Machine Learning Approach to Classify Precipitation Type from A Passive Microwave Sensor

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Abstract

Precipitation flag (precipitating or not; stratiform or convective) is a key parameter for us to make betterretrieval of precipitation characteristics as well as to understand the cloud-precipitation physicalprocesses. The Global Precipitation Measurement (GPM) Core Observatory's Microwave Imager (GMI)and Dual-Frequency Precipitation Radar (DPR) together provide ample information on globalprecipitation characteristics. As an active sensor in particular, DPR provides an accurate precipitation-flag assignment, while passive sensors like GMI were traditionally believed not to be able to tell apartprecipitation types. Using collocated precipitation flag assignment from DPR as the "truth", this project employs machinelearning models to train and test the predictability and accuracy of using passive GMI-only observationstogether with ancillary atmosphere information from reanalysis. Precipitation types are classified intothe following classes: convective, stratiform, convective-stratiform mixed, no precipitation, and otherprecipitation. Sub-sampling with different probabilities is employed to construct a balanced trainingdataset. A variety of classification algorithms are tested, including Support Vector Machines, NaiveBayes, Random Forests, Gradient Boosting, and Neural Networks (Multilayer Perceptron Network), andtheir results are evaluated and compared. The trained model has ˜ 85% of prediction accuracy for everytype of precipitation. High-frequency channels (166 GHz and 183 GHz channels) and 166 GHzpolarization difference are found among the most important factors that contribute to the modelperformance, which shed light on future instrument channel selection.

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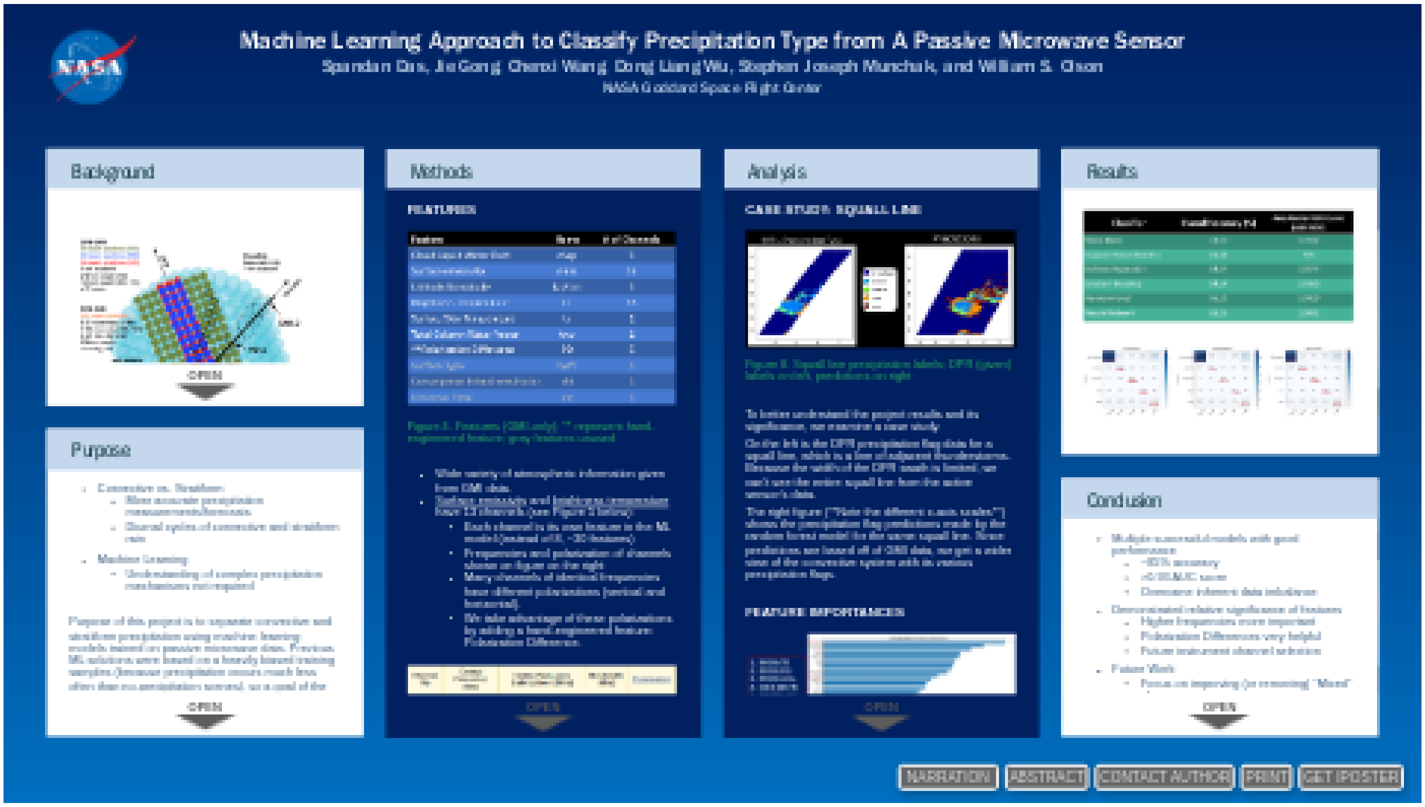

