Statistical and Physical Modeling and Prediction of Land Surface Microwave Emissivity

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Sponsored by NASA PMM Program (PI: C. Peters-Lidard)

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Outline

1. Motivation for predicting microwave emissivity
2. Review of existing approaches
3. Statistical and physical modeling results
4. Summary of discussions

1. Motivation

1.PMW-based precipitation retrieval is sensitive to land surface characteristics and variations.

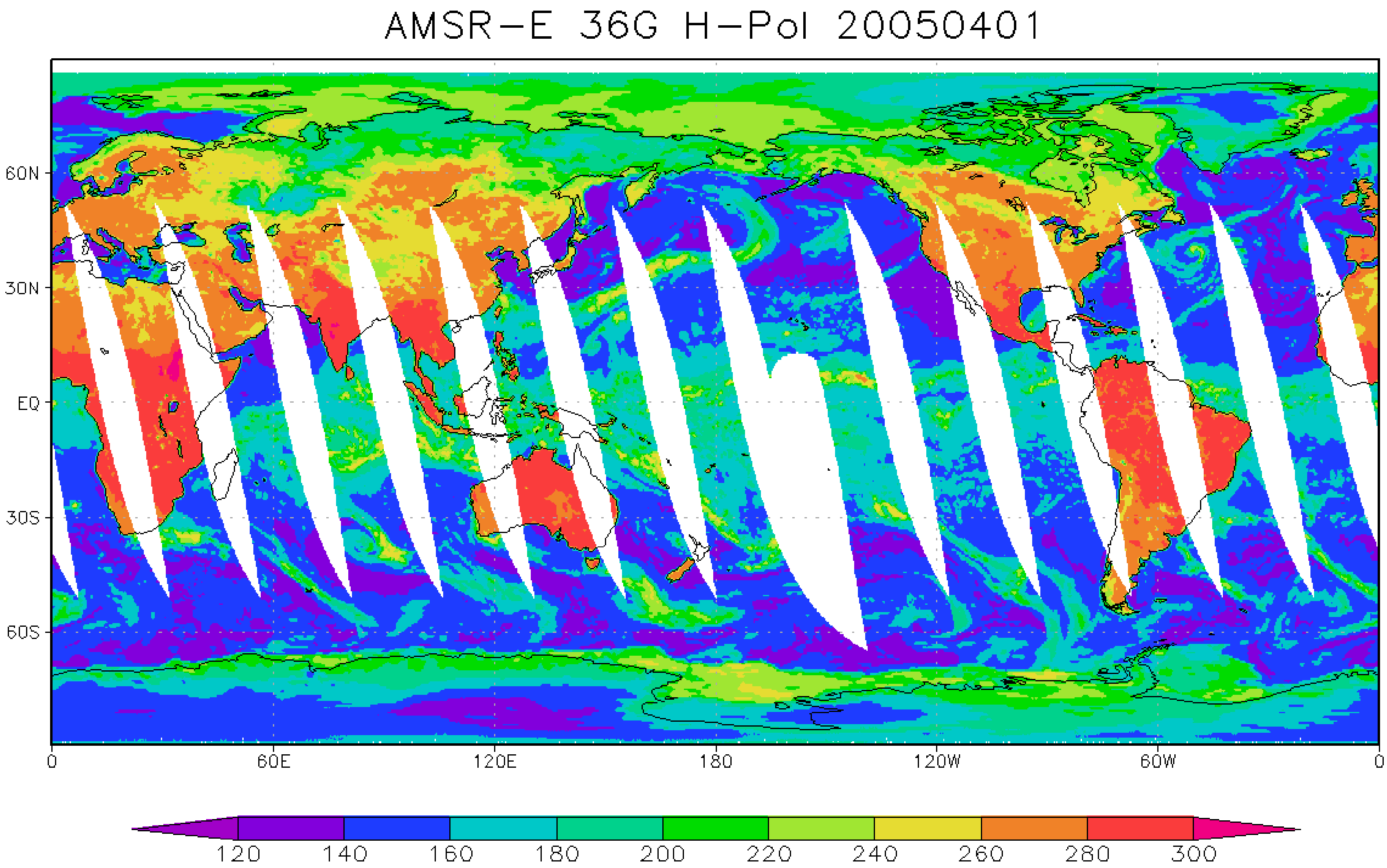
2.GPM radiometer algorithm (GPROF) needs

