



Advances of the Community Surface Emissivity Models (CSEM) in Support of NWP Data Assimilation

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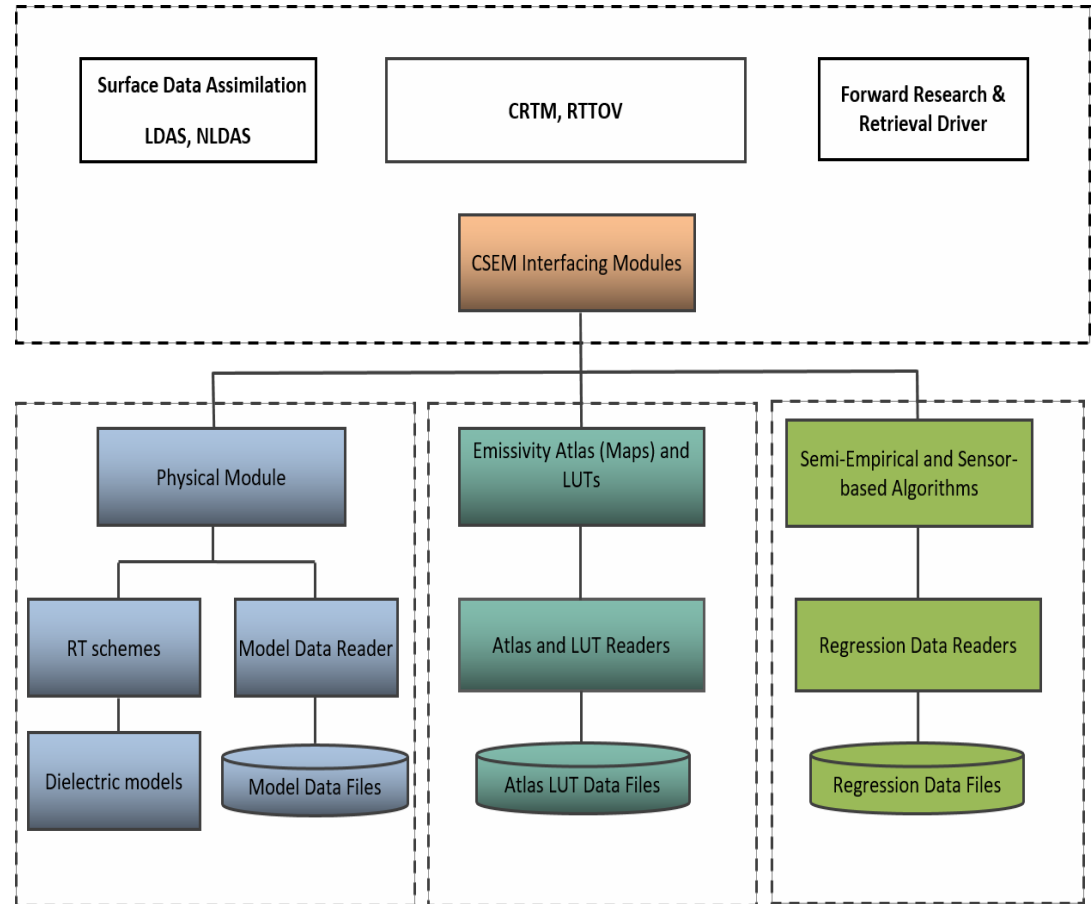
Outline

1. A short introduction to the CSEM framework and the surface emissivity models currently implemented
2. Improvements of the existing physical MW land surface emissivity model
3. Development of the prognostic MW land surface emissivity model based on machine learning
4. Summary and further efforts

CSEM Infrastructure and Interfacing Design

- ❖ Developed from CRTM surface modules, but with refined software structures based on OOP design to ease new model development efforts and to support different applications.
- ❖ Emissivity & BRDF simulations of **visible, infrared and microwave channels** over **all surface types** (land, water, snow and sea ice, desert).
- ❖ **Forward, tangent-linear, and adjoint** operators to support surface data assimilation and surface variational retrievals.

Top-Down: abstract layer for different apps



Bottom-Up: abstract containers to facilitate new model development & to support multiple model options

CSEM Model Register & Configuration File

A formatted text file is used as Algorithm Register for developers to easily add their new models to the model repository, and meanwhile serves as a Configuration file for users to specify model options in research or operational applications.

Special Chars “[]” Model Class “,” - Delimiter “#” - Comment lines

[MW_LAND]			[IR_LAND]			[VIS_LAND]		
NESDIS_Land_MW	,	1	NPOESS_LUT	,	1	NPOESS_LUT	,	1
NESDIS_Land_MW213	,	0	UWIR_ATLAS	,	0	RTTOV_BRDF_ATLAS	,	0
TELSEM_ATLAS_V1	,	0,						
TELSEM_ATLAS_V2	,	0,						
CNRM_AMSUA_ATLAS	,	0,						
[MW_WATER]			[IR_WATER]			[VIS_WATER]		
NESDIS_FASTEM_V5	,	0,	NESDIS_IRW_Nalli	,	1,	NPOESS_LUT	,	1,
NESDIS_FASTEM_V6	,	1,	NESDIS_IRW_WuSmith	,	0,	RTTOV_VIS_BRDF	,	0,
RTTOV_FASTEM_V5	,	0,	NPOESS_LUT	,	0,			
RTTOV_FASTEM_V6	,	0,	RTTOV_IRSSEM_V1D1	,	0,			
RTTOV_TESSEM	,	0,	RTTOV_IRSSEM_V2D1	,	0,			
[MW_SNOW]			[IR_SNOW]			[VIS_SNOW]		
NESDIS_Snow_MW	,	0	NPOESS_LUT	,	1	NPOESS_LUT	,	1
SensorBased	,	1						
[MW_ICE]			[IR_ICE]			[VIS_ICE]		
NESDIS_Ice_MW	,	0	NPOESS_LUT	,	1	NPOESS_LUT	,	1
SensorBased	,	1						