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Background

OPEN

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Analysis

CASE STUDY: SQUALL LINE

FEATURE IMPORTANCES

OPEN

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BACKGROUND

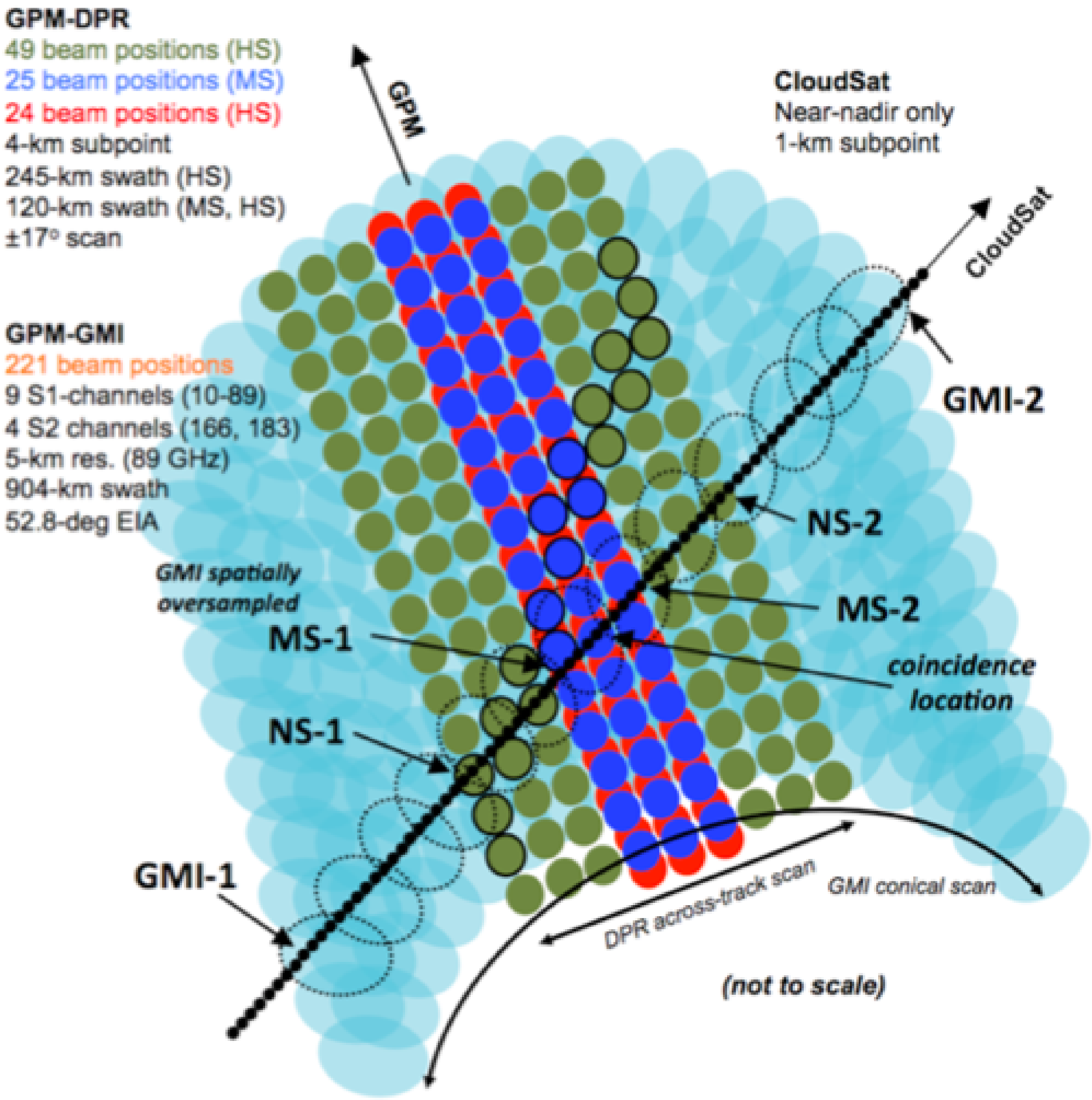


Figure 1. Details of GPM Core Observatory Scan; light-blue is GMI scan and green is DPR scan

NASA's Global Precipitation Measurement (GPM) mission's Core Observatory Satellite has two sensors:

- Microwave Imager (GMI)
  - Features for training
  - Passive Microwave Sensor
- Dual-Frequency Precipitation Radar (DPR)

  - Active Sensor
  - Precipitation Flag

Note the difference in scan-width of the two sensors. Goal of the project is to use ONLY passive microwave data to determine precipitation type.