-- Historical emissivity data to construct the a priori database

-- Real-time emissivity data to search the database

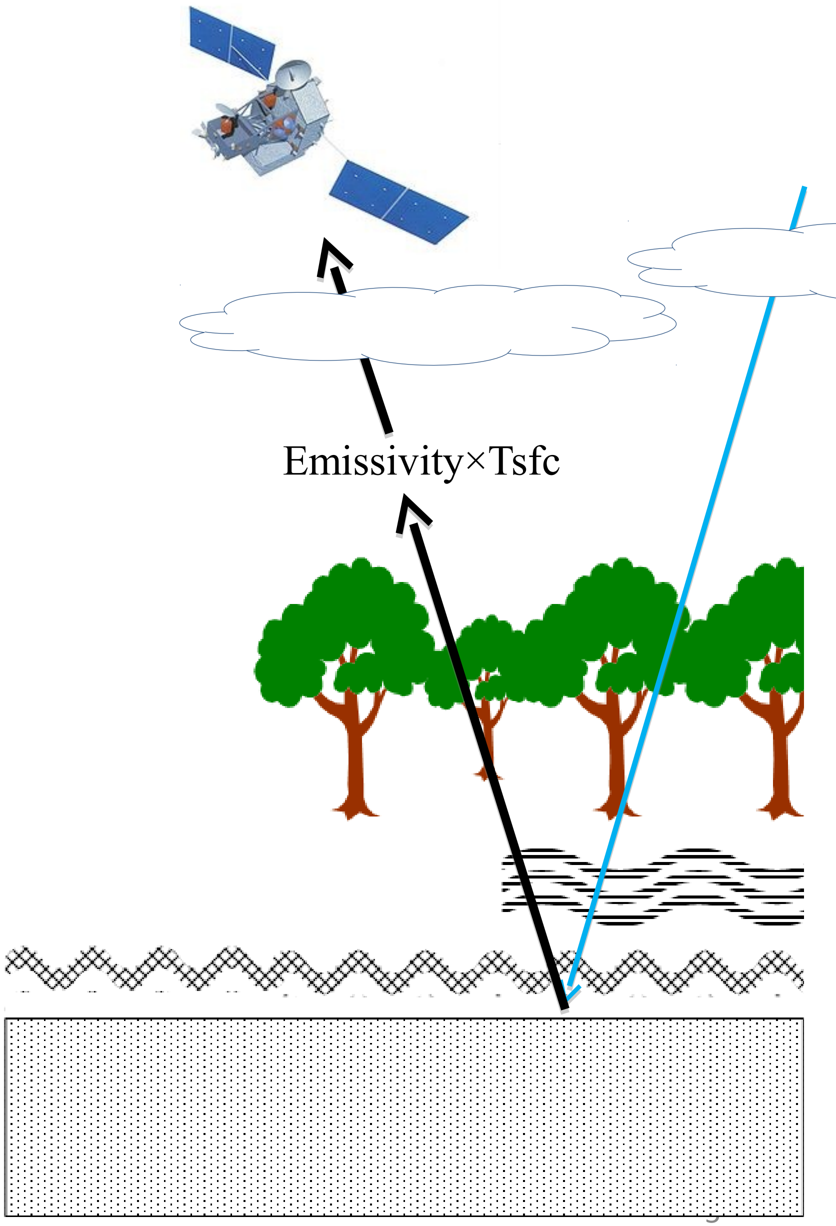
3. Emissivity contains rich information of other variables, such as soil moisture, snow, water body, and vegetation.

Land surface emissivity affects precipitation retrievals



-- heterogeneous and dynamic

Microwave emissivity contains rich information of terrestrial states



Vegetation

(e.g., Choudhury et al., 1987; Owe et al., 2001; Joseph et al., 2010; Kurum et al, 2012)

Snow

(e.g., Pulliainen et al, 1999; Tedesco and Kim, 2006; Foster et al., 2009)

Soil moisture

(e.g., Njoku and O'Neill, 1982; O'Neill et al., 2011)

2. Approaches to estimate emissivity

1.Interpolation/extrapolation of historical data (TELSEM).

2. Physical modeling (CRTM, CMEM, etc.)

3. Statistical modeling (based on relationship between historical data and predictors)

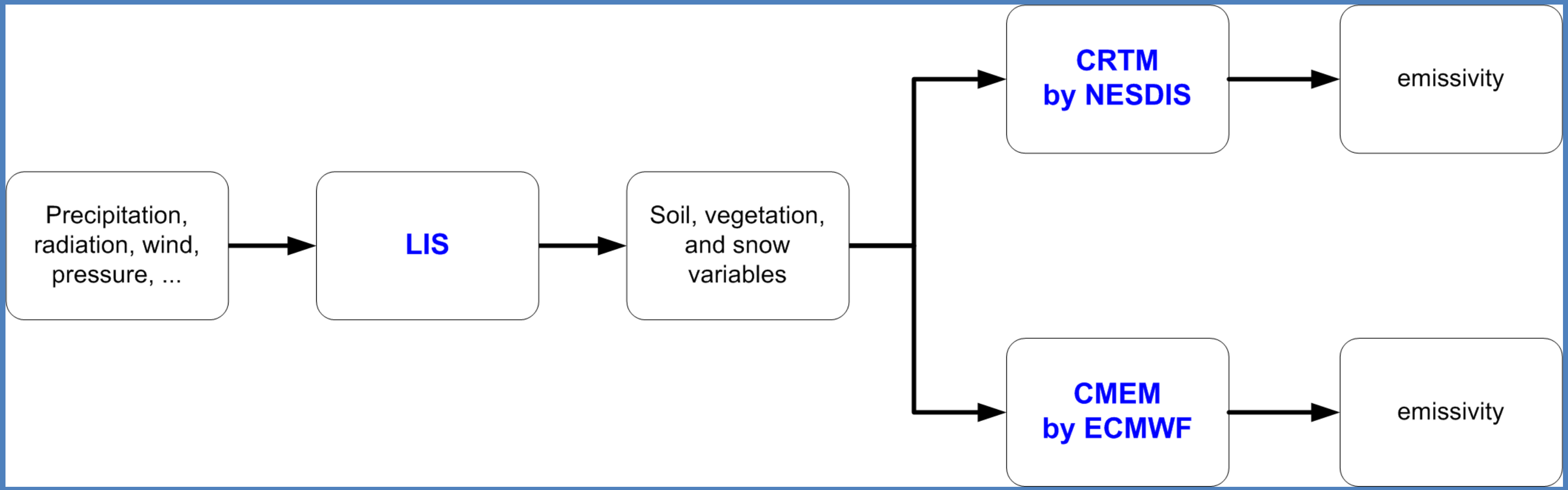
This talk reports studies of 2 and 3.