Microwave Physical Land Emissivity Model of Three Dielectric Medium Layer

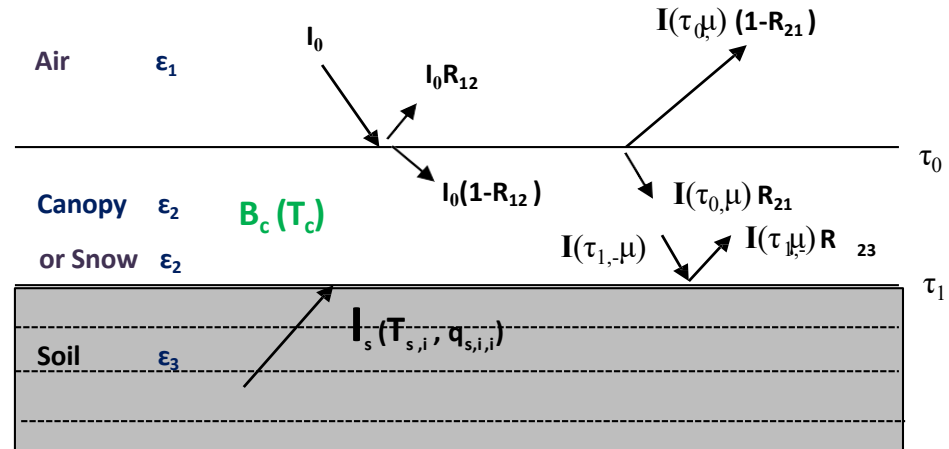
MODEL INPUTS

- Frequency (GHz)
- Zenith_Angle
- Soil_Moisture_Content
- Vegetation_Cover_Fraction
- Soil_Temperature
- Land_Skin_Temperature
- Snow_Depth
- Leaf_Area_Index (LAI)

MODEL OUTPUTS

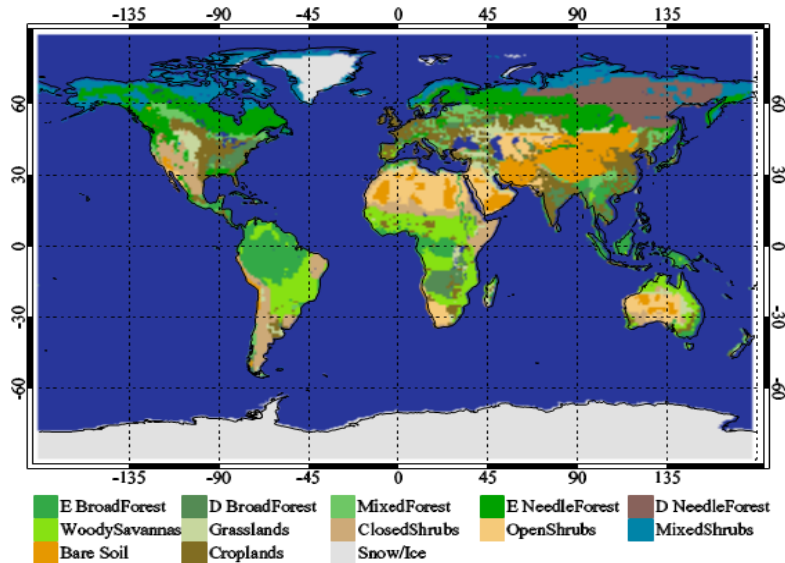
- Emissivity V_Pol
- Emissivity H_Pol

Weng *et al*, 2001; Chen & Weng, 2016



- Two-Stream Physical RT Model
- Volumetric scattering of the middle layer
- Reflection at medium interfaces are considered.
- Roughness attenuation & polarization mixing
- Angular dependency
- Calibrated Range: 19GHz to 89 GHz

Type-based Static Built-in Parameters of MW Physical Land Model



TYPE Vegetation_Parameters

GFS vegetation type Index (1-12)

lthick ! leaf thickness (mm)

langl ! canopy dominant leaf inclination angle

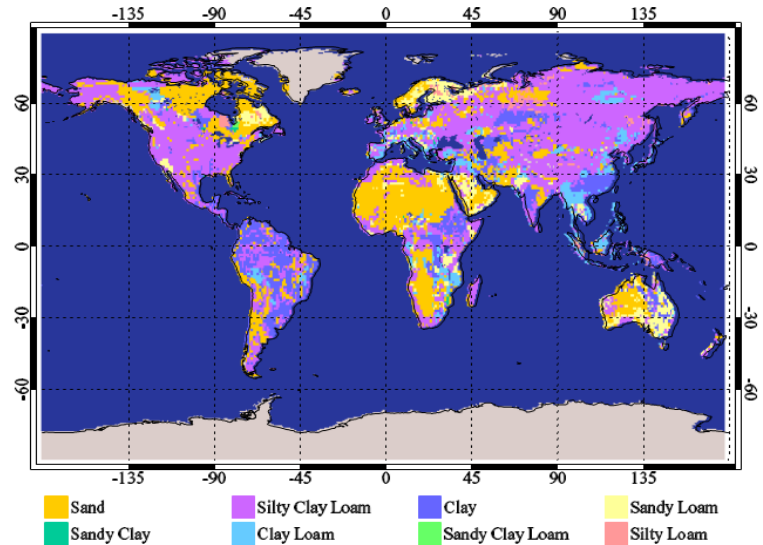
vrho ! Bulk density of dry vegetation material

vmge ! leaf gravimetric water content

maxlai ! maximum leaf area index

minlai ! minimum leaf area index

END TYPE Vegetation_Parameters



TYPE Soil_Parameters

GFS soil type Index (1-9)

