ISSI team meeting
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Development and evaluation of the SURface Fast Emissivity Model for ocean (SURFEM-Ocean)

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1. Introduction

- We develop SURFEM-Ocean in the context of a NWP SAF visiting scientist mission, to replace FASTEM that is implemented in RTTOV.
- It is based on the PARMIO physical model (the configuration of PARMIO has been presented in the previous presentation).
- Artificial Neural Network (NN) methods will be used to reproduce the results obtained with PARMIO much faster.
- SURFEM-Ocean extends the frequency range available with FASTEM to cover 0.5-700 GHz.
- It provides emissivities for vertical and horizontal polarizations and the 3rd and 4th Stokes parameters.
- The jacobians, the tangent linear model and its adjoint are provided for an efficient use in NWP applications.

2. Methodology

- The total ocean surface emissivity is generally written:

$$e_{ocean} = e_{flat} + e_{rough} + e_{azimuth}$$

- In the SURFEM scheme, we keep the computation of the flat sea emissivity with the physical equations of the dielectric constant model and the fresnel equations
- Then, the isotropic and anisotropic emissivities (that depend on OWS) are estimated with 2 different neural networks
- Finally the total ocean surface emissivity is computed using the following equations:

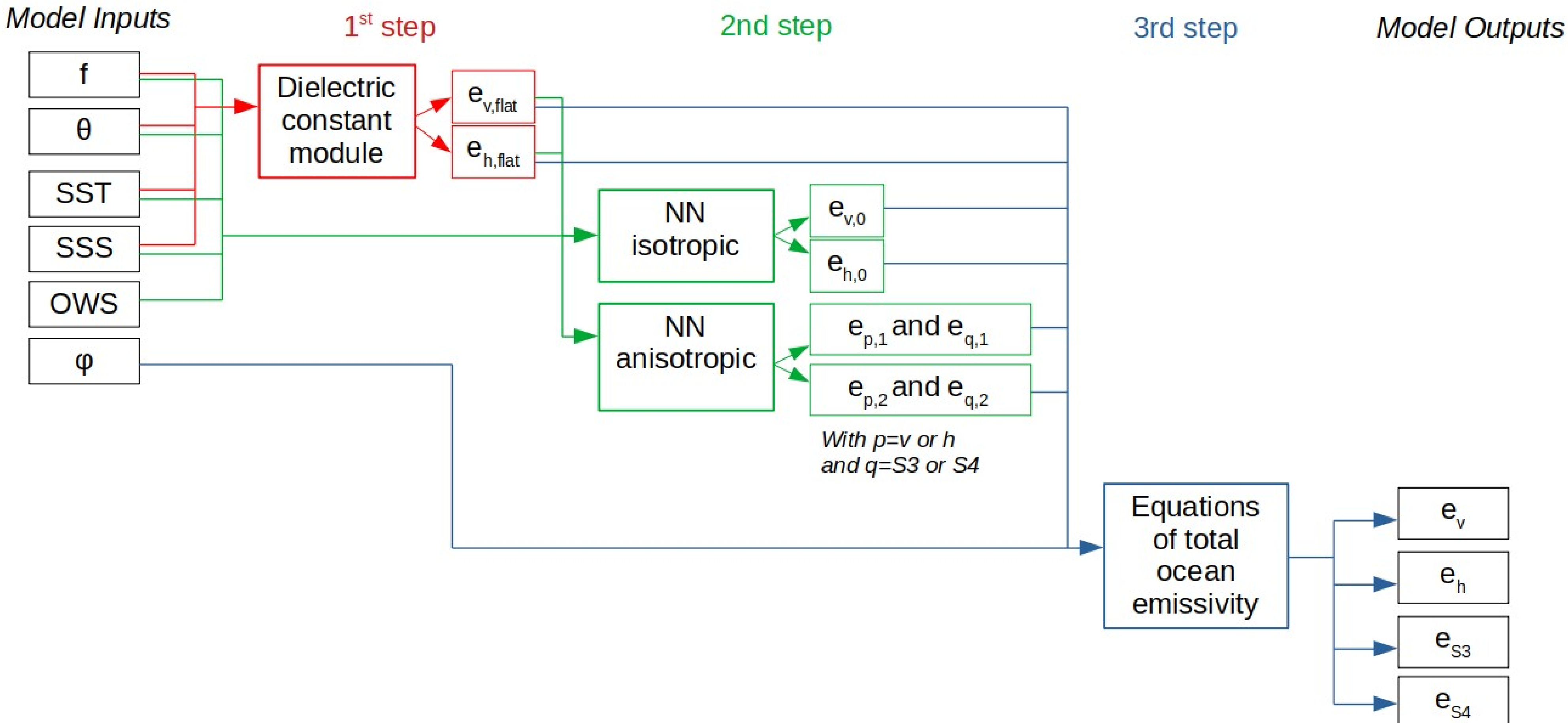
$$e_p = e_{p,flat} + e_{p,0} + e_{p,1} \times cos(\phi) + e_{p,2} \times cos(2\phi)$$

