



# Machine Learning Applications in Community Surface Emissivity Modeling (CSEM) System

Ming Chen<sup>1</sup>, Kevin Garrett<sup>2</sup>

1. CISS-University of Maryland 2. NOAA/NESDIS/Center for Satellite Applications and Research



## Introduction

The Community Surface Emissivity Modeling (CSEM) system developed at NOAA/NESDIS/STAR will be used in the next major release of the Community Radiative Transfer Model (CRTM) to support the direct radiance assimilation of satellite surface sensitive channels and to provide accurate surface emissivity condition in support of the quality-control processes of data assimilation. Both model accuracy and model computing efficiency are essential for data assimilation.

Machine learning techniques have been applied in developing the accurate and fast CSEM models from physically sound but computationally expensive physics models and from enormous observation data.

We present our latest work on utilizing the machine learning (ML) techniques to reconstruct fast microwave ocean surface emissivity from a computationally expensive two-scale physics model, and to develop prognostic land surface microwave emissivity model from the instantaneous satellite retrievals.

## CRTM Ocean Surface Microwave Emissivity Model

The MW ocean surface emissivity model (FASTEM) in CRTM is a fast emulator of the two-scale physics model by Yueh, 1997.

$$\vec{T}_s = \begin{bmatrix} I_{vs} \\ I_{hs} \\ U_s \\ V_s \end{bmatrix} = \bar{P}(\vec{k}_s, \vec{k}_i) \begin{bmatrix} I_{vi} \\ I_{hi} \\ U_i \\ V_i \end{bmatrix}$$

where  $\vec{T}_s$  is Stokes vector for scattered waves, and  $\bar{P}(\vec{k}_s, \vec{k}_i)$  is phase matrix.

$$\bar{P}(\vec{k}_s, \vec{k}_i) = \bar{P}_0(\vec{k}_s, \vec{k}_i) + \bar{P}_1(\vec{k}_s, \vec{k}_i) + \bar{P}_2(\vec{k}_s, \vec{k}_i)$$

where  $\bar{P}_0, \bar{P}_1, \bar{P}_2$  are in terms of the zero, first and second orders of small perturbation method (SPM). (•) Stands for the ensemble averages over ocean surface waves

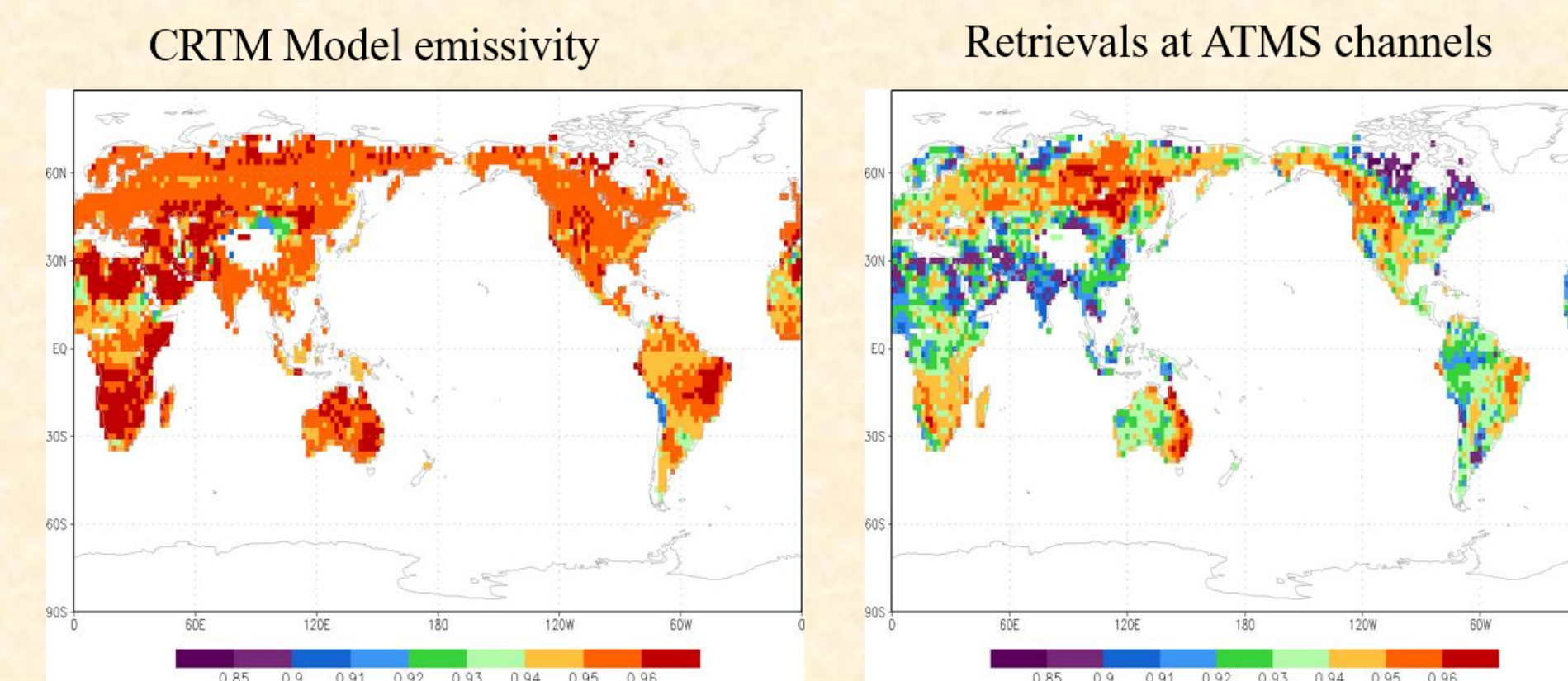
The ocean surface wave spectrum  $W(k_p, \phi_k)$  [Durdan and Vesecky, 1985] is decomposed into large-scale and small-scale domains in light of the relative sizes of EM wave to the ocean waves.