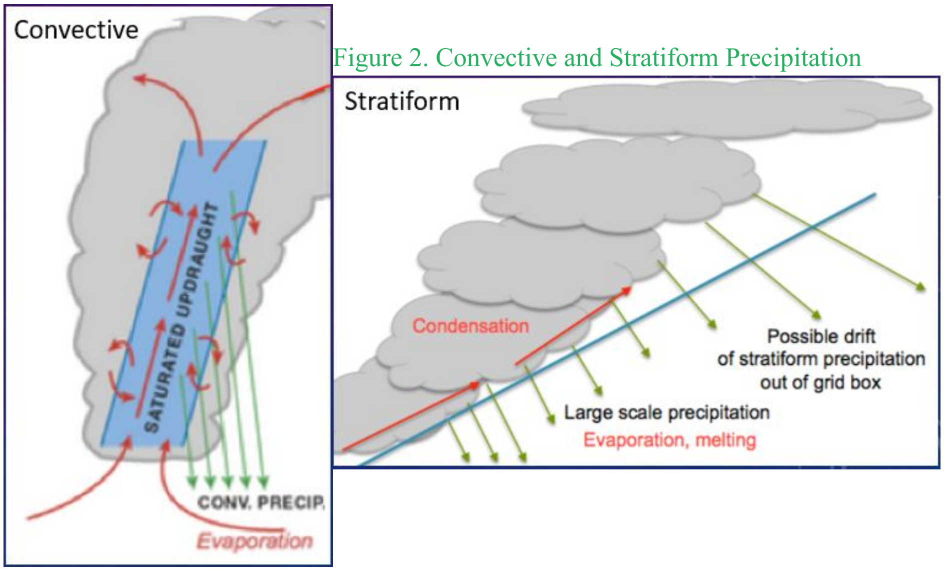


Figure 2. Convective and Stratiform Precipitation

In this project, we differentiate between 5 different types of precipitation:

- No Precipitation
- Convective
- Stratiform
- Mixture
- Other

PURPOSE

- Convective vs. Stratiform
  - More accurate precipitation measurements/forecasts
  - Diurnal cycles of convective and stratiform rain
- Machine Learning
  - Understanding of complex precipitation mechanisms not required

Purpose of this project is to separate convective and stratiform precipitation using machine learning models trained on passive microwave data. Previous ML solutions were based on a heavily biased training samples (since no-precipitation scenes are much more frequent than precipitation scenes), so one aim of the project was to overcome the inherent data bias.

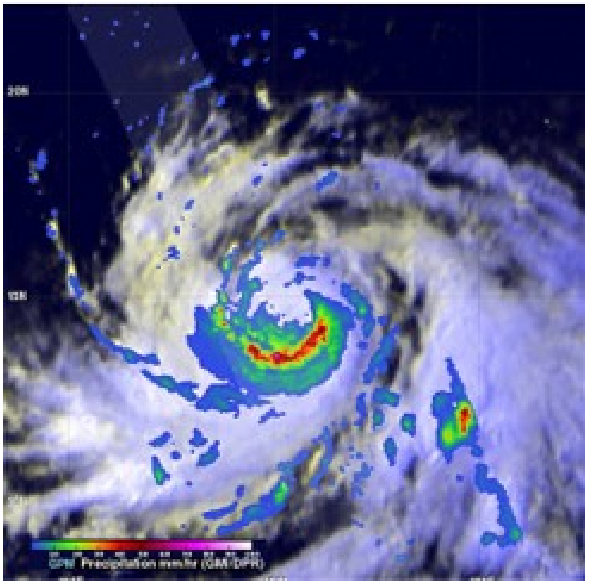
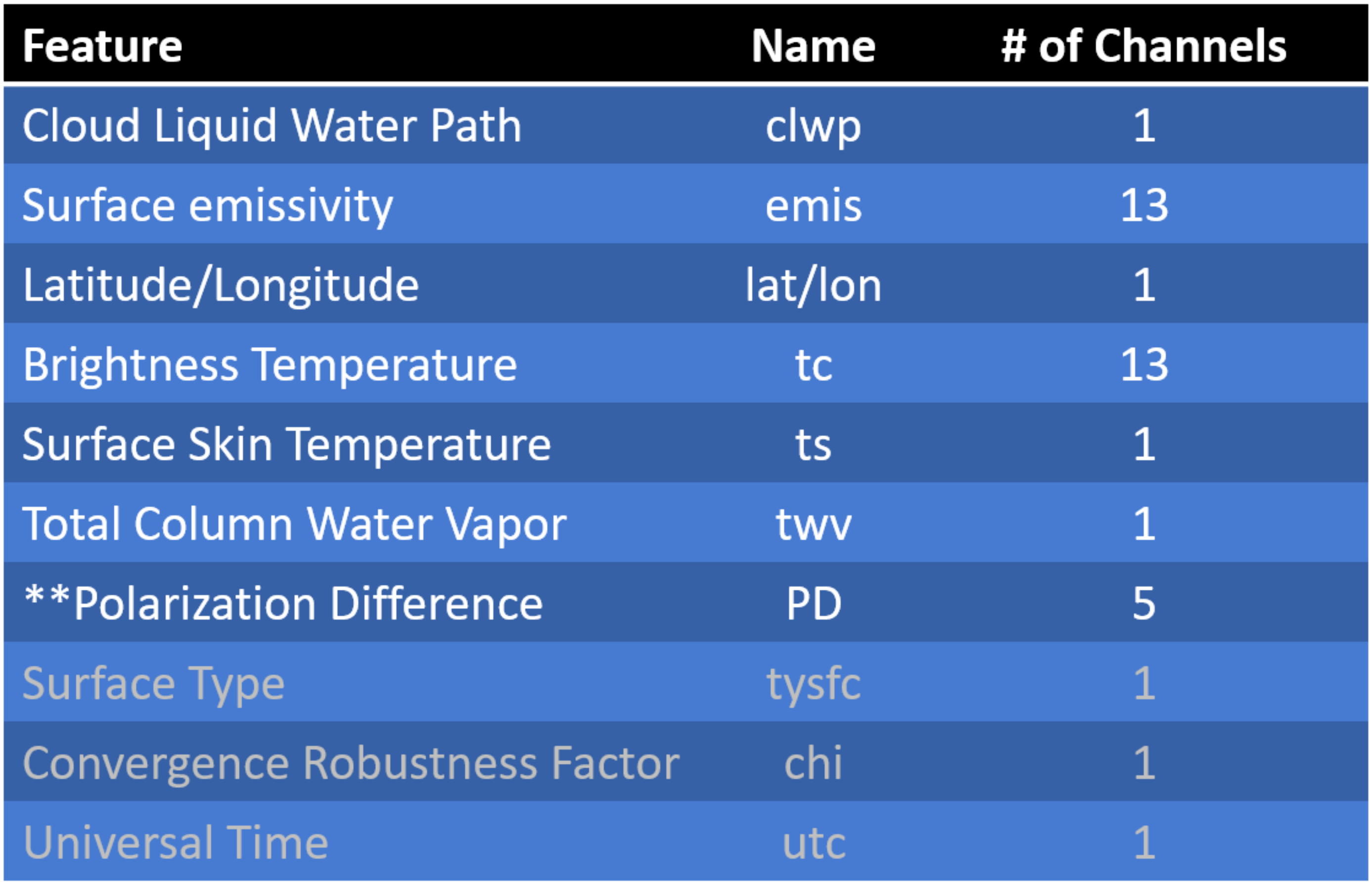