Physical modeling

- Feeding emissivity models with land surface states from land surface models (LIS)

1. CRTM (Weng et al., 2001)
2. CMEM (Holmes et al., 2008)

-Models can be calibrated with historical data (Harrison et al., 2016)
-We examined two physical models, driven by NASA's Land Information System (LIS):
LIS-CRTM
LIS-CMEM



Principles of physical modeling of land surface emissivity

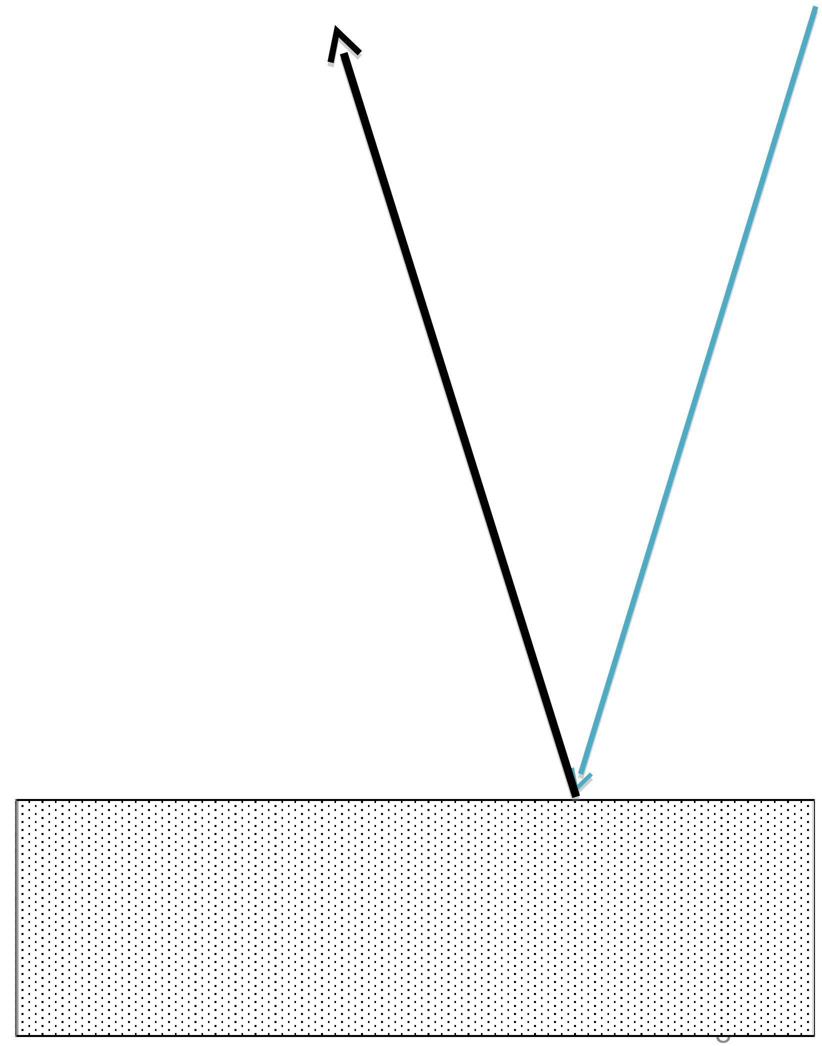
-- a layered, bottom-up approach
-- a semi-physical, semi-empirical business

Vegetation: tau-omega model
(e.g., Mo et al., 1982; Owe et al., 2001)