- Geometric Optics (GO) for large-scale waves
- Small Perturbation Method (SPM) for small-scale waves
- Hydrodynamic modulation for the small-scale ocean waves on the leeward faces of large-scale waves.
- Empirical foam models and the semi-physical foam models based on the non-uniform permittivity profile assumptions of seawater foam layers.

Due to the limitation of the polynomial regressions, FASTEM is unable to approximate the original physics model on the entire physics space. The current version **FASTEM-6** doesn't have the 3<sup>rd</sup> (U) and 4<sup>th</sup> (V) Stokes components. And the earlier FASTEM version **FASTEM-5** had the 3<sup>rd</sup> and 4<sup>th</sup> Stokes components, but the azimuthal variation of the 3<sup>rd</sup> component is out of phase. FASTEM is only valid up to 200GHz with view angle less than 60 degree.

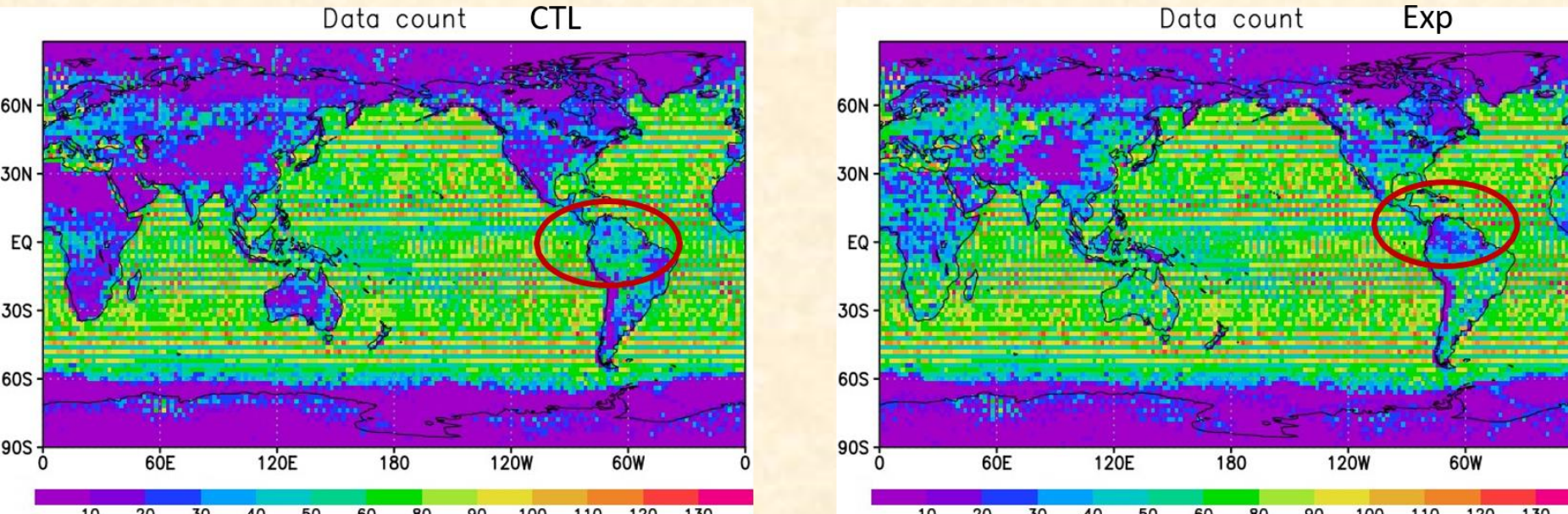
## CRTM Land Surface Microwave Emissivity Model