rhos ! density of the soil solids

rhob ! soil bulk volume density

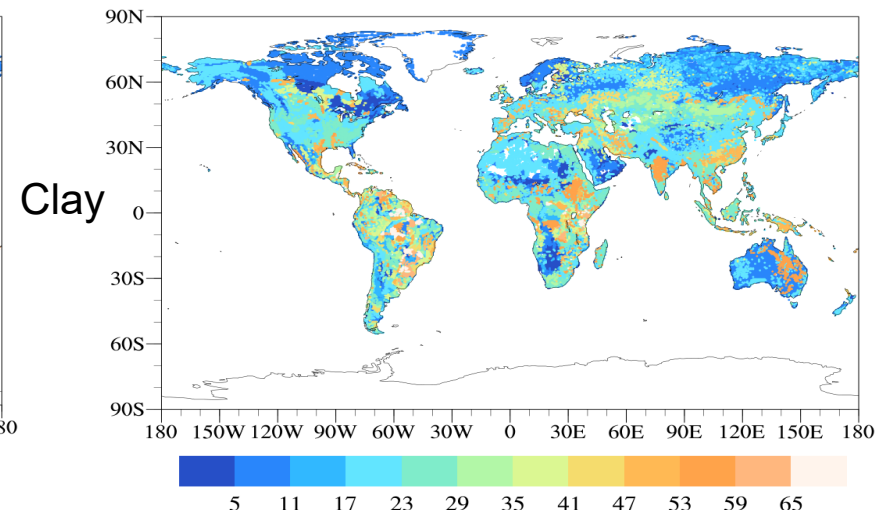
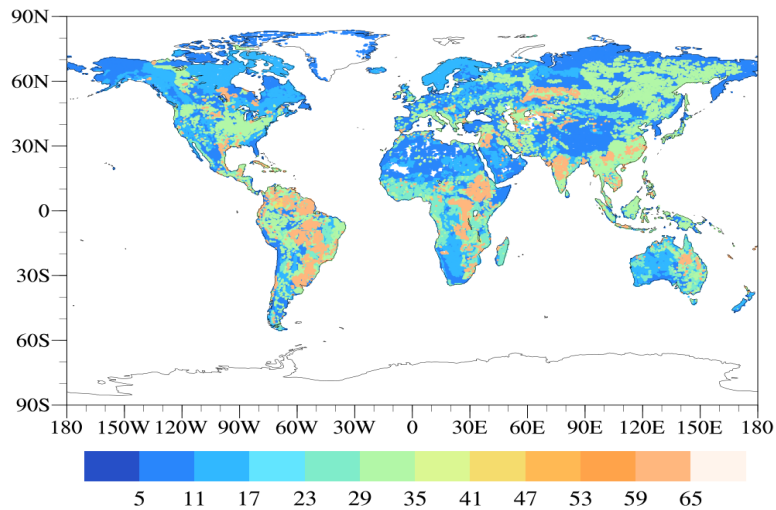
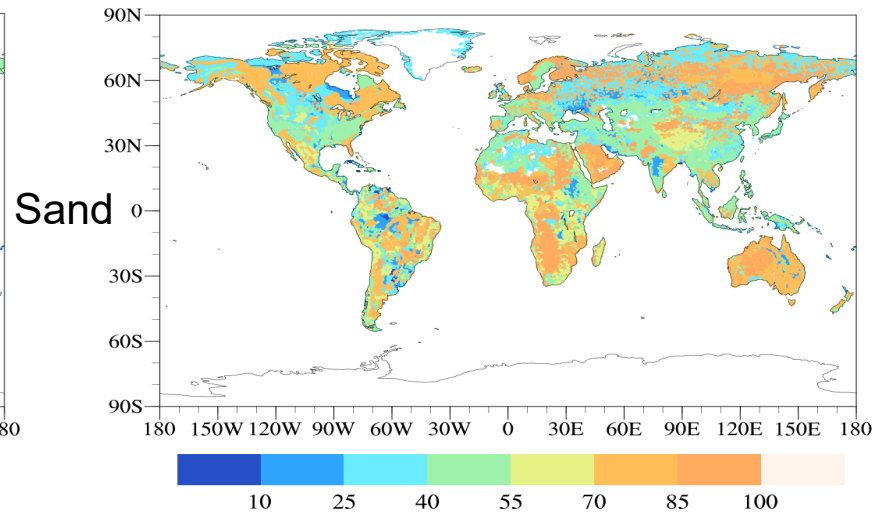
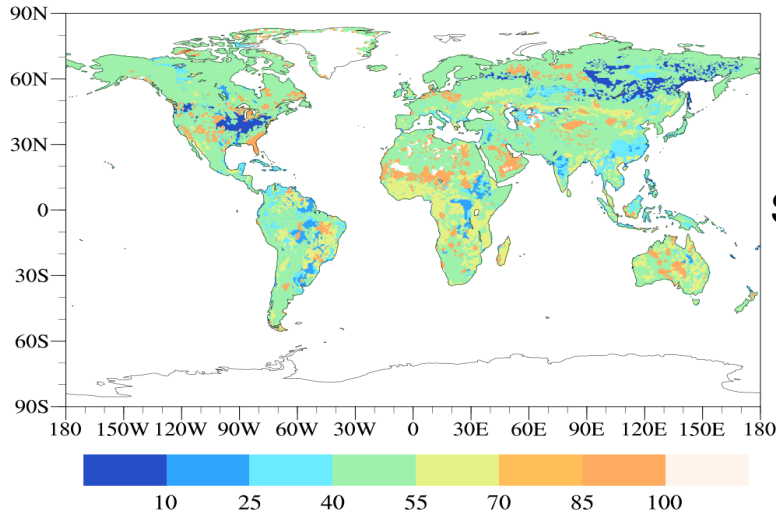
sand ! sand fraction