Figure 3. GPM Satellite Data Visualization

METHODS

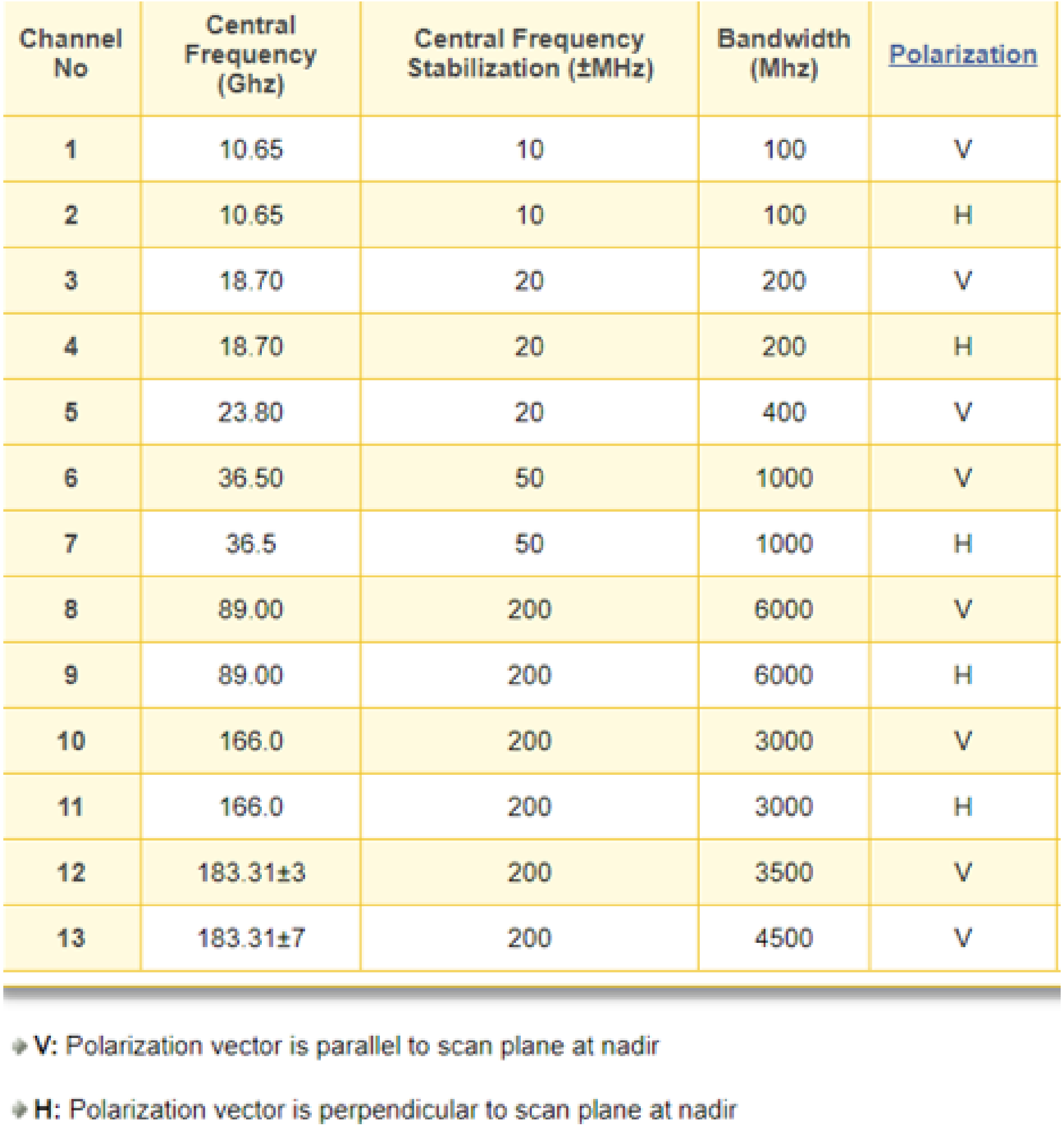
FEATURES



Feature	Name	# of Channels
Cloud Liquid Water Path	clwp	1
Surface emissivity	emis	13
Latitude/Longitude	lat/lon	1
Brightness Temperature	tc	13
Surface Skin Temperature	ts	1
Total Column Water Vapor	twv	1
**Polarization Difference	PD	5
Surface Type	tysfc	1
Convergence Robustness Factor	chi	1
Universal Time	utc	1

Figure 4. Features (GMI-only); ** represent hand-engineered feature; gray features unused

- Wide variety of atmospheric information given from GMI data.
- Surface emissivity and brightness temperature have 13 channels (see Figure 5 below):
  - Each channel is its own feature in the ML model (instead of 8, ~30 features)
  - Frequencies and polarization of channels shown on figure on the right
  - Many channels of identical frequencies have different polarizations (vertical and horizontal).