Over land, the surface MW emissivity is simulated with a three-medium-layer two-stream radiative transfer model (Weng et al. 2001, Chen et al. 2016). In comparison with observations, the simulated land surface emissivity is generally larger than the instantaneous retrievals, and shows much less spatial variability.



In light of the usage of satellite radiance observations in data assimilation, instantaneous land emissivity retrievals generally outperform the surface model except over the Amazon rainforest area, where the surface model has certain advantage to capture the surface state variations (Y. Zhu, 2019)

AMSU-A NOAA19 channel 3 April 28 – May 28, 2019, Y. Zhu



## Multi-layer Perceptron NN Learning System

- Fortran 2008 OOP Programming with scalable for parallel computing features implemented
- Hybrid setting of the activation function types for different neuron layers
- Variational and Evolutional Optimizers

$$X_{k+1} = X_k - [J^T(X_k)J(X_k) + \mu_k I]^{-1} J^T(X_k)v(X_k)$$

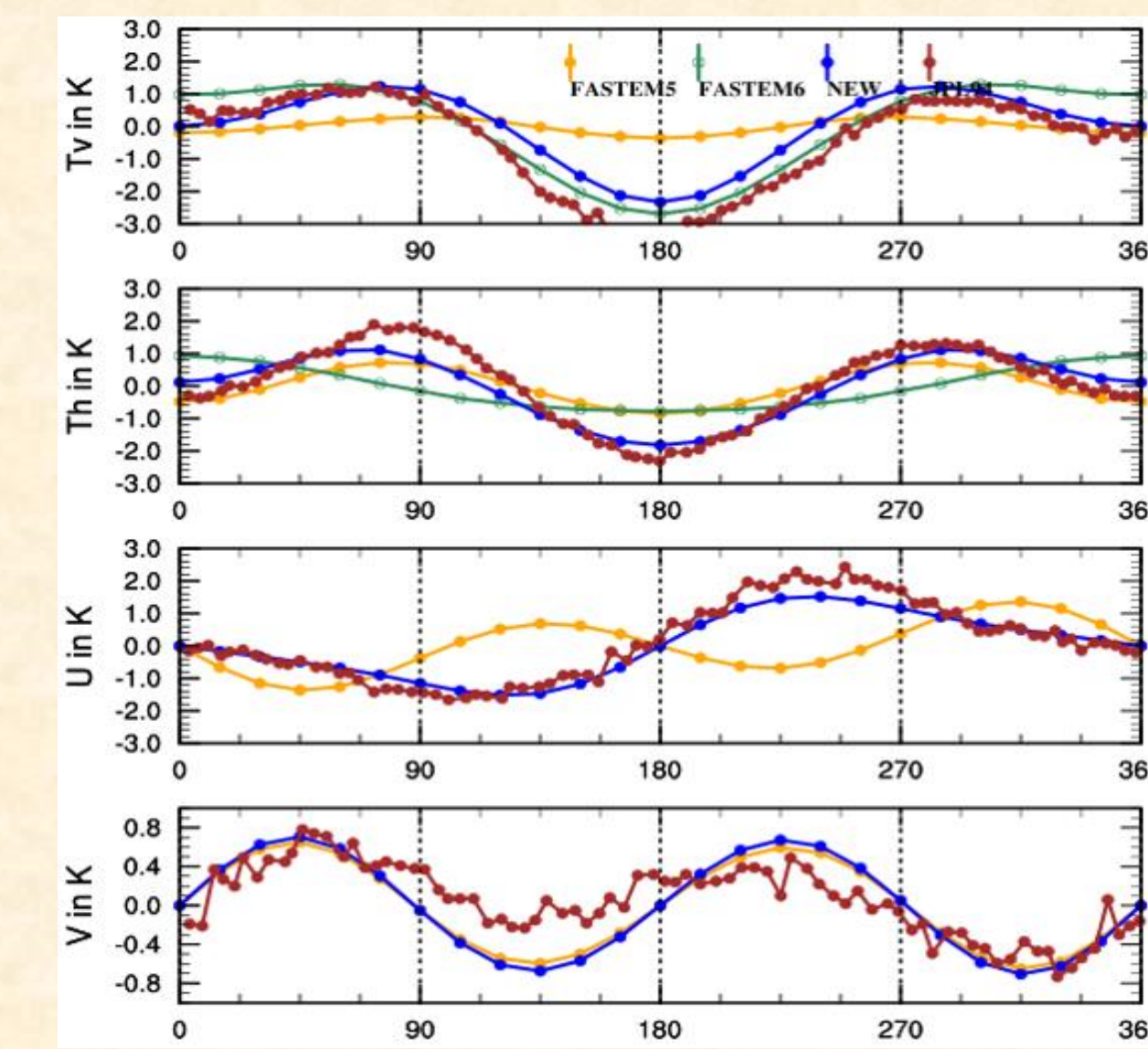
where J(x) is Jacobian Matrix

$$J(X) = \begin{bmatrix} \frac{\partial v_1(X)}{\partial x_1} & \frac{\partial v_1(X)}{\partial x_2} & \dots & \frac{\partial v_1(X)}{\partial x_n} \\ \frac{\partial v_2(X)}{\partial x_1} & \frac{\partial v_2(X)}{\partial x_2} & \dots & \frac{\partial v_2(X)}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial v_N(X)}{\partial x_1} & \frac{\partial v_N(X)}{\partial x_2} & \dots & \frac{\partial v_N(X)}{\partial x_n} \end{bmatrix}$$

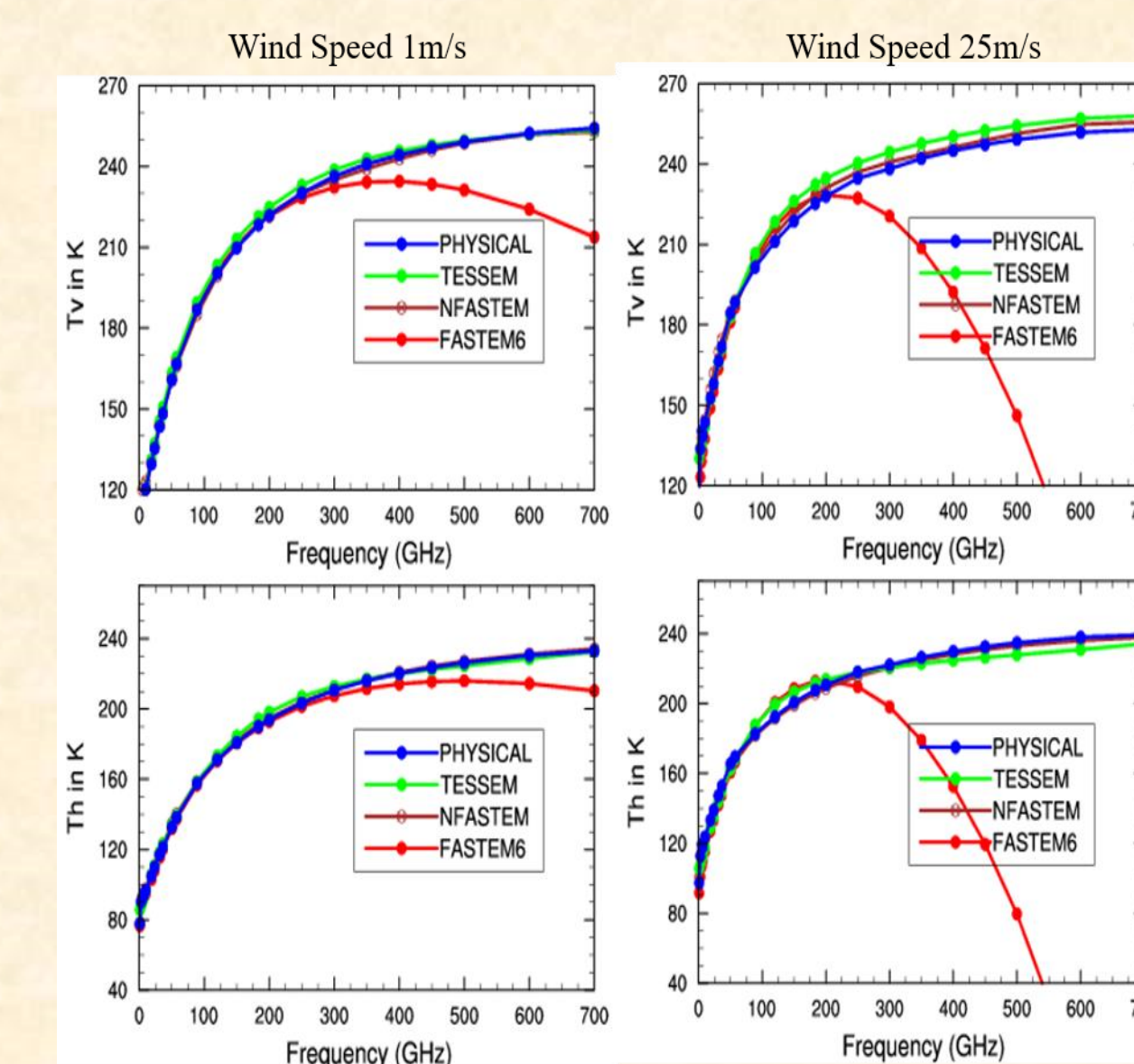
Steepest descent if  $\mu_k$  is very large, and Gauss-Newton if  $\mu_k$  is near zero, and otherwise Levenburg-Marquardt