clay ! clay fraction

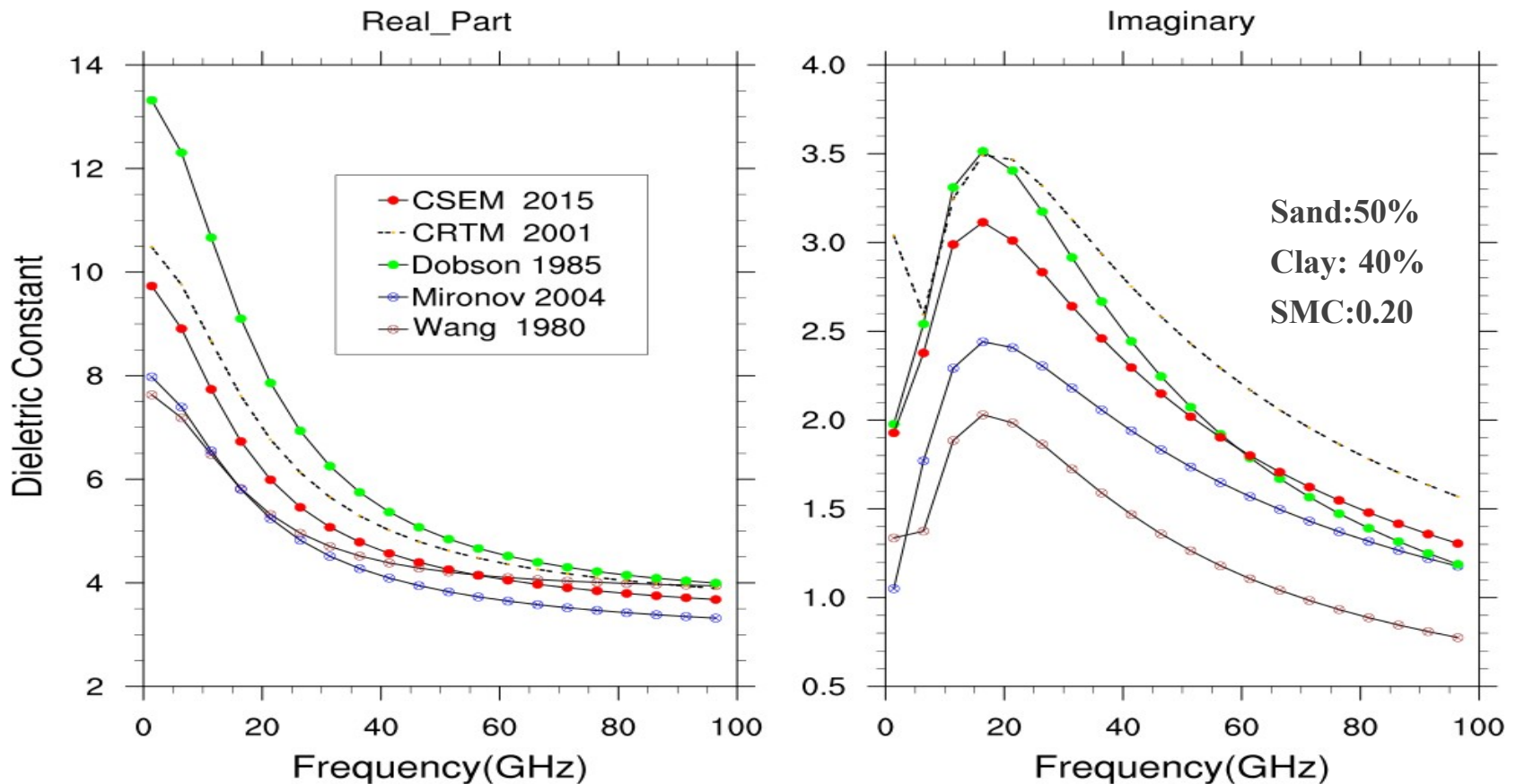
END TYPE Soil_Parameters

Options of Model Built-in Parameters

GFS Type-Based (Left) Vs STATSGO Map (Right)



Model Expansion & Dielectric Model Options

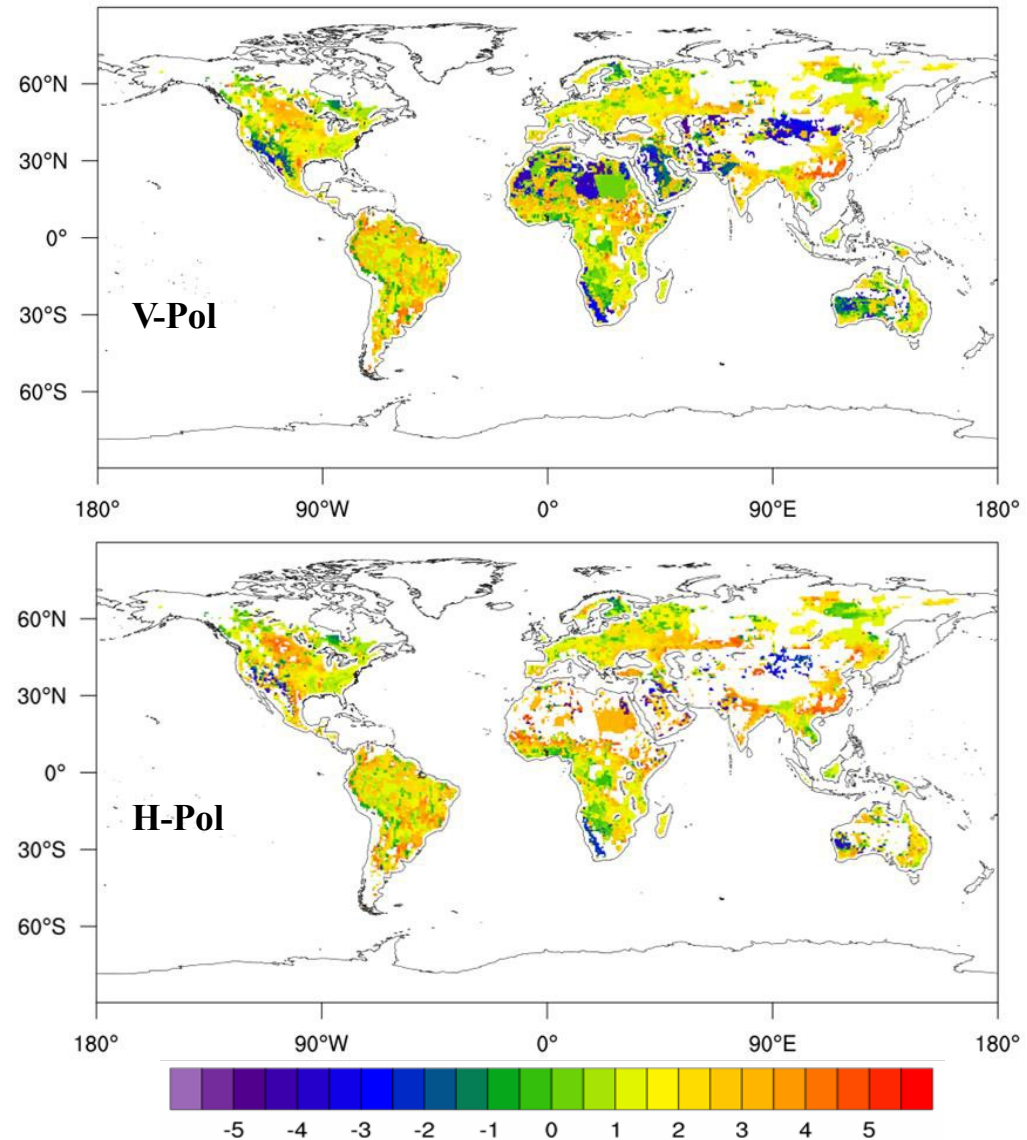


There exists large uncertainty involved in the calculation of the media permittivity (e.g., soil). Several soil MW permittivity model (Weng et al 2001; Wang et al, 1980; Mironov et al, 2004; Dobson et al., 1985) are implemented in CSEM for research purpose and model optimization purpose.

Impact of MW Soil Dielectric Model in CRTM Brightness Temperature Simulations

This figure shows the differences between the CRTM simulation with the “optimized” MW soil dielectric model and the default one in the current CRTM at AMSR-2 6.9 GHz channels.