  - We take advantage of these polarizations by adding a hand-engineered feature: Polarization Difference.



Channel No	Central Frequency (Ghz)	Central Frequency Stabilization (±MHz)	Bandwidth (Mhz)	Polarization
1	10.65	10	100	V
2	10.65	10	100	H
3	18.70	20	200	V
4	18.70	20	200	H
5	23.80	20	400	V
6	36.50	50	1000	V
7	36.5	50	1000	H
8	89.00	200	6000	V
9	89.00	200	6000	H
10	166.0	200	3000	V
11	166.0	200	3000	H
12	183.31±3	200	3500	V
13	183.31±7	200	4500	V

- **V:** Polarization vector is parallel to scan plane at nadir
- **H:** Polarization vector is perpendicular to scan plane at nadir

Figure 5. Channel Frequencies and Polarization

POLARIZATION DIFFERENCES

Polarization Differences (hand-engineered feature):

- Difference between brightness temperature values of vertical and horizontal polarizations: tc[V] – tc[H]
- Frequencies used: 10.65, 89.00, 166.0 GHz

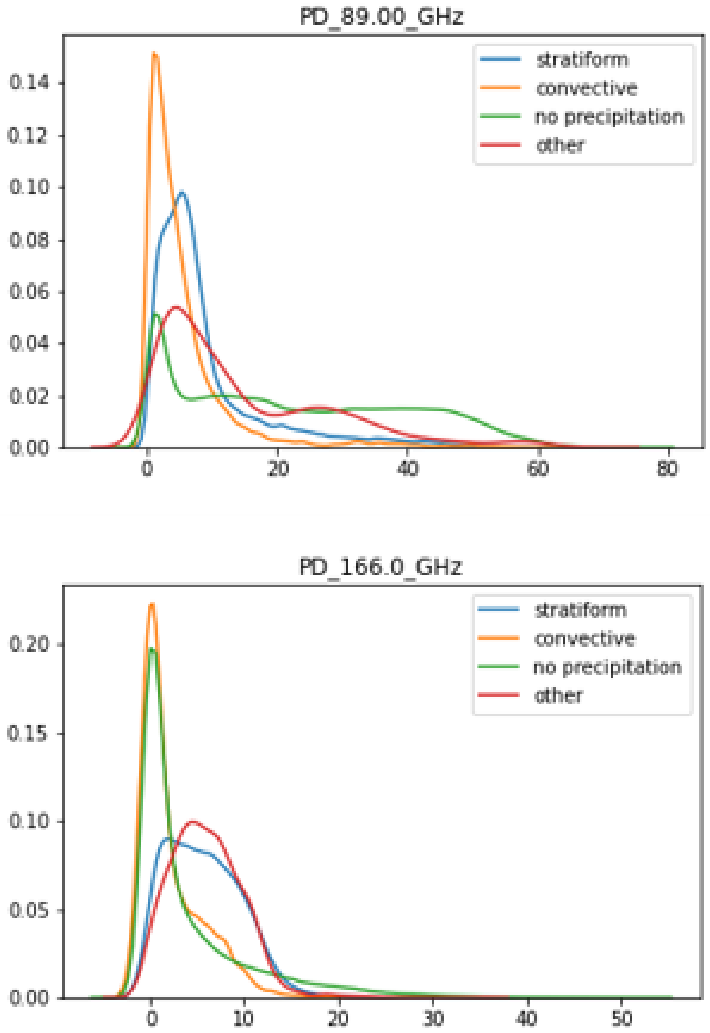


Figure 6. Distribution of Polarization Differences by flag (89.00, 166.0 GHz)