## CSEM Model Improvements & Functionality Expansion

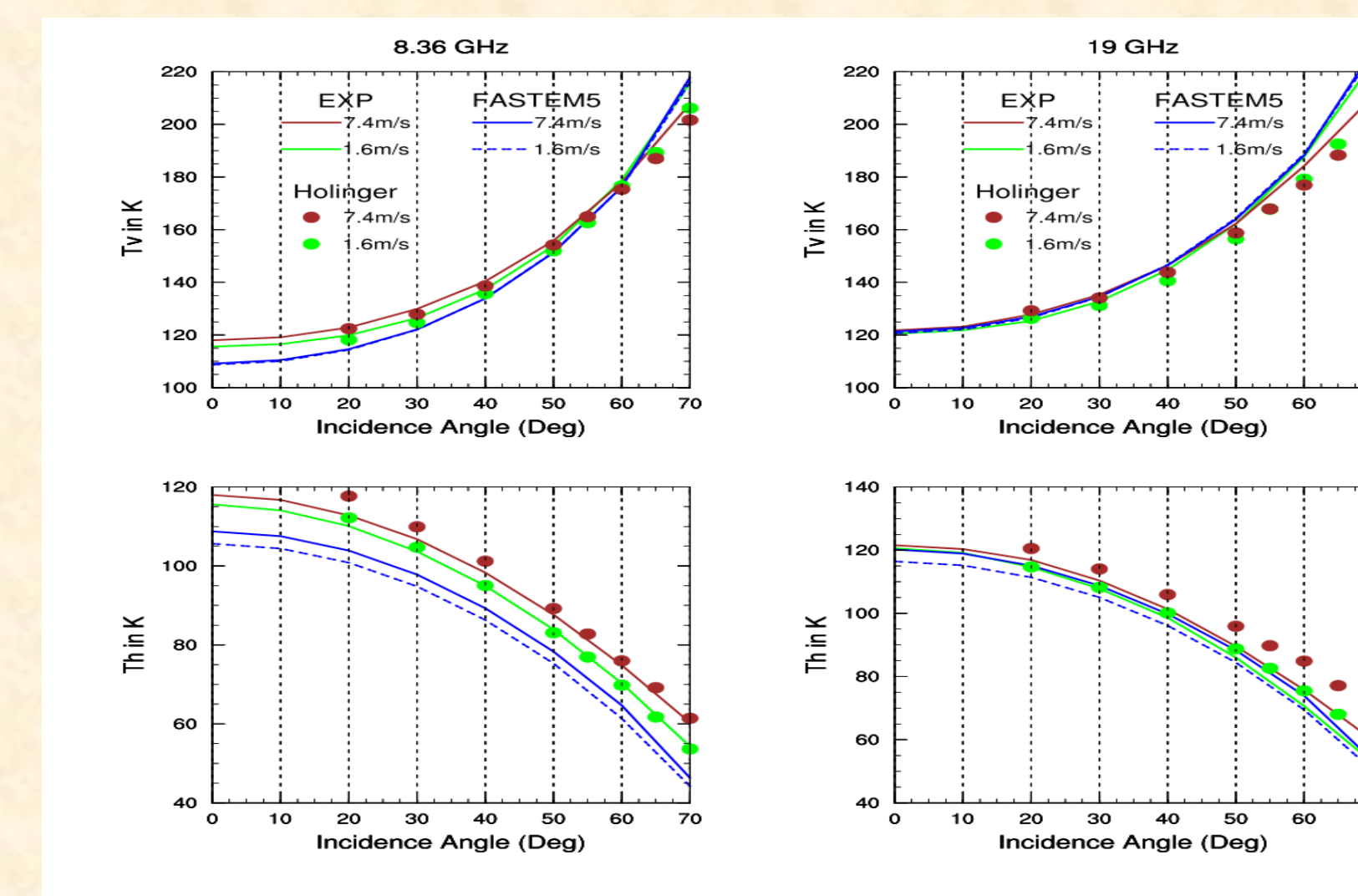
- A new FASTEM version (**NFASTEM**) has been developed, which is based on physical two-scale ocean surface emissivity model and the latest machine learning technique. All the Stokes components of NFASTEM are in good agreement with the **OBSERVATION** in terms of both magnitude and phase.



