or more independent variables (i.e., what are the weights of each variable?)

Naïve Bayes

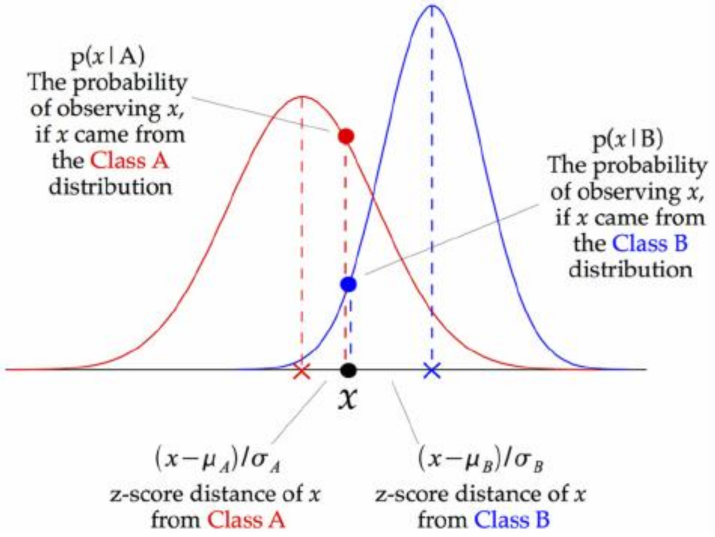
- Assume that the value of a particular variable is independent of the value of any other variable, given a particular class. In other words, does not consider any correlation between a variables.



From Dimitriadas and Liparas (2018)



From Saishruthi Swaminathan (2018)



From Raizada and Lee (2013)