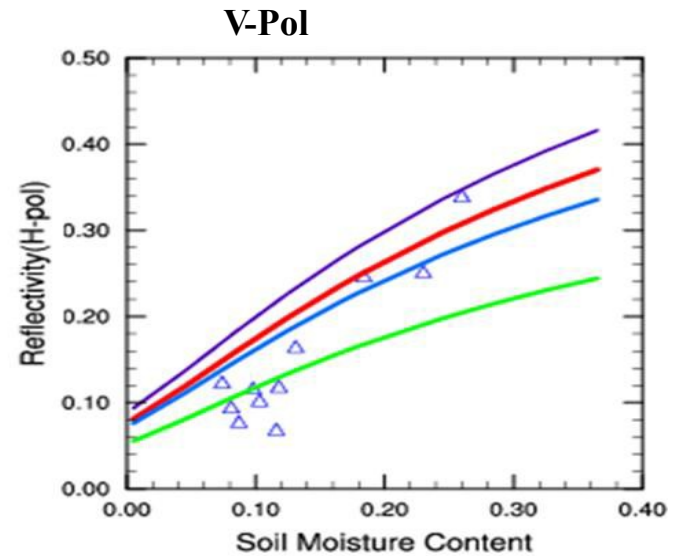
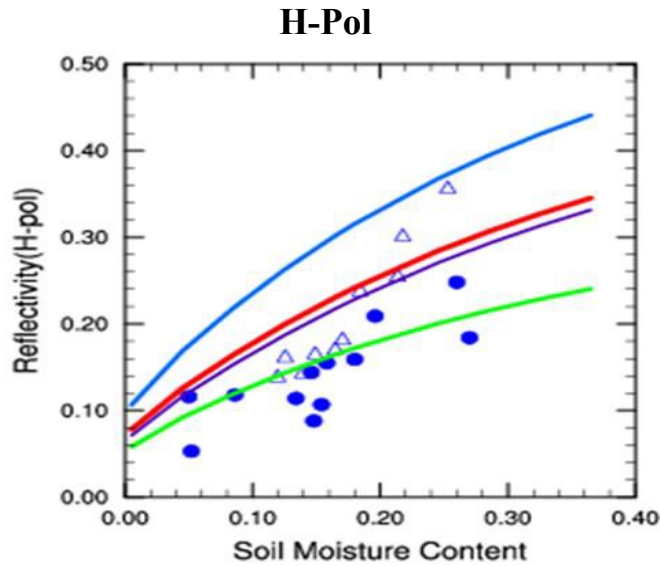
Different soil dielectric model may result in about $\pm 2\text{K}$ difference in CRTM TB simulations.



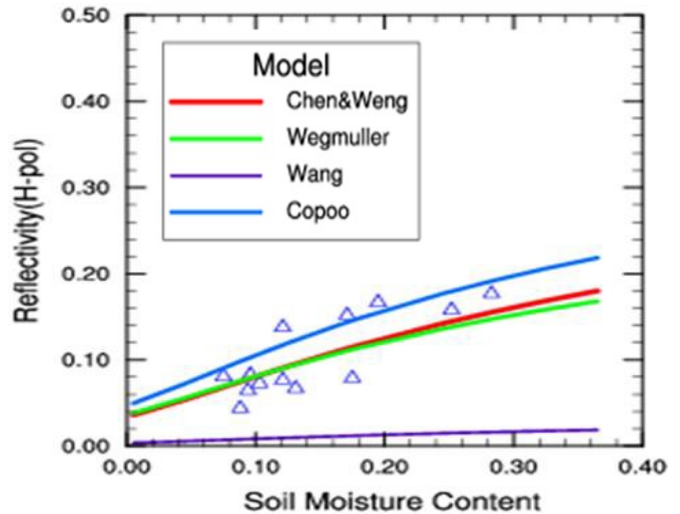
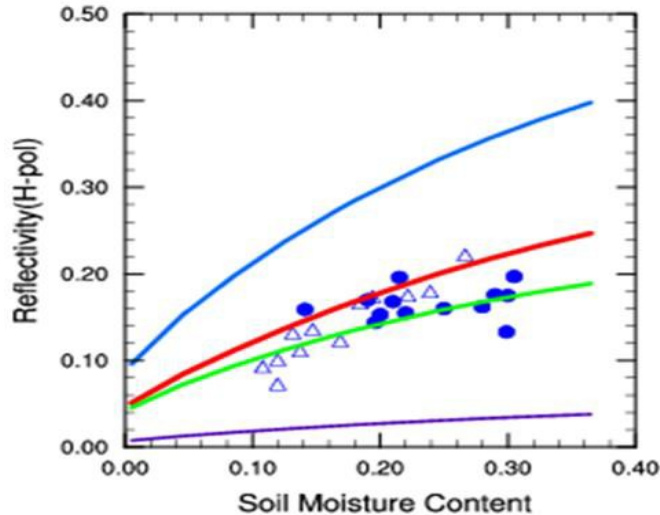
Improvement of Soil Surface Roughness Attenuation and Polar Mixing Models

L-Band

Smooth Surface
Sigma: 0.25



Rough Surface
Sigma: 1.25



Implementation of Tangent-linear & Adjoint Modules of Physical MW Land Model

Surface Planck:

$$T_b = \epsilon \bullet T_s$$

Physical Emissivity:

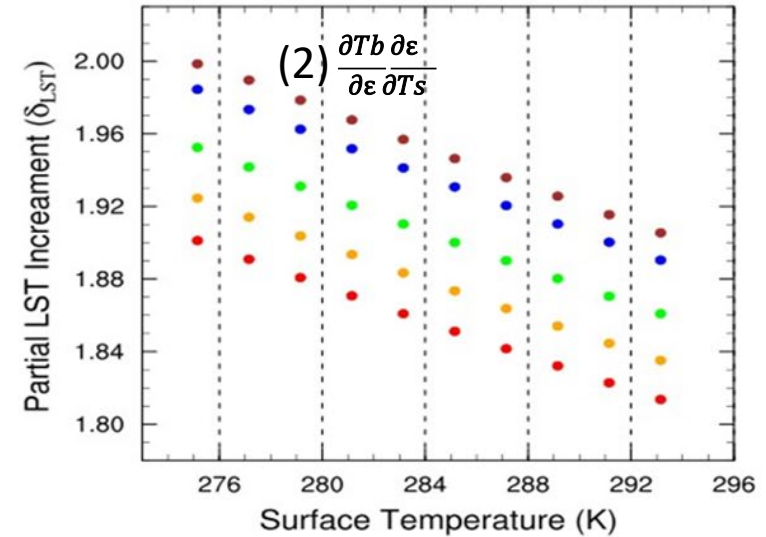
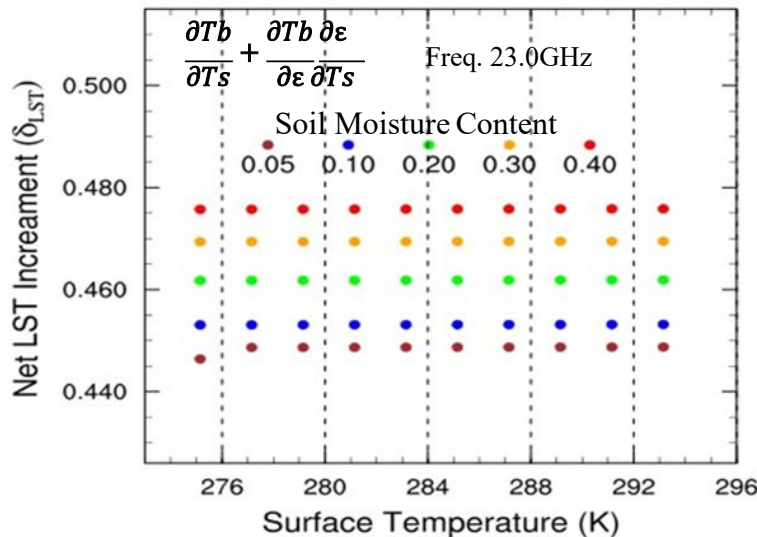
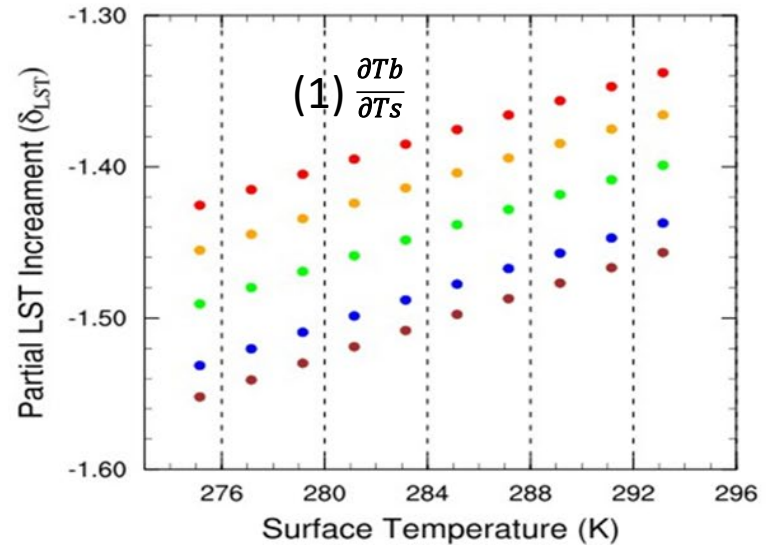
$$\epsilon = \epsilon(T_s, \text{SMC}, \text{VFR} \dots)$$

If Emissivity is used as an independent control variable, the property of the adjoint (K-matrix) will be totally different from the truth, which will direct the optimization algorithm of the cost function in a wrong way, and result in a misleading T_s analysis increment.

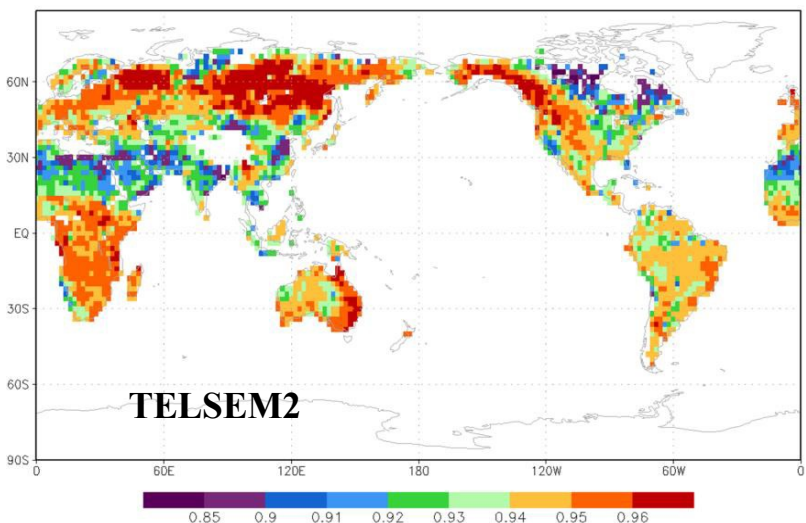
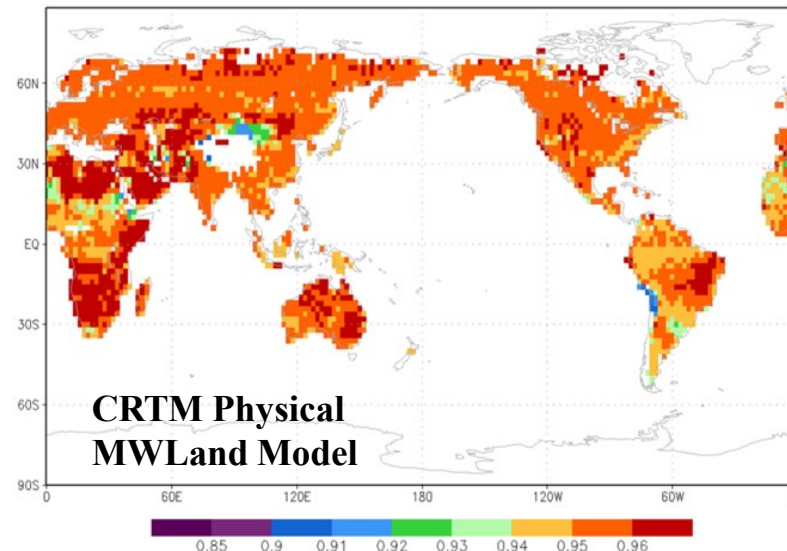
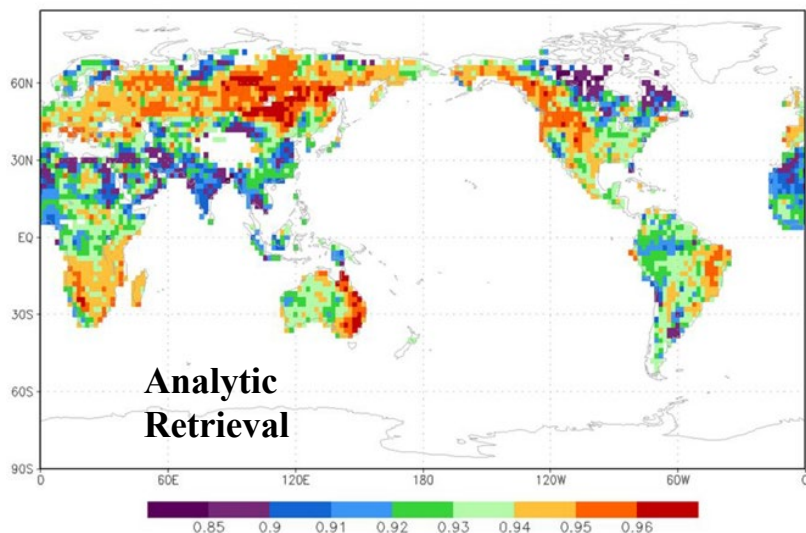
(1) (2)



$$\frac{\delta T_b}{\delta T_s} = \frac{\partial T_b}{\partial T_s} + \frac{\partial T_b}{\partial \epsilon} \frac{\partial \epsilon}{\partial T_s}$$