- With adequate NN architecture (hidden layers, neurons of each layers, etc), multi-layer perceptron learning system is able to approximate complex physics models of high nonlinearity. It is found that NFASTEM may emulate the original two-scale ocean surface emissivity model at very high accuracy from 1GHz to 700GHz, and view angle from 0° to 85°.



- NFASTEM also shows better agreement with in-situ observations.



- A prognostic MW land emissivity model based on machine learning of the emissivity retrieval ensembles has been developed to retain the dynamic response to surface state variables (e.g., soil moisture) while alleviating the uncertainties of the surface state variables.

## MW Land Model Based on Machine Learning

Multiple Layer Perceptron Neuron Network

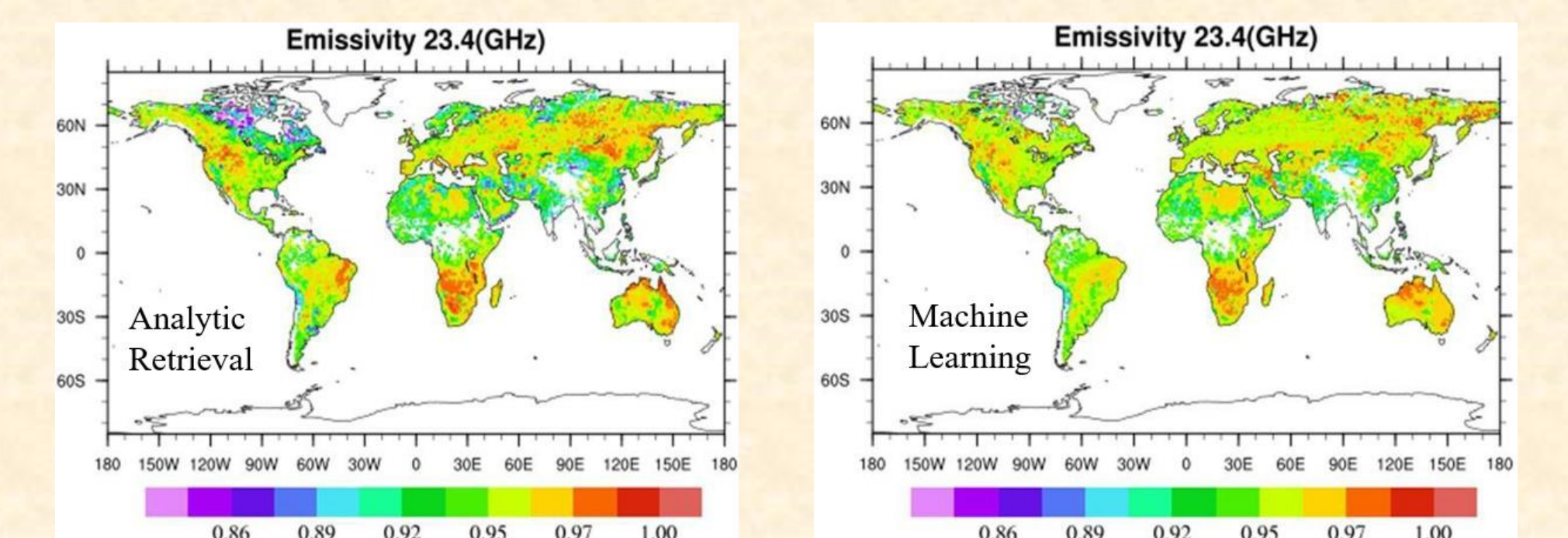
- Input Layer: 6 Features, which is the same as the physics-based model
- 1<sup>st</sup> Hidden Layer: 15-30 Neurons
- 2<sup>nd</sup> Hidden Layer: 2 Neurons
- Output Layer: 2 Targets