Training Variables for Dust

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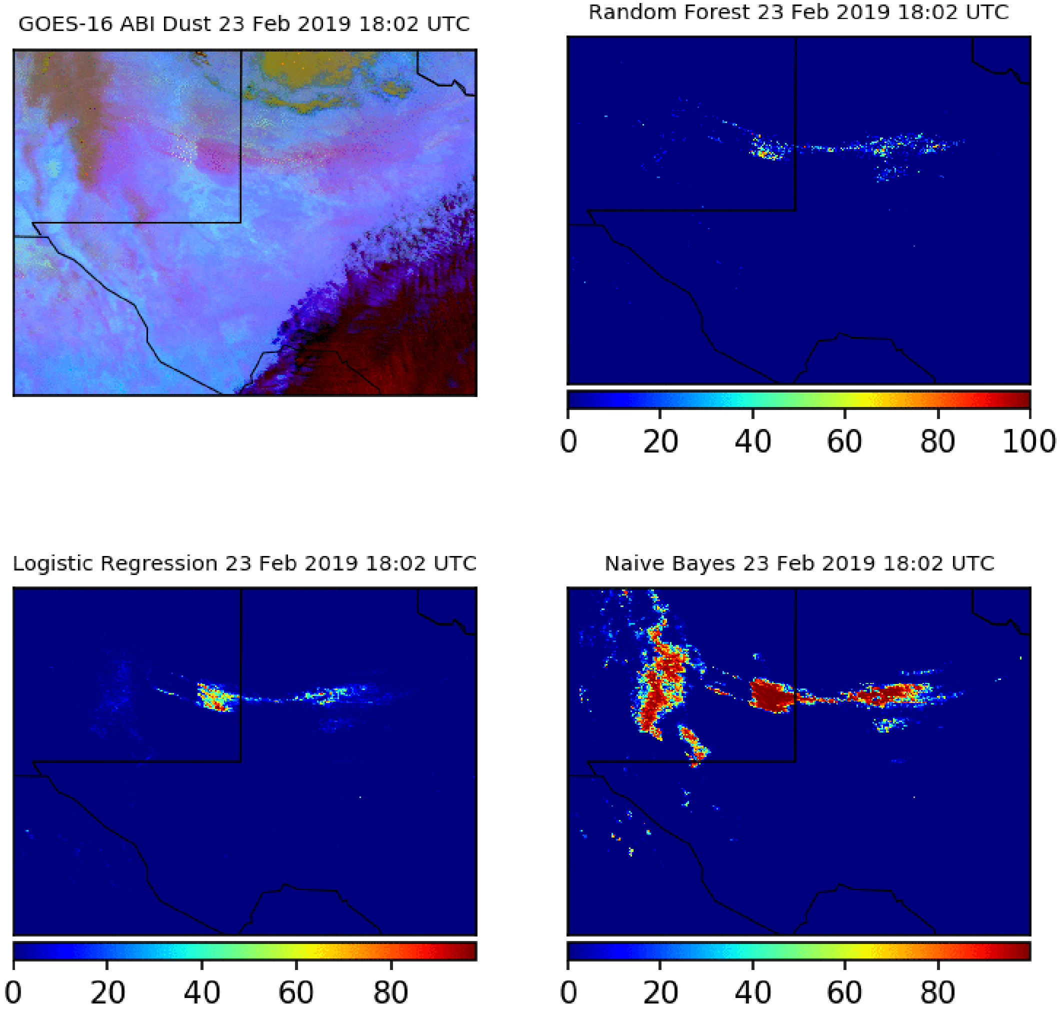
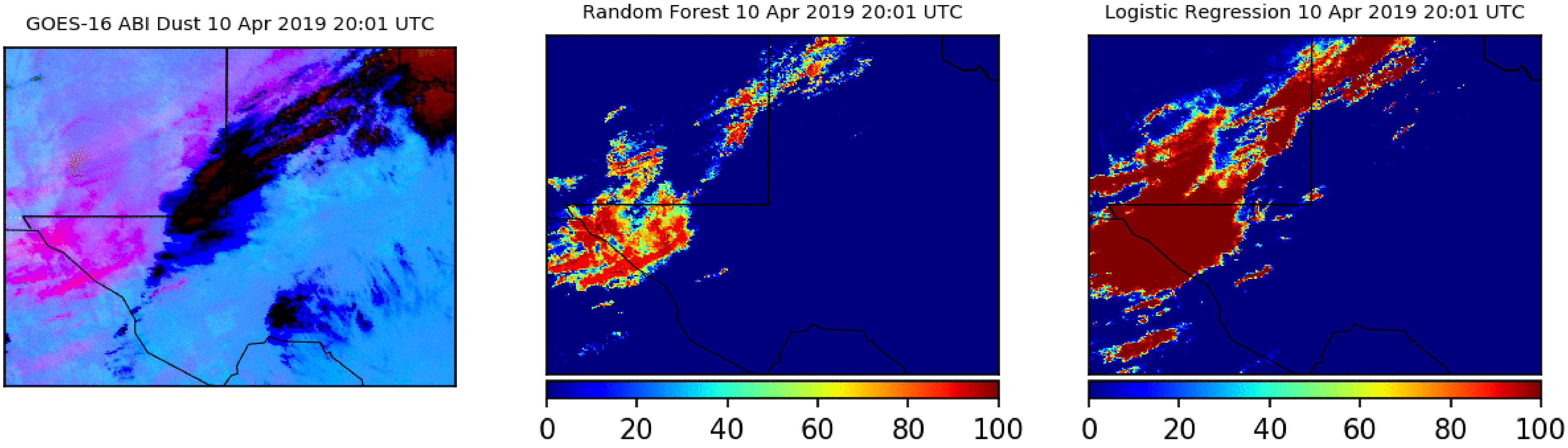
Training Variable	Common Name
7.3 µm	“lower-level” water vapor band
10.35 µm and 11.2 µm	“thermal” infrared bands
12.3 µm	“dirty” infrared band
13.3 µm	“CO_2” longwave infrared band
12.3-10.35 µm Difference	split window technique
11.2-8.4 µm Difference	particle phase band difference
RGB Image Red Color Intensity	pixel-level contribution of Red color to the image (0-255)
RGB Image Green Color Intensity	pixel-level contribution of Green color to the image (0-255)
RGB Image Blue Color Intensity	pixel-level contribution of Blue color to the image (0-255)