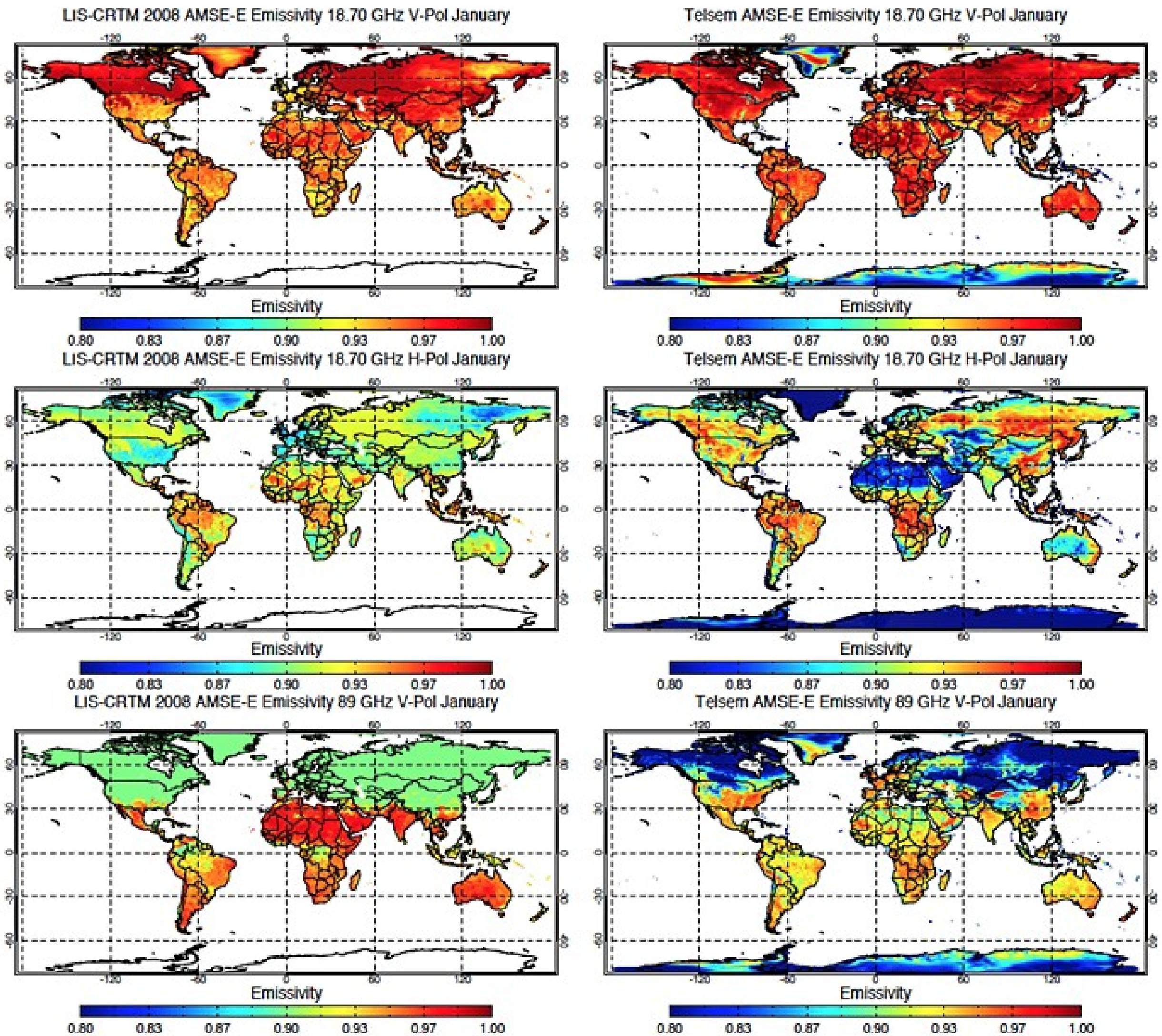
Snow: HUT model
(e.g., Pulliainen et al, 1999; Tedesco and Kim, 2006)

Surface roughness:
(e.g., Choudhury et al., 1979)

Bare, smooth soil:
Dielectric constant -> Fresnel equation -> emissivity
(e.g., Wang and Schmugge, 1980)



Physical modeling validation example: global, monthly



(Prigent et al. 2015)

Statistical modeling

Methodology:

1.Establish statistical relationship between emissivity and Tb or Tb-based indices, with historical data

2.Use the relationship for real-time estimation of emissivity

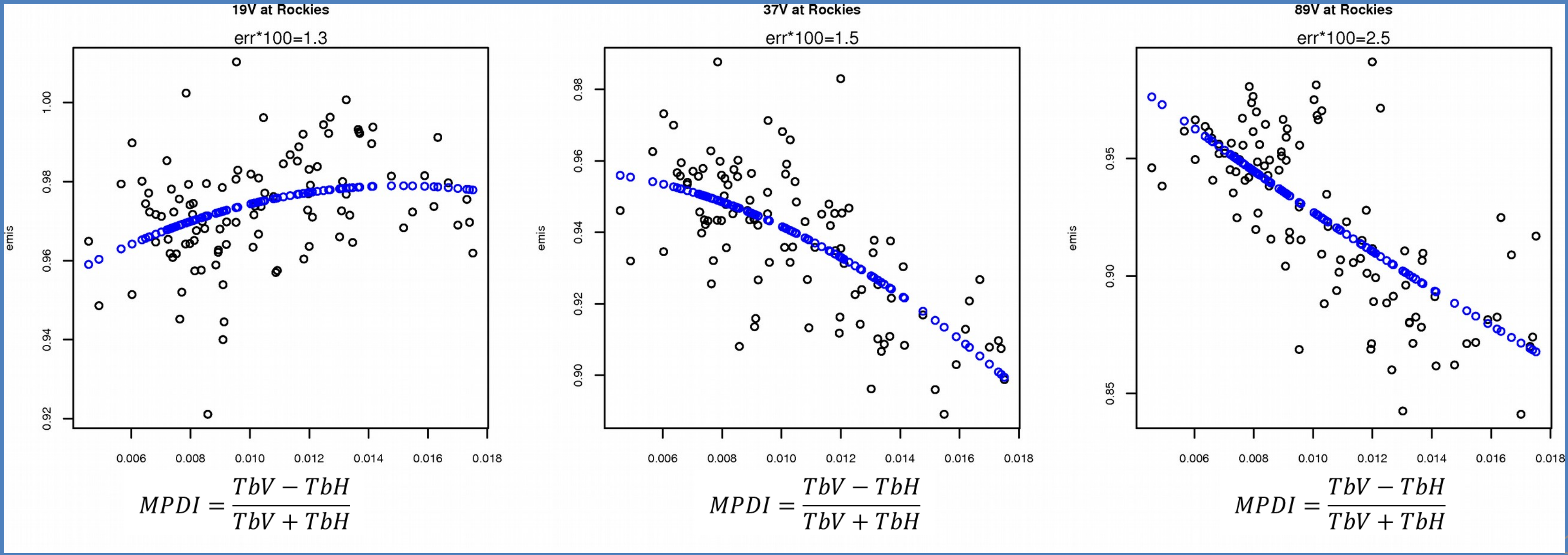
Various statistical relationships (regressions) can be tested:

Emis = M1 (Tb)

Emis = M2 (Tb)

…

Statistical relationship between emissivity and MPDI



Statistical modeling

We tested five (5) statistical models (Tian et al., 2016)

M1) method 1: single channel MPDI: 10G and its square (2-predictor)

M2) method 2: five-channel MPDI: 10~89G, linear terms only (5-predictor)

M3) method 3: 10-channel Tbs: 10~89G, linear terms only (10-predictor)

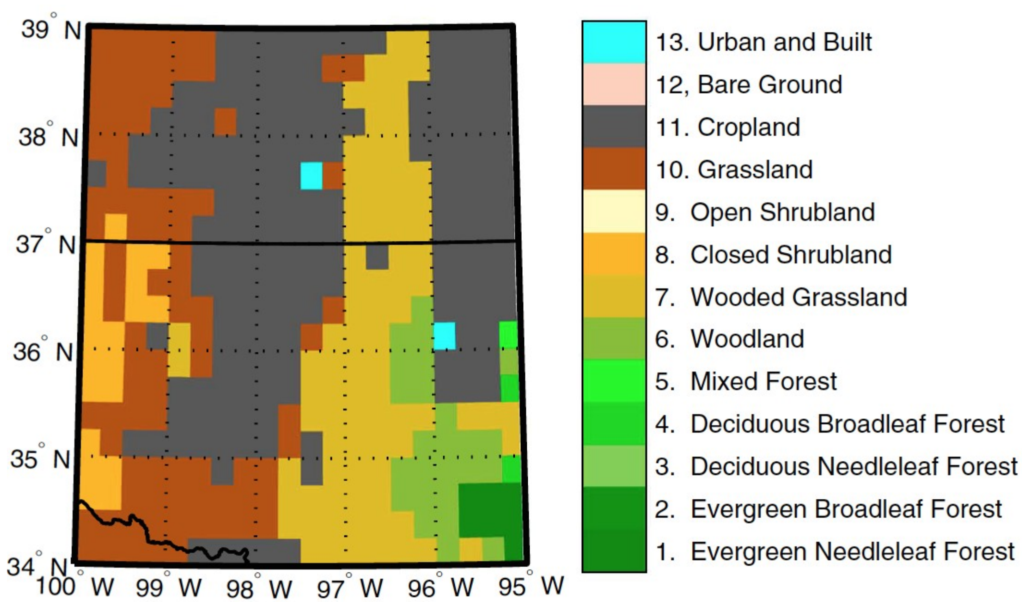
M4) method 4: 10-channel Tb and 5-channel MPDI, linear terms only (15-predictor)

M5) method 5: 10-channel Tb, 10-channel Tb^2, and 5-channel MPDI (25-predictor)