With p the vertical or horizontal polarization (p=v or h)

$$e_q = e_{q,1} \times sin(\phi) + e_{q,2} \times sin(2\phi)$$

With q the 3rd or 4th Stokes parameter (q=S3 or S4)

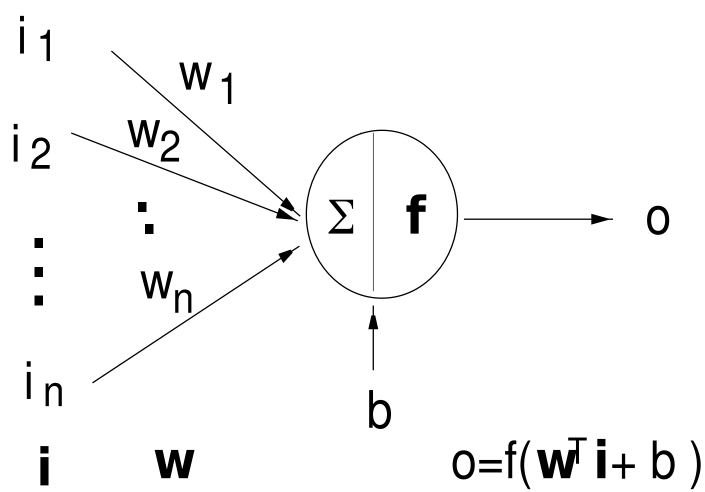
2. Methodology

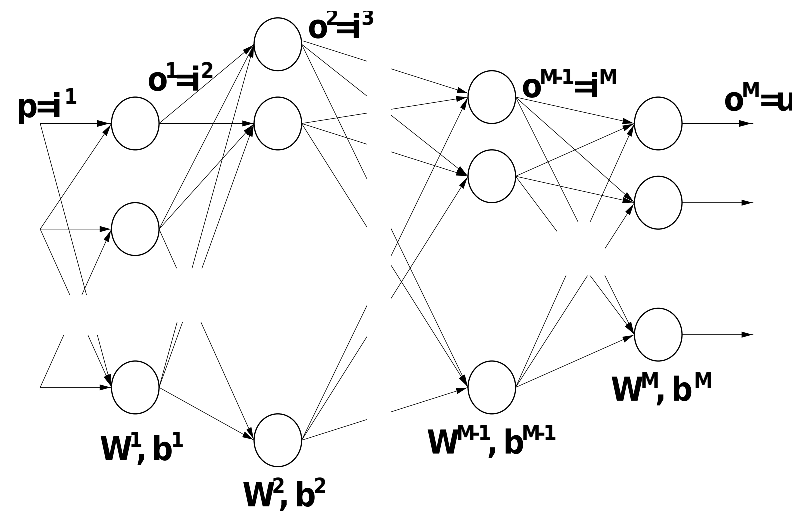


- The model inputs will be the classical inputs for ocean emissivity models : frequency incidence angle, Sea Surface Temperature (SST), Sea Surface Salinity (SSS), OWS, and the relative wind direction (ϕ).
- For the neural networks, we will add as inputs $e_{v,flat}$ and $e_{h,flat}$

3. Neural Network implementation

- **What is a Neural Network?**





$$\mathbf{u} = \mathrm{f}_M[\mathbf{W}^M \mathbf{i}^M + \mathbf{b}^M] =$$
$$\mathrm{f}_M[\mathbf{W}^M \mathrm{f}_{M-1}(\mathbf{W}^{M-1}\mathbf{i}^{M-1} + \mathbf{b}^{M-1}) + \mathbf{b}^M] = \dots$$

- A Neural Network (NN) is an interconnected assembly of processing units called nodes organized in a number of layers.