2019 Feb 23 Dust Event

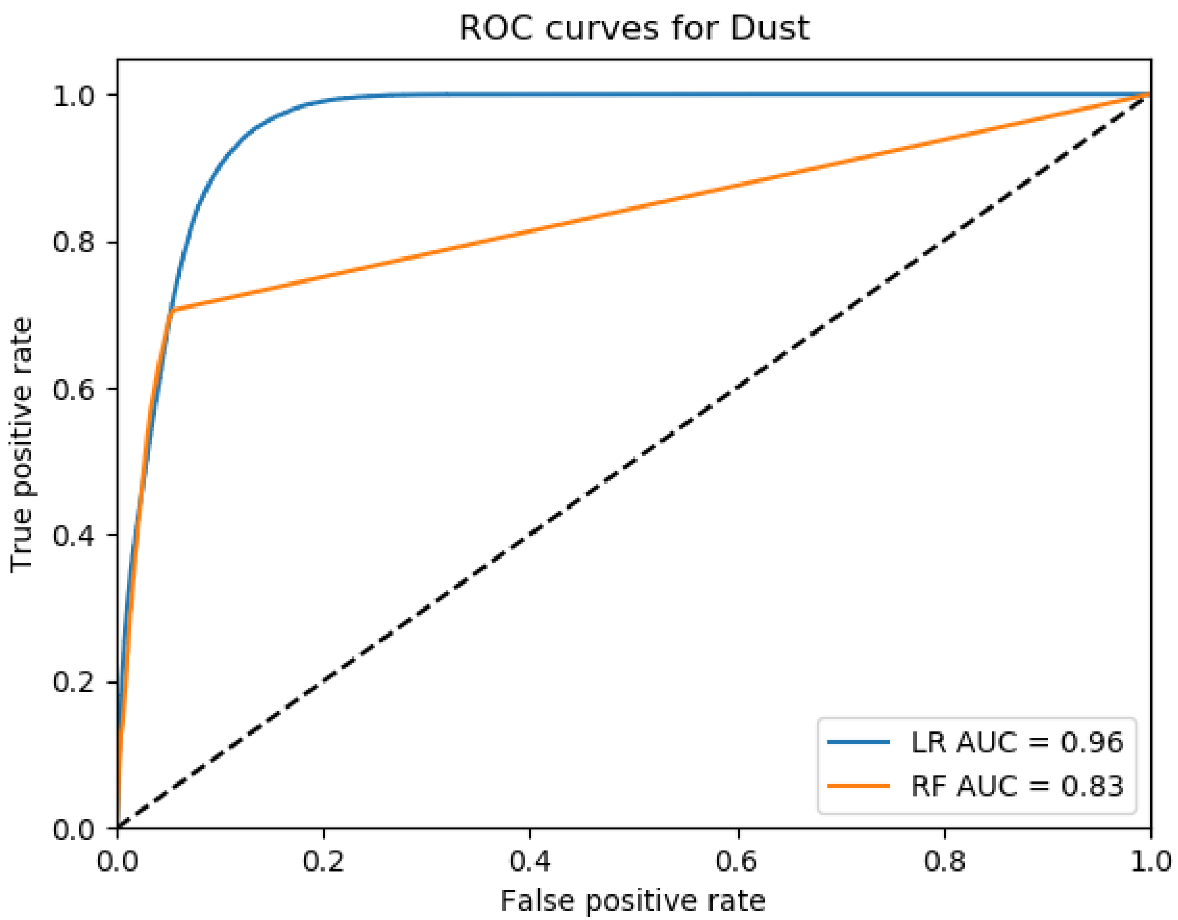


Dust RGB and Model Results



Preliminary Validation

- Preliminary verification of results with Receiver Operating Characteristic (ROC) curves
  - 96% chance the Logistic regression model will distinguish dust
    - does not appear sensitive to the thickness of the dust
    - pretty much all or nothing except near plume edges
  - 83% chance Random Forest probabilities will distinguish dust
    - fluctuate depending on the thickness of the dust
    - lower thicknesses tend to equate to lower probabilities



Logistic regression over-performs in identification of dust while Random Forest probabilities fluctuate depending on the thickness of the dust

