1. Background
- Land surface emissivity is of critical importance for the microwave based precipitation retrieval algorithm development.
- Land surface emissivity is highly heterogeneous and dynamic, makes it difficult to estimate using physical model.
- We have developed a statistical framework to estimate land surface emissivity directly from brightness temperature (TBs).
- This method is successfully applied to Southern Great Plains (SGP) by Tian et. al. (2015), which outperforms the physical model and hybrid of physical and statistical model.
- We now extend this framework to the GPM-covered region (65S-65N).

2. Methodology
- Emissivity from 10 to 166 GHz is regressed directly from TB-based predictors.
- Predictors include: TB, TB^2, and Microwave Polarization Difference Index (MPDI, e.g., (V10-H10)/(V10+H10)).
- We have tested six different regression models:
  - Method 1 (M1): single channel MPDI (10 GHz) and its square (2-predictor).
  - Method 2 (M2): 4-channel MPDI (10, 19, 37, and 89G), linear terms only (4-predictor).
  - Method 3 (M3): 9-channel TBs: 10–89 GHz, linear terms only (9-predictor).
  - Method 4 (M4): 9-channel TB and 4-channel MPDI, linear terms only (13-predictor).
  - Method 5 (M5): 9-channel TB, 9-channel TB2, and 4-channel MPDI (22-predictor).
  - Method 6 (M6): 11-channel TB, 11-channel TB2, and 5-channel MPDI (27-predictor).
- Data are randomly divided into two sub-sets: one for training and the other for validation.

3. Datasets
- Emissivity retrieved from GMI observed TBs via radiative transfer model (Joe Munchak).
- GMI TBs (V10, H10, V19,...,V166, and H166).
- IMERG 30-minute precipitation data.
- TELSEM climatology (Monthly) emissivity.
- MODIS Normalized Difference Vegetation Index (NDVI) (8-day and 250-meter).
- Temporal coverage: 09/2014 to 08/2015.
- Spatial coverage: 65S-65N.

4. Cases over different regions
- Texas, Shrub land
- Kansas, Winter wheat
- Alaska, Snow covered
- Amazon, forest
- Many factors can lead to a large emissivity variation, including precipitation, irrigation, snow melting.
- Under all conditions, our method performs very well, able to capture the dynamical change of the emissivity.
- Over the Amazon forest region, a constant emissivity estimate is sufficient.

5. Emissivity error estimates
- Error estimates (M1)
- Error estimates (M6)
- Error table

<table>
<thead>
<tr>
<th>Error estimates (M1)</th>
<th>Error estimates (M6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>V10</td>
<td>1.36</td>
</tr>
<tr>
<td>H10</td>
<td>1.26</td>
</tr>
<tr>
<td>V19</td>
<td>1.40</td>
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<tr>
<td>H19</td>
<td>1.53</td>
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<tr>
<td>V24</td>
<td>1.56</td>
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<td>V37</td>
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<td>H37</td>
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<td>V89</td>
<td>3.42</td>
</tr>
<tr>
<td>H89</td>
<td>3.73</td>
</tr>
<tr>
<td>V166</td>
<td>4.29</td>
</tr>
<tr>
<td>H166</td>
<td>4.65</td>
</tr>
</tbody>
</table>

- In general, more predictors produce lower errors. Over-fitting may be an issue due to the sample size.
- Emissivity estimated by 10GHz TB for all channels from 10 to 166 GHz is very accurate over the forest region (e.g., Amazon).
- High-latitude (cold surface) is less accurate.

Conclusions:
- A real-time land surface emissivity estimation method is extended to the GPM-covered region.
- This method captures the dynamic and heterogeneous emissivity characteristics over various regions, with average error of 0.97% to 2.80%.
- The parameters in this method are directly derived from TBs without any ad hoc tuning, making it ideal for real-time application.
- Future work seeks to: (1) use a better cloud/precipitation screening method; (2) obtain more data for training and validation; (3) investigate the estimation over different seasons; (4) test the dynamic emissivity in the GPM radiometer retrieval algorithm.