- A Multi-Layer Perceptron (MLP) is a NN including at least one hidden layer with non-linear differentiable activation functions and no feedback loops.

3. Neural Network implementation

- **Why using a NN to implement SURFEM?**

MLPs with two layers are capable of approximating any continuous functional mapping

↓

MLPs can be used to approximate the isotropic and anisotropic emissivity of the PARMIO model.

Pros

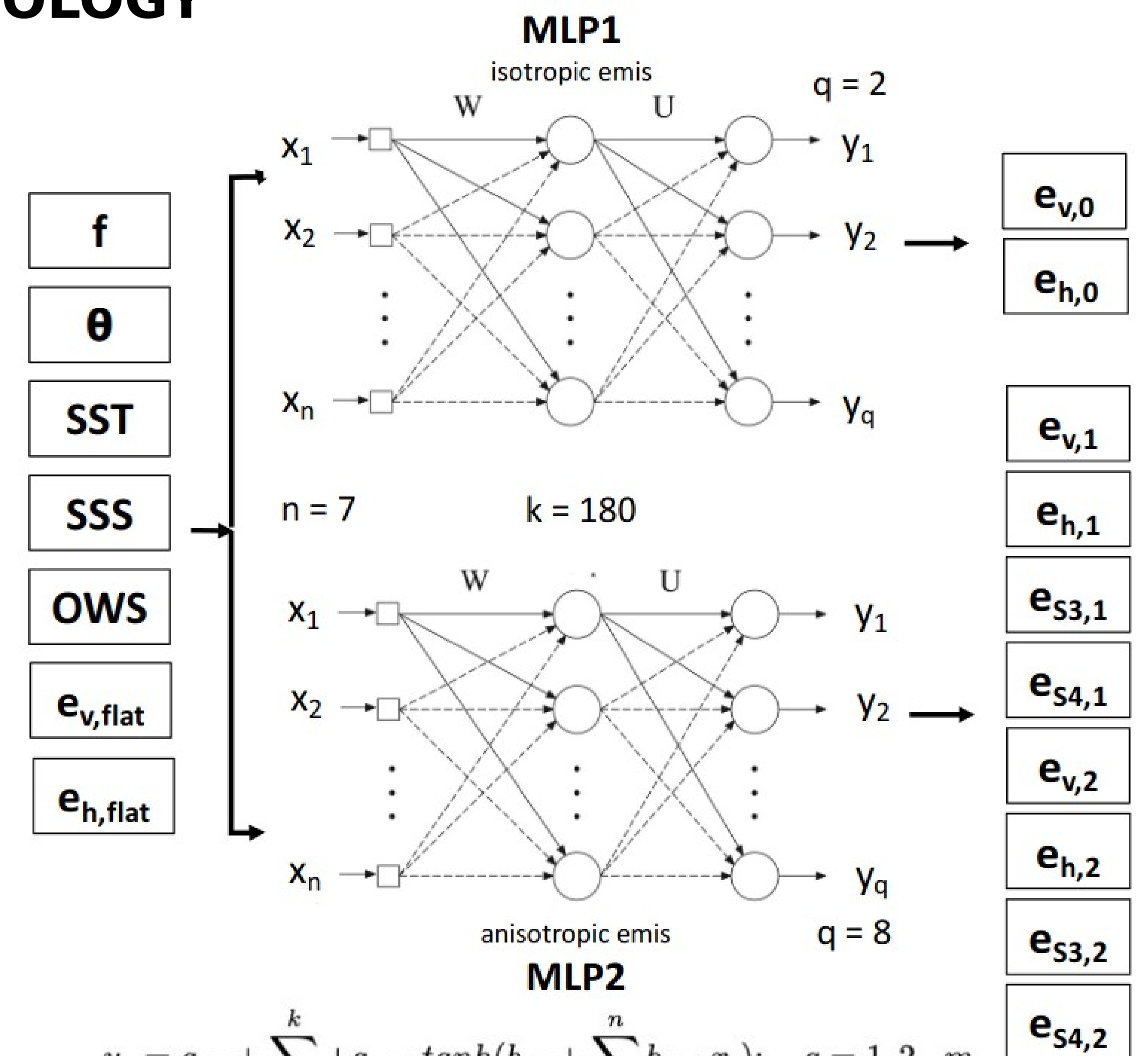
- Very fast computations. Once trained, running an MLPs only requires a few matrix multiplications together with the application of a few simple analytical functions.
- Minimal storage. Very few MLP weight and bias parameters to store compared with other solutions to approximate input-output mappings, such as look-up tables.
- Analytical differentiation. The analytical expression describing the MLP is differentiable, so it is possible to obtain the derivatives of the MLP output with respect to the MLP inputs by analytical differentiation.