Real-time Mesoscale Analysis

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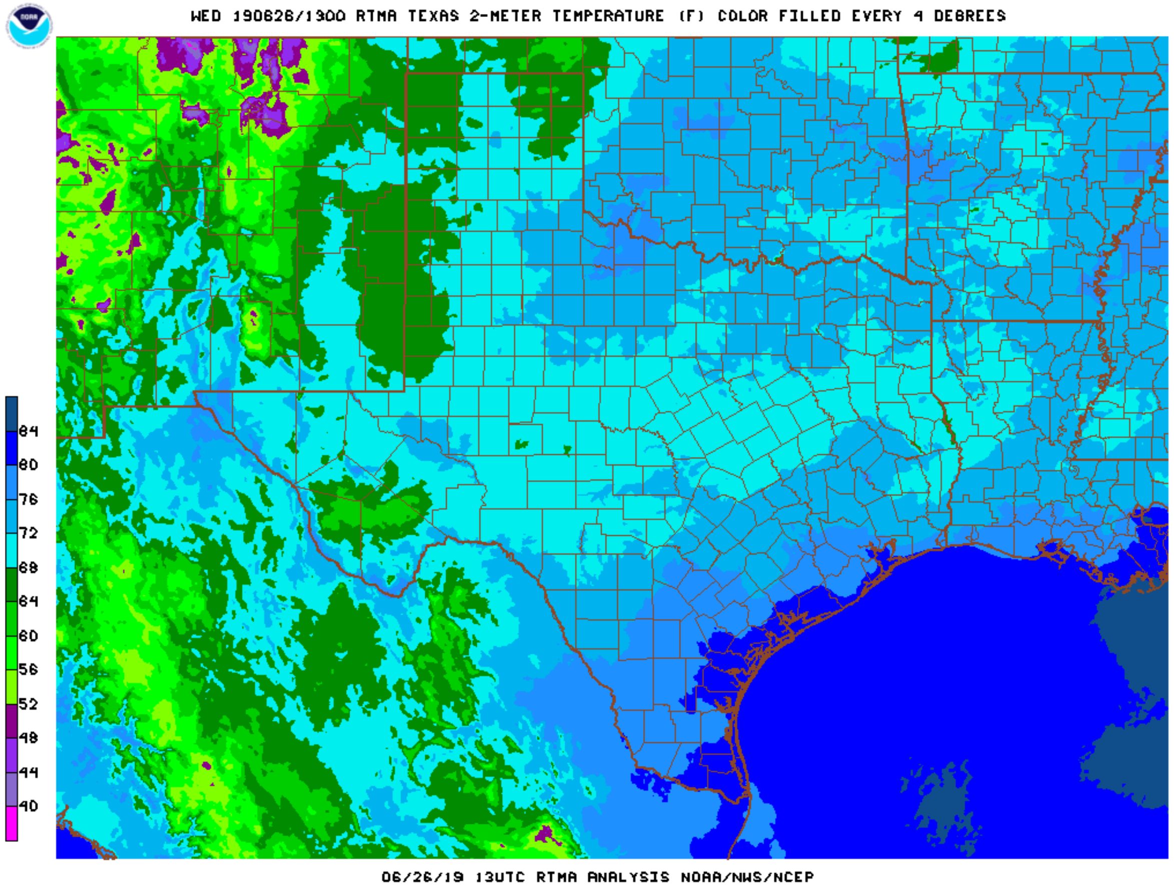
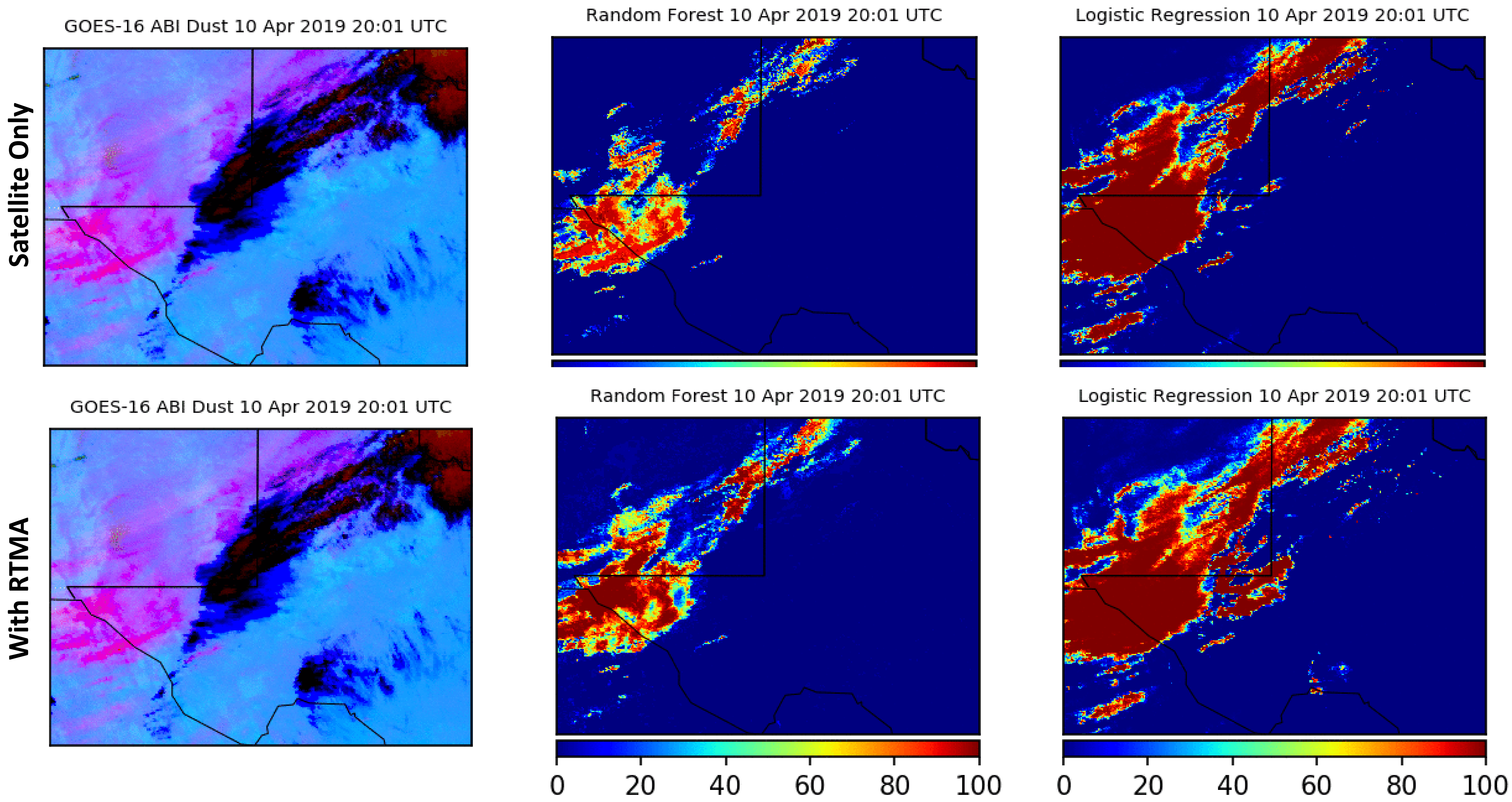
- Does adding surface observations help the models?
- Real-Time Mesoscale Analysis was developed by NOAA as a measurement for validation of their National Digital Forecast Database
  - Components include Temperature, Dewpoint, Wind Speed
  - Gridded surface observations match the National Digital Forecast Database grid (2.5 km)
- RTMA data was remapped to the same grid as the satellite data and new models were run to include the RTMA data.