Application Challenges of Physical Model at Global Scale



- Insufficient characterization of spatial variation
- Desert areas
- Tundra & frozen regions

MW Land Model Based on Machine Learning

Multiple Layer Perceptron Neuron Network

- Input Layer: 6 Features
- 1st Hidden Layer: 15–30 Neurons
- 2nd Hidden Layer: 2 Neurons
- Output Layer: 2 Targets
- Levenburg–Marquardt optimizer
- Backpropagation based on adjoint coding

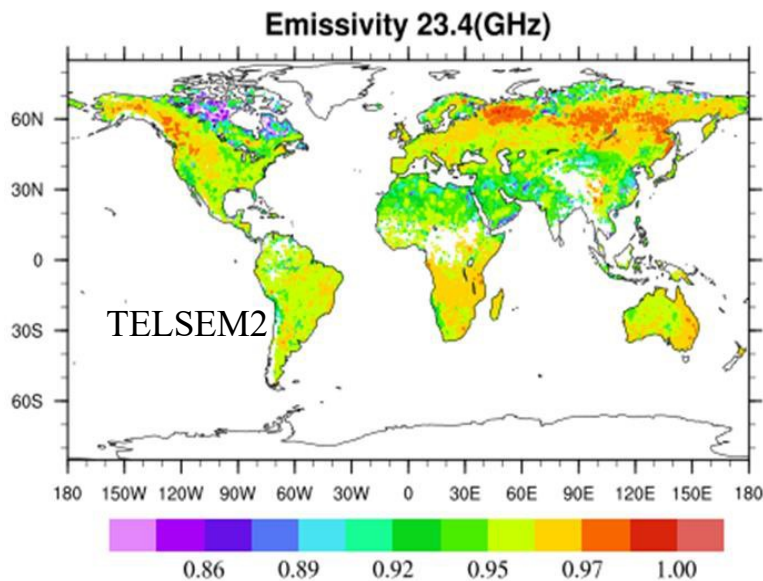
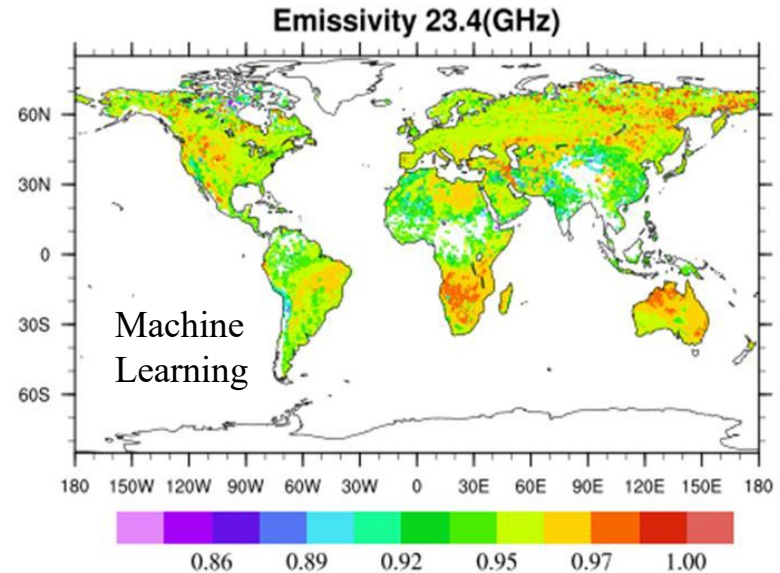
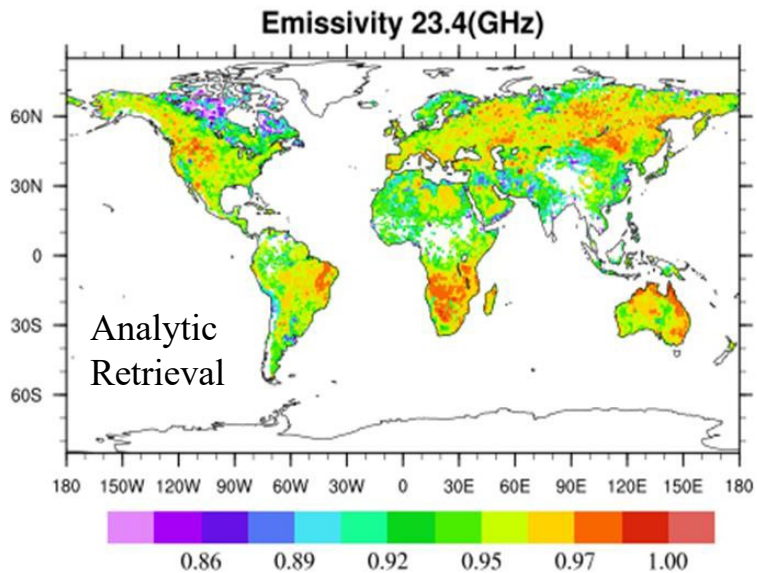
Training data sets

- Three months of instantaneous retrieval in GSI under strict clear-sky or non-scattering conditions with ATMS & AMSUA obs
- TELSEM2 monthly atlas
- Paired GFS surface state variables