Cons

- Similar to all approximation methods, the MLP outputs reproduce the PARMIO emissivities with some approximation error, i.e., there is a trade-off between calculation accuracy and speed.

3. Neural Network implementation

- **The MLP for SURFEM - TOPOLOGY**

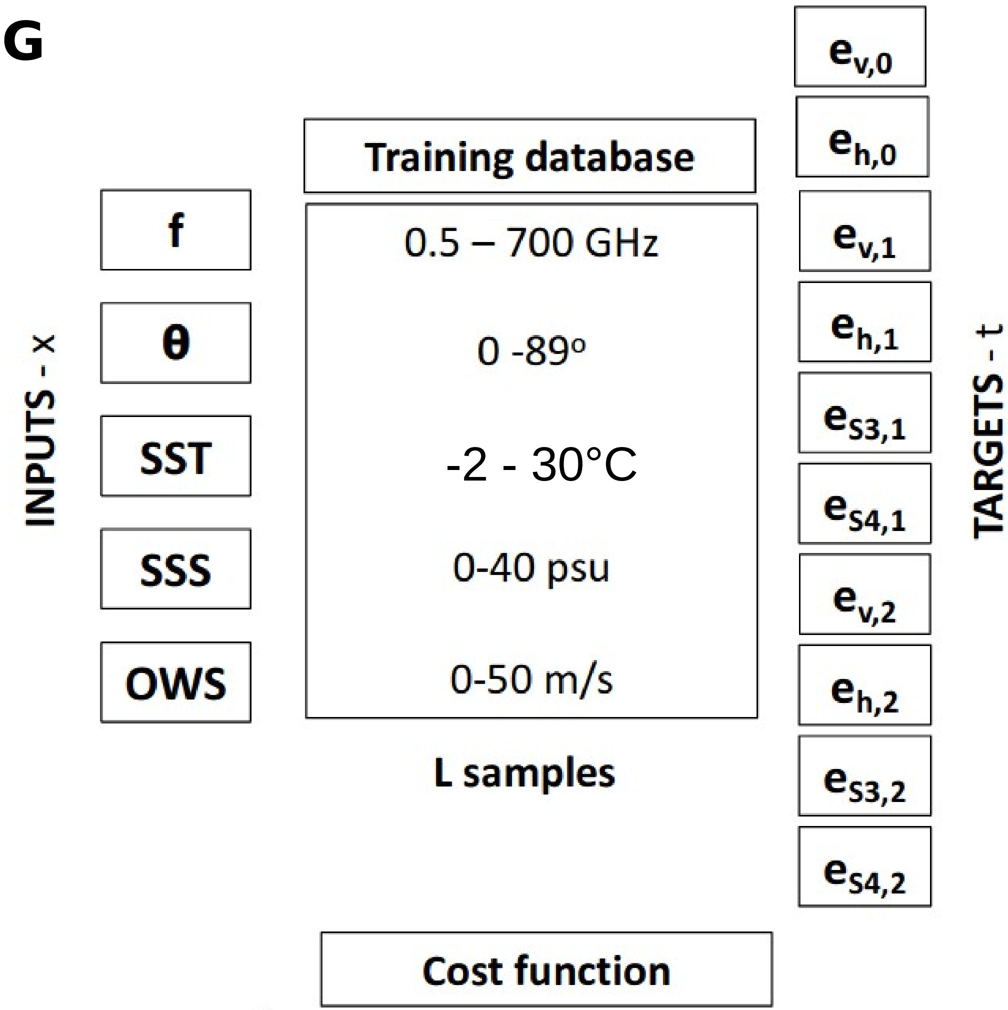


$$y_q = a_{q0} + \sum_{j=1}^{k} + a_{qj} \cdot tanh(b_{j0} + \sum_{i=1}^{n} b_{ji} \cdot x_i); \quad q = 1, 2...m$$