Dust RGB and Model Results with RTMA data



Preliminary Validation

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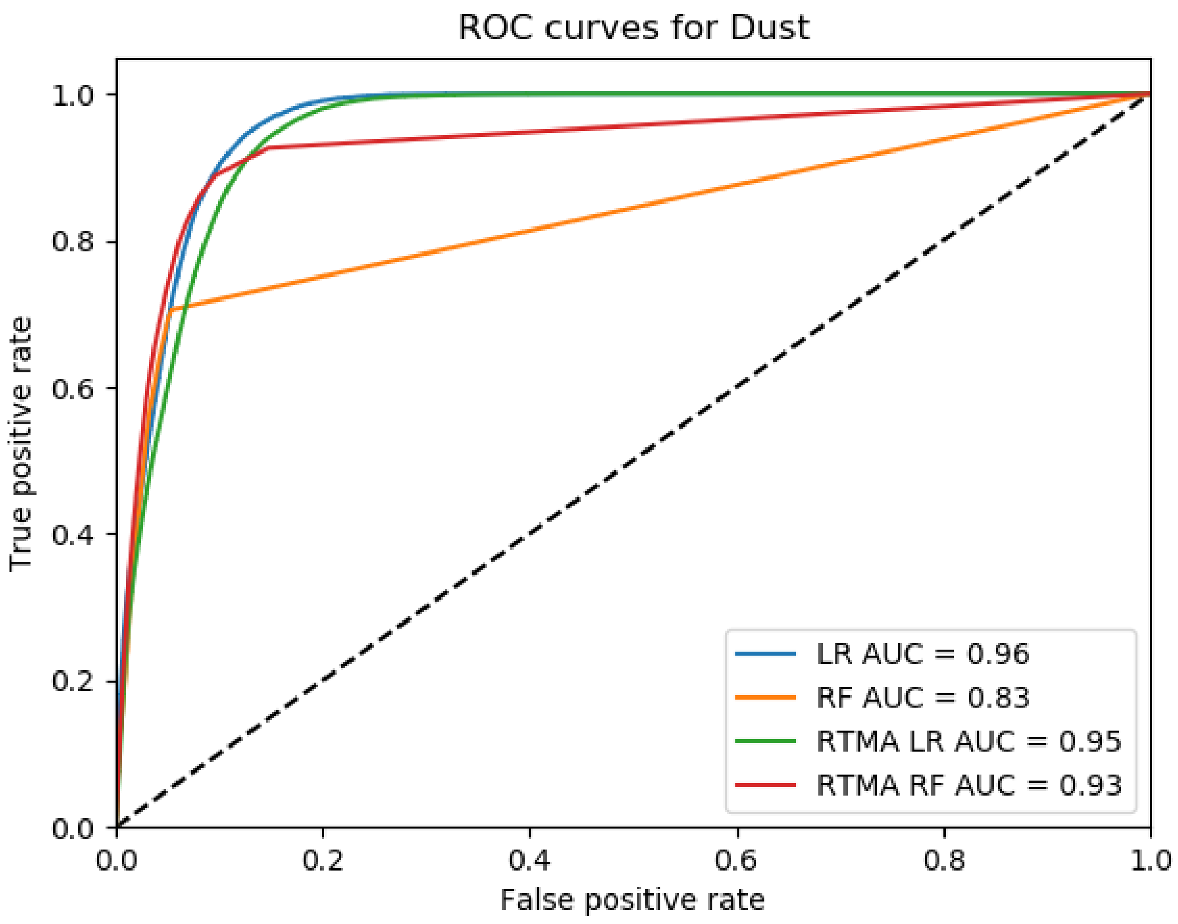
- Similar AUC for Logistic regression when including RTMA data.
  - Potentially capturing dust obscured by clouds?
  - Or increase in false positives?
- AUC increases for Random Forest when including RTMA data
  - Less fluctuations in dust probabilities; less dependence on plume thickness
  - Better ratio of true positives to false positives
  - Increased sensitivity
- Need further validation and user feedback to determine the value of including RTMA data
  - Desired classification threshold
  - Optimal true positive rate compared to false positives (what is tolerable for dust classified as no dust)