Data Stratification by GFS Surface Types

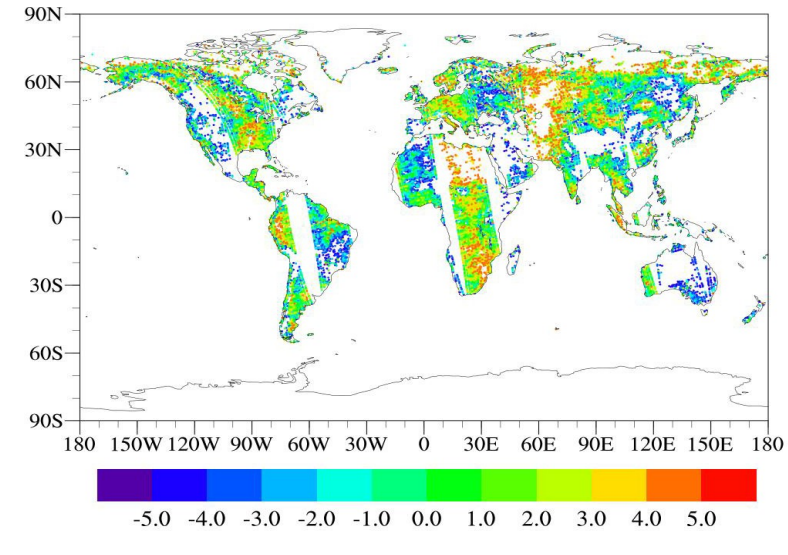
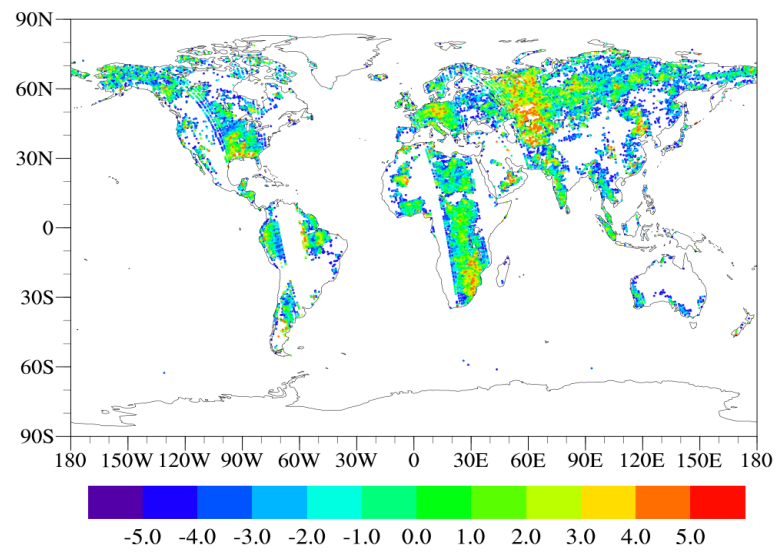
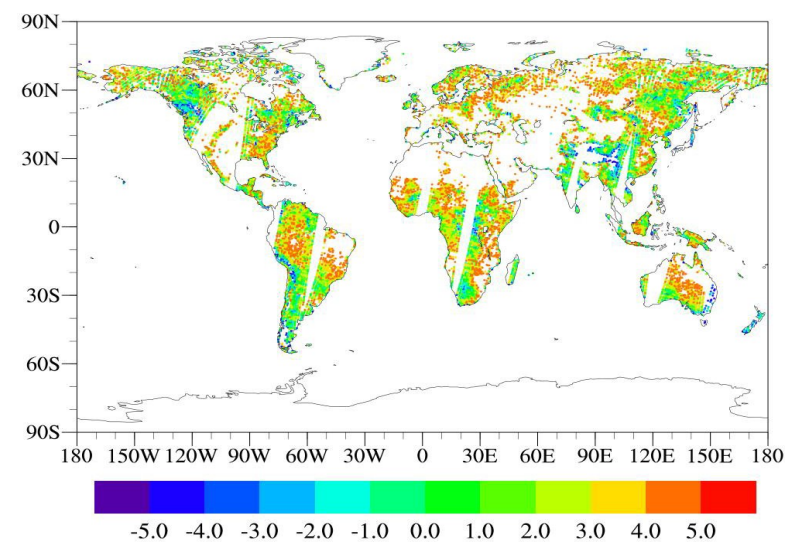
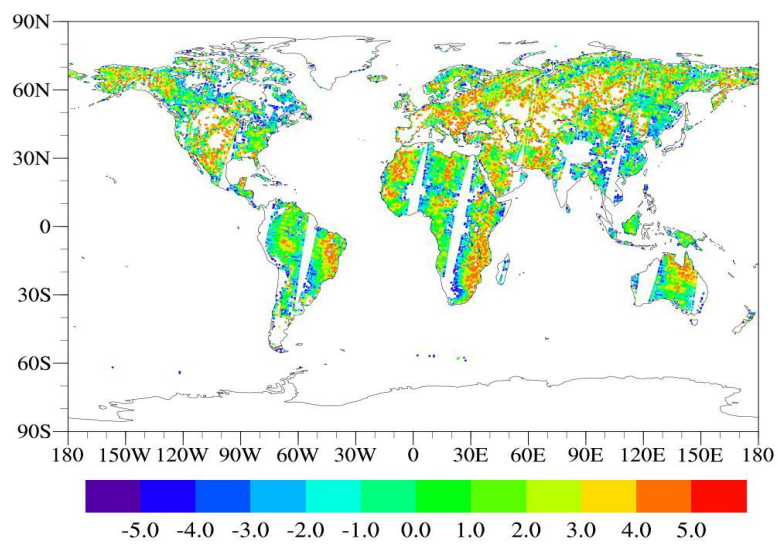
Type Index	Type Names	Total Samples	Training Used (%)
1	E. BROADLEAF_FOREST	34000	8.8
2	D. BROADLEAF_FOREST	9100	19.7
3	E. BROADLEAF_PINE_FOREST	41000	5.8
4	E. PINE_FOREST	36700	5.9
5	D. PINE_FOREST	7700	13.7
6	BROADLEAF_BRUSH	67230	5.5
7	SCRUB	56000	8.7
8	SCRUB	703	56.9
9	SCRUB_SOIL	90000	5.5
10	TUNDRA	21200	8.0
11	COMPACTED_SOIL	50000	3.0
12	TILLED_SOIL	87600	6.1

Comparison of ML Emissivity Model With Instantaneous Analytic Retrieval and TELSEM Monthly Atlas



- Consistent spatial variations, indicating comparable quality at global scale with TELSEM
- Better performance in desert areas
- Lower performance over tundra & frozen regions (surface typing).

Brightness Temperature O-B at AMSUA 50.3GHz with **ML-Based Model** (left) Vs. with **TELSEM2** (Right)



Summary and Further Efforts

- CSEM is a very flexible surface emissivity and BRDF modeling platform, supporting both operational and research model development and diverse applications.
- The prognostic land surface emissivity model based on machine learning shows very promising performance toward operation application in DA system. Training data sets from different seasons and sensors are needed. High resolution surface typing is essential for the model training and the model subsequent performance stability.
- Refine the artificial neuron network architecture.
- Refine the non-linear optimization algorithms, especially the computational efficiency (parallelization).
- Optimization of physical model built-in parameters