TRAINING AND VALIDATION DATASETS

Training Dataset (2017 data):

- 84 days of data
  - 7 days/month
  - Randomly selected days
- Sub-sample daily data
  - Avoid bias caused by data imbalance (since ~95% of daily data is non-precipitating)

Validation Dataset (2017 data):

- 12 days of data
  - 1 day/month

    - Randomly selected days
- No sub-sampling
    - Resemble distribution of real-world data

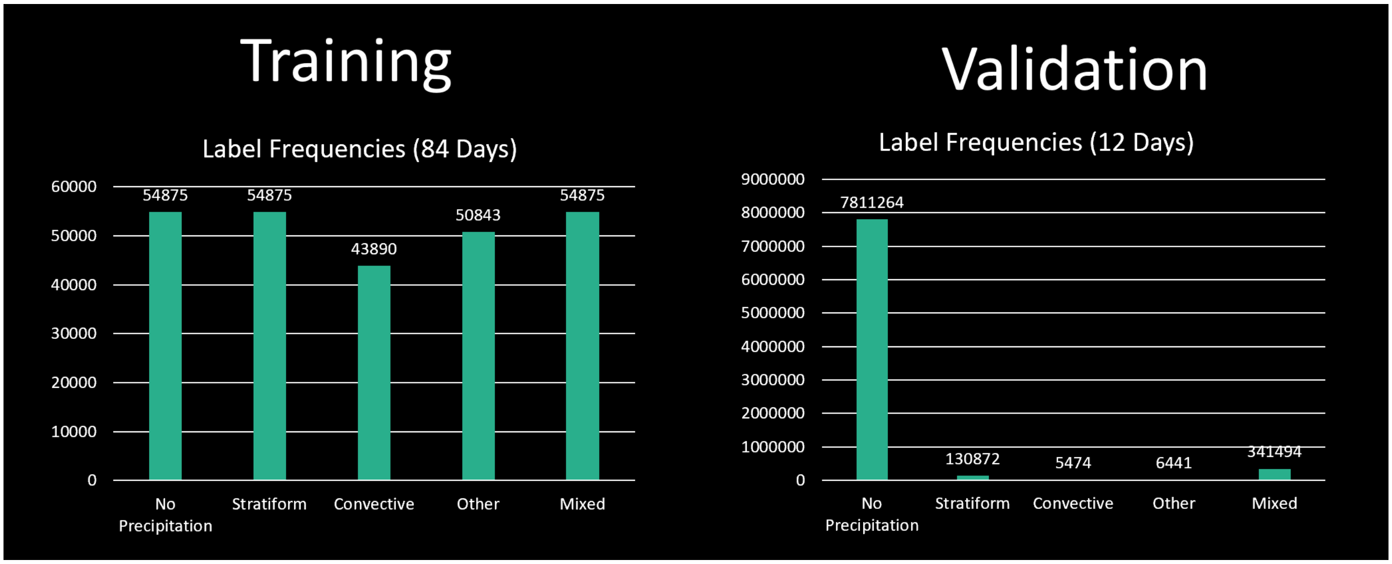


Figure 7. Training and Validation Label Frequencies; all labels from DPR sensor

MACHINE LEARNING MODELS

We use train and test 6 different machine learning models:

1. Naive Bayes Classifier
2. Support Vector Machine
3. Softmax Regression
4. Random Forest
5. Gradient Boosting Classifier
6. Neural Network

All of the models are created, trained, and evaluated using Scikit-learn.