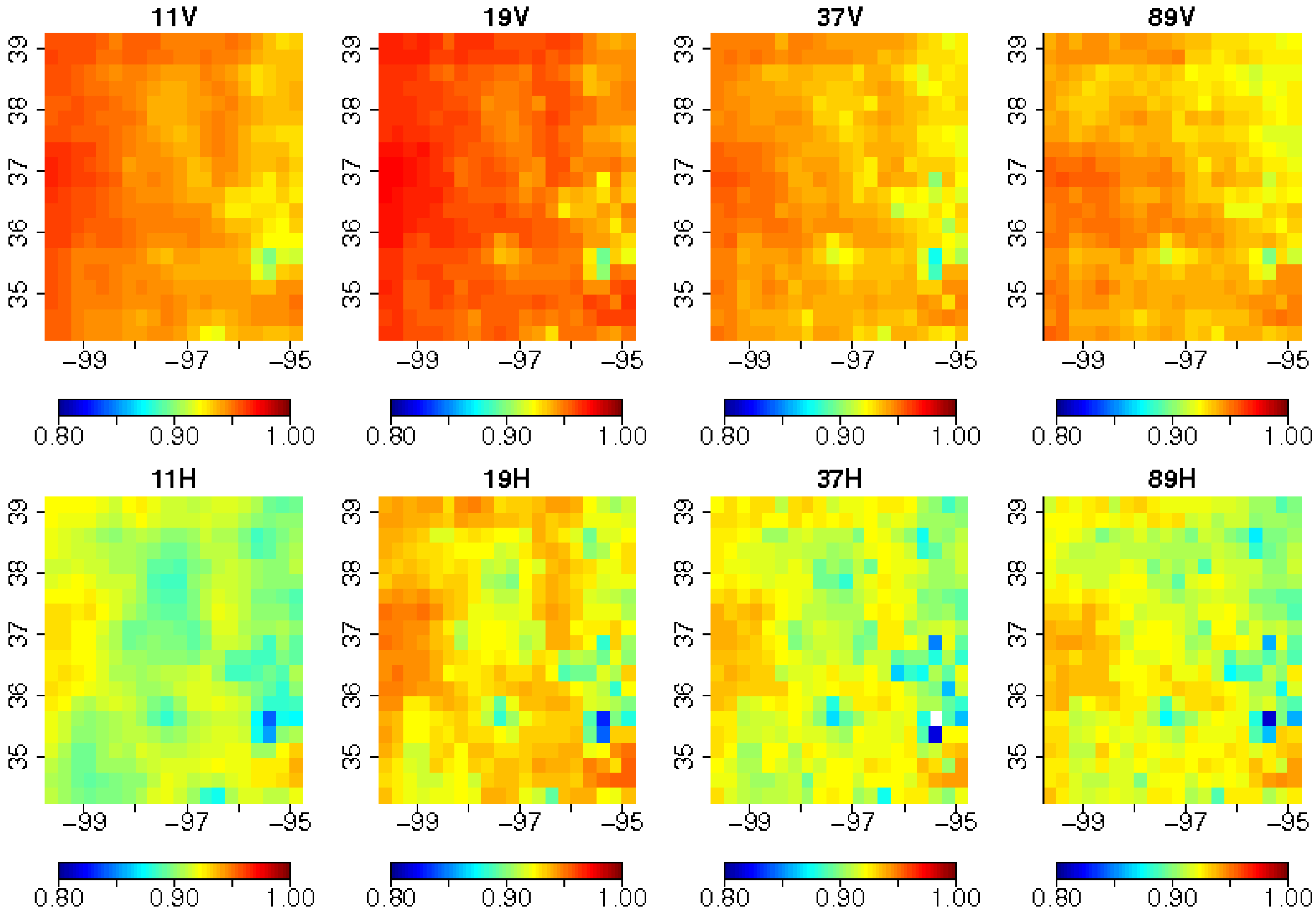
Evaluation of physical and statistical models

1. Study domain: SGP
2. Study period: 2009-2010 (2 years)
3. AMSR-E channels
4. Reference data: retrieved AMSR-E (Ringerud et al. 2014)
5. Performance metric: rmse difference