Summary / Next Steps

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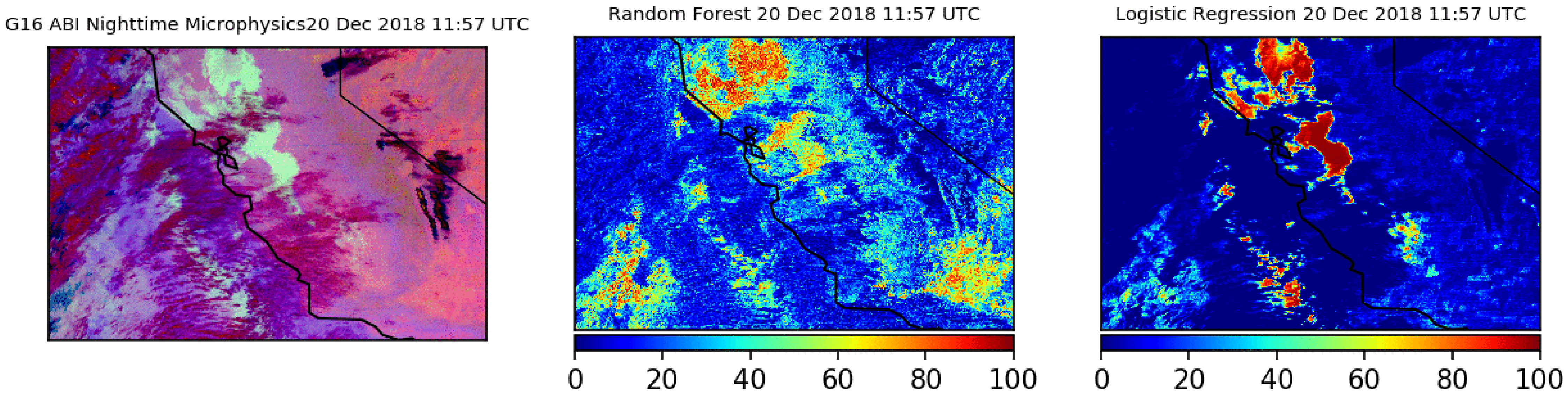
- Application of machine learning models to GOES-16 ABI bands shows promise for objective classification of features such as dust and fog
- SPoRT plans to test image classification with existing partners and end users to determine the value of image classification in the operational environment.
  - What is a tolerable false positive rate?
  - Does this capability ease RGB interpretation and analysis?
- Expand the training database to night-time cases to enhance identification and detection of dust at night
- Apply a similar technique to the Night-time Microphysics RGB



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