ANALYSIS

CASE STUDY: SQUALL LINE

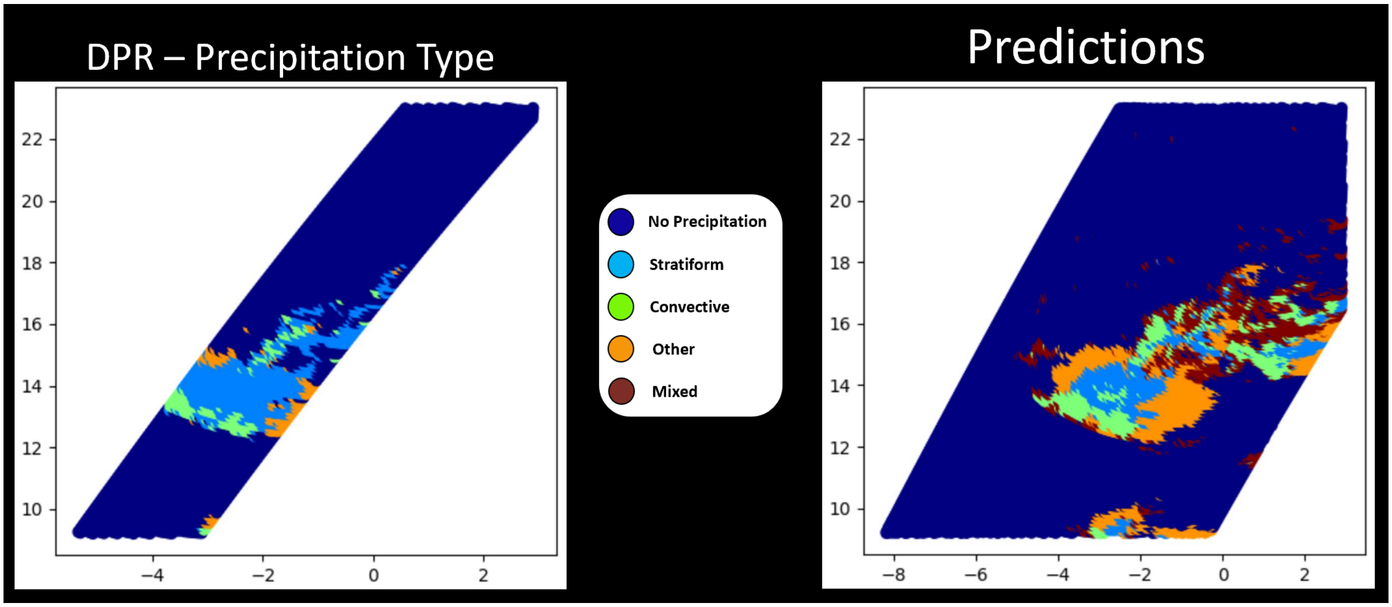


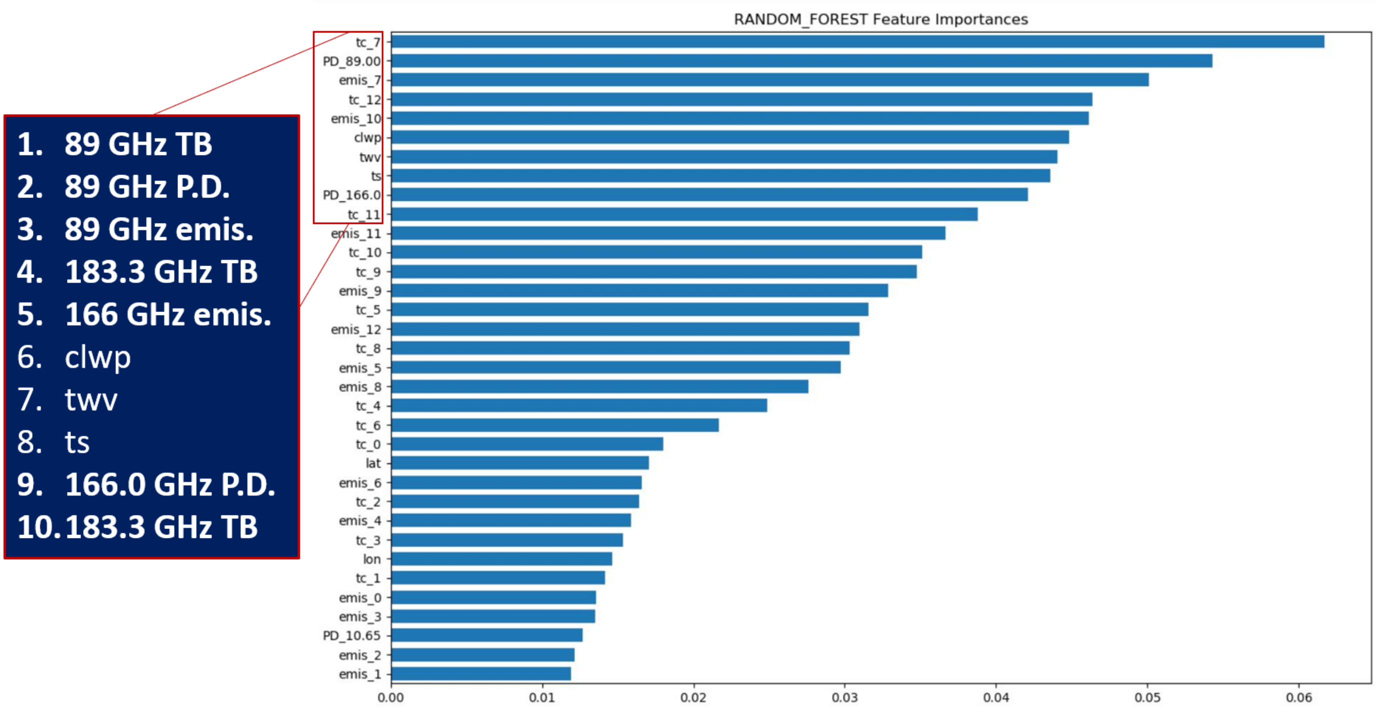
Figure 8. Squall line precipitation labels; DPR (given) labels on left, predictions on right

To better understand the project results and its significance, we examine a case study.

On the left is the DPR precipitation flag data for a squall line, which is a line of adjacent thunderstorms. Because the width of the DPR swath is limited, we can't see the entire squall line from the active sensor's data.

The right figure (**Note the different x-axis scales**) shows the precipitation flag predictions made by the random forest model for the same squall line. Since predictions are based off of GMI data, we get a wider view of the convective system with its various precipitation flags.