Surface characteristics of study domain

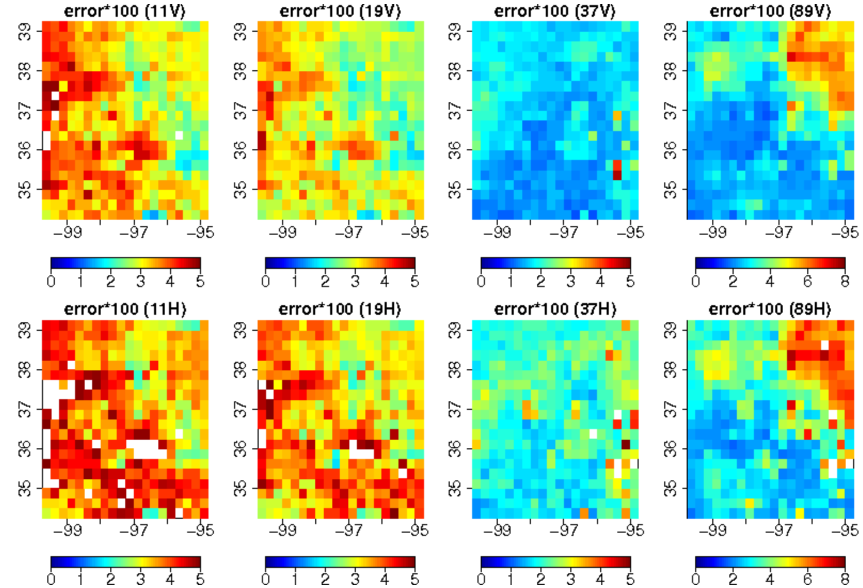


Reference mean emissivity

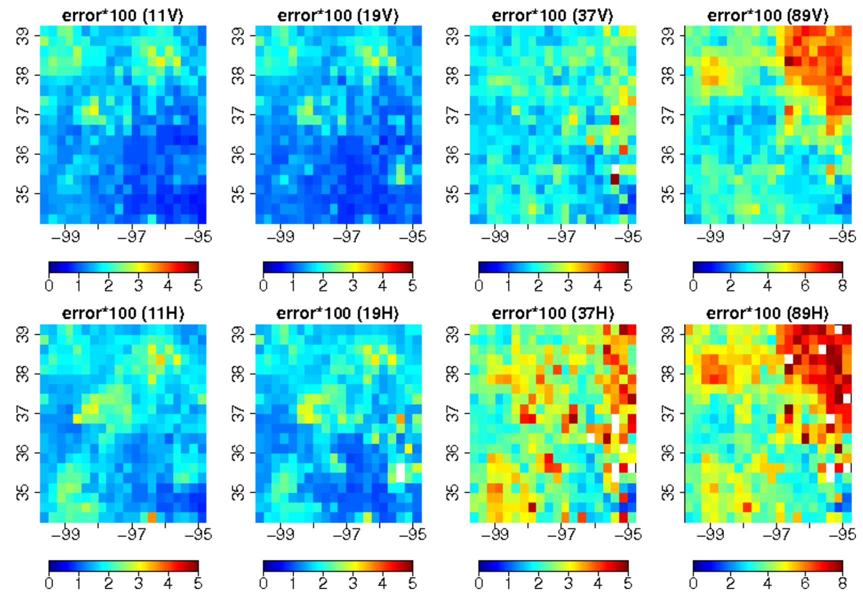


LIS-CMEM modeled emissivities

un-calibrated

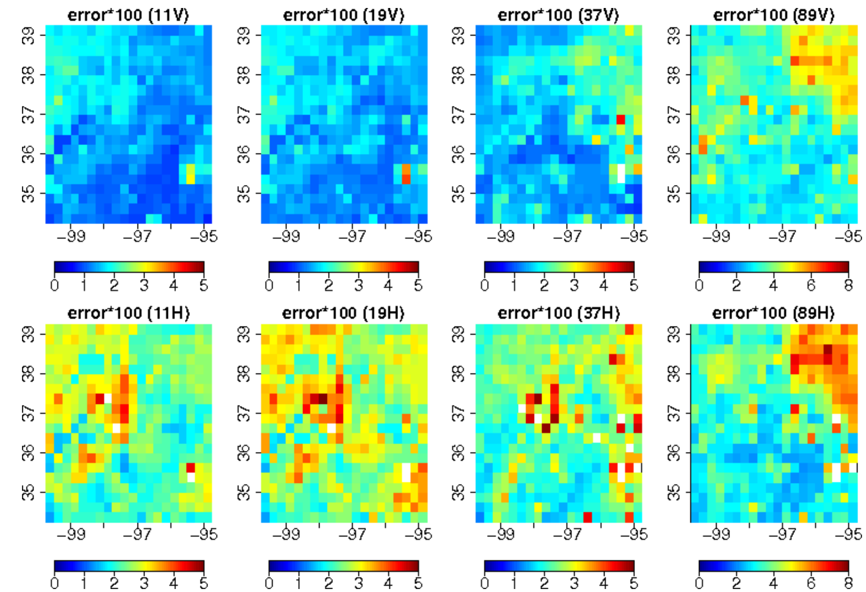


calibrated

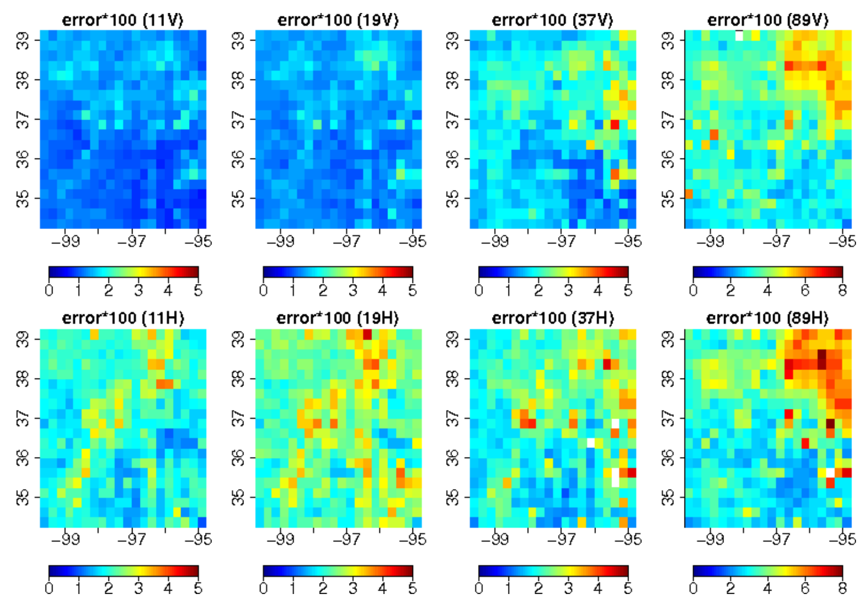


LIS-CRTM modeled emissivities

un-calibrated

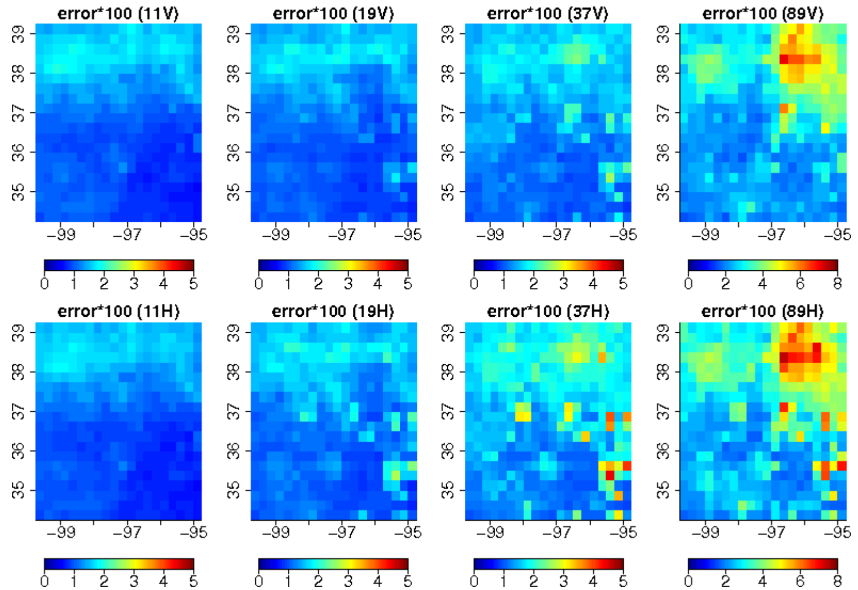


calibrated

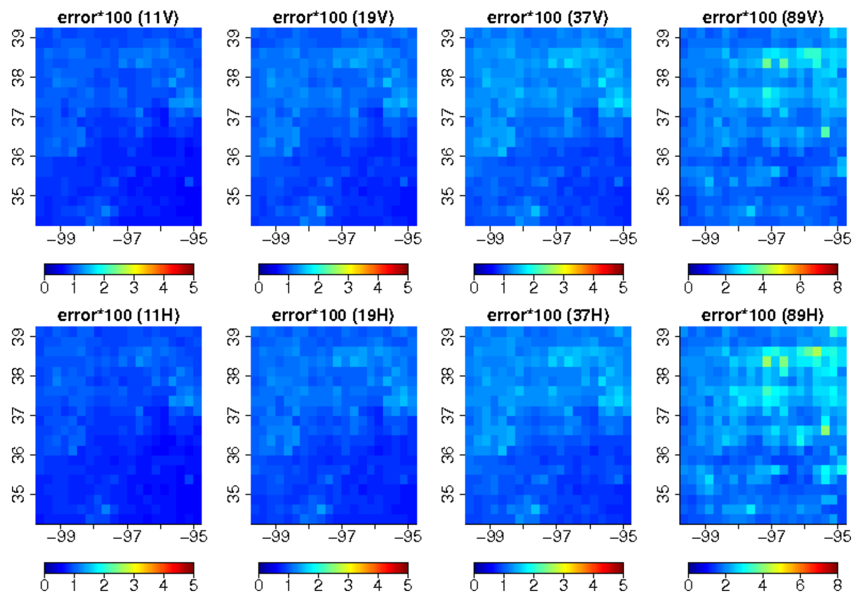


Statistically modeled emissivities

Worst model (M1)



Best model (M4)



Summary of performance metrics

Table 1. Spatial Mean of the Room-Mean-Square Difference (RMSD) Between Each Method's Estimate and the Retrieved Emissivity Multiplied by 100

Method Name		11V	11H	19V	19H	37V	37H	89V	89H
PHYS	CMEM3_uncal	3.38	3.88	2.97	3.53	1.62	2.22	3.15	3.70
	CMEM3_cal	1.47	1.71	1.39	1.68	1.94	2.77	3.83	4.73
	CRTM2_uncal	1.43	2.52	1.50	2.81	1.72	2.55	3.58	3.72
	CRTM2_cal	1.25	2.04	1.37	2.45	1.83	2.22	3.63	3.74
STAT	M1	1.18	1.13	1.23	1.33	1.41	1.69	2.88	3.20
	M2	1.12	1.07	1.18	1.19	1.35	1.35	2.64	2.75
	M3	0.90	0.87	1.01	1.00	1.14	1.13	1.96	2.12
	M4	0.90	0.86	1.01	1.00	1.14	1.13	1.94	2.09
	M5	1.00	0.96	1.10	1.09	1.25	1.22	2.21	2.28

- higher errors for higher-frequency channels
- statistical models systematically outperformed physical models

Summary:
We evaluated two approaches to estimate dynamic emissivity

- Physical modeling (CRTM, CMEM, etc.)

Pros: sound physical principles and processes
Cons: contains many uncertain parameters and requires many inputs which are inaccurate (e.g., soil moisture)

- Statistical modeling (based on relationship between historical data and predictors)

Pros: simple, ignorant of underlying physical processes
Cons: needs to find reliable predictors, if any. Ignorant of underlying physical processes. Quality training data are critical.

We found:

Statistical models systematically outperformed physical models

Explanations and discussions:

1.Physical models rely on a large number of inputs, many of which are currently not accurately simulated.
2.Real-time Tbs contains much information of emissivity dynamics. Physical models are not currently exploiting this. This can be improved with radiance data assimilation (e.g., MIRS).
3.We are extending our studies to the global scale. Some surface types, such as snow cover, may be more challenging to physical models than statistical ones.