Training data sets

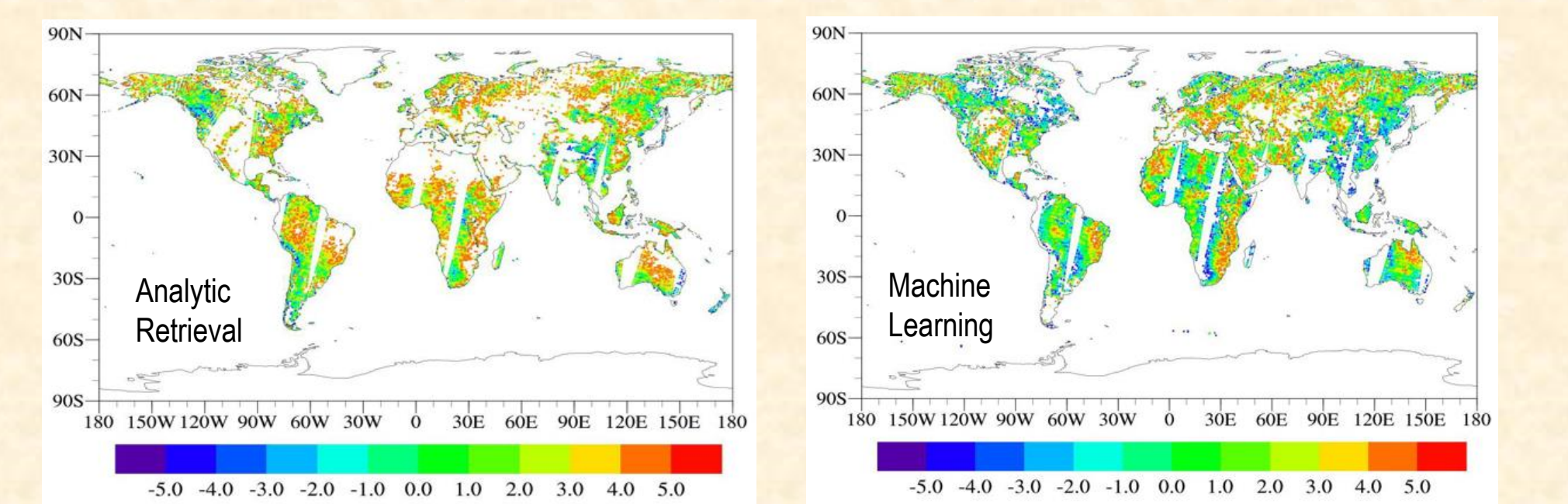
- Three months of instantaneous retrieval in GSI under strict clear-sky or non-scattering conditions with ATMS & AMSUA obs
- TELSEM2 monthly atlas
- Paired GFS surface state variables

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



- The improvements have significant impacts on CRTM forward simulations. About 25% more observations can be assimilated into GSI system.



- The tangent linear and adjoint modules of the ML-based MW land physical model were also implemented to support the radiance data assimilation of surface key variables.

## References

Chen M., Garrett K. and Y. Zhu, "Advances in Land Surface Microwave Emissivity Modeling", JCSDA Quarterly No. 65, Fall 2019.  
 Chen M., and F. Weng, "Modeling Land Surface Roughness Effect on Soil Microwave Emission in Community Surface Emissivity Model", IEEE. Trans. Geosci. Remote Sens., 54(3), 1716-1726, 2016.  
 Chen M., F. Weng, "Development and Improvement of Community Surface Emissivity MODEL (CSEM) system," 4th RSMSP, Grenoble, France, 2016.

Contact: ming.chen@noaa.gov