FEATURE IMPORTANCES



1. **89 GHz TB**
2. **89 GHz P.D.**
3. **89 GHz emis.**
4. **183.3 GHz TB**
5. **166 GHz emis.**
6. clwp
7. twv
8. ts
9. **166.0 GHz P.D.**
10. **183.3 GHz TB**

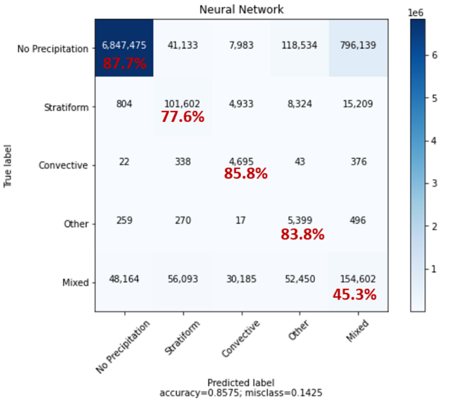
Figure 9. Feature importances for random forest model

The figure above shows a list of the feature importances for the random forest model.

From here, we see that the high frequency channels are the most important features for distinguishing between precipitation types. We also see that the polarization differences that we added to the data are very helpful for classification.

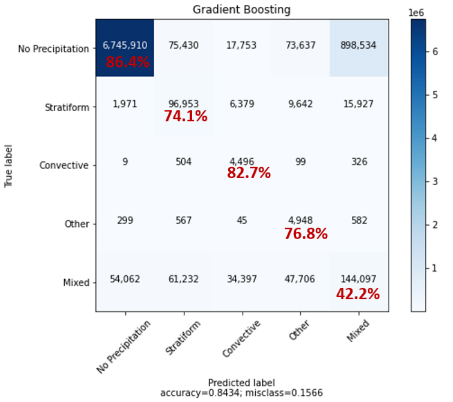
RESULTS

Classifier	Overall Accuracy (%)	Area Under ROC Curve (AUC ROC)
Naive Bayes	32.71	0.7312
Support Vector Machine	85.98	N/A
Softmax Regression	84.17	0.9077
Gradient Boosting	84.34	0.9360
Random Forest	86.52	0.9429
Neural Network	85.75	0.9432


Neural Network

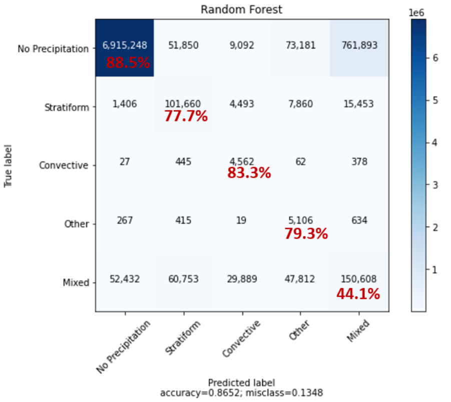
True label \ Predicted label	No Precipitation	Stratiform	Convective	Other	Mixed
No Precipitation	6,847,475 87.7%	41,133	7,983	118,534	796,139
Stratiform	804	101,602 77.6%	4,933	8,324	15,209
Convective	22	338	4,695 85.8%	43	376
Other	259	270	17	5,399 83.8%	496
Mixed	48,164	56,093	30,185	52,450	154,602 45.3%

Predicted label
accuracy=0.8575; misclass=0.1425


Gradient Boosting

True label \ Predicted label	No Precipitation	Stratiform	Convective	Other	Mixed
No Precipitation	6,745,910 86.4%	75,430	17,753	73,637	898,534
Stratiform	1,971	96,953 74.1%	6,379	9,642	15,927
Convective	9	504	4,496 82.7%	99	326
Other	299	567	45	4,948 76.8%	582
Mixed	54,062	61,232	34,397	47,706	144,097 42.2%

Predicted label
accuracy=0.8434; misclass=0.1566


Random Forest

True label \ Predicted label	No Precipitation	Stratiform	Convective	Other	Mixed
No Precipitation	6,915,248 88.5%	51,850	9,092	73,181	761,893
Stratiform	1,406	101,660 77.7%	4,493	7,860	15,453
Convective	27	445	4,562 83.3%	62	378
Other	267	415	19	5,106 79.3%	634
Mixed	52,432	60,753	29,889	47,812	150,608 44.1%

Predicted label
accuracy=0.8652; misclass=0.1348

CONCLUSION

- Multiple successful models with good performance
  - ~85% accuracy
  - >0.93 AUC score
  - Overcame inherent data imbalance
- Demonstrated relative significance of features
  - Higher frequencies more important
  - Polarization Differences very helpful
  - Future instrument channel selection
- Future Work
  - Focus on improving (or removing) “Mixed” class
  - Add nearby-pixel associations

Acknowledgements

- NASA Internship Program
- GSFC Climate and Radiation Lab

ABSTRACT

Precipitation flag (precipitating or not; stratiform or convective) is a key parameter for us to make better retrieval of precipitation characteristics as well as to understand the cloud-precipitation physical processes. The Global Precipitation Measurement (GPM) Core Observatory's Microwave Imager (GMI) and Dual-Frequency Precipitation Radar (DPR) together provide ample information on global precipitation characteristics. As an active sensor in particular, DPR provides an accurate precipitation flag assignment, while passive sensors like GMI were traditionally believed not to be able to tell apart precipitation types.

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