- MLPs having one hidden layer containing k nodes with weights **b** and hyperbolic tangent activation functions, followed by an output layer with q nodes with weights **a** and linear activation functions.

3. Neural Network implementation

- **The MLP for SURFEM - TRAINING**



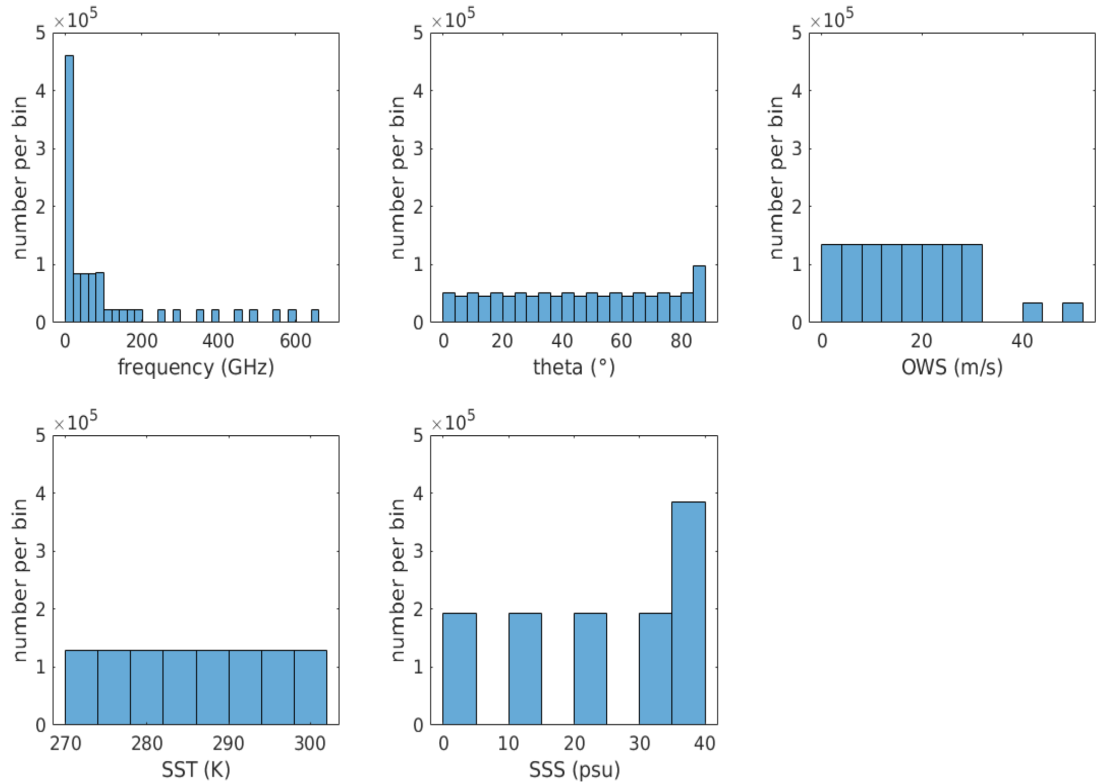
minimising $\sum_{l=1}^{L} \|\mathbf{u}(\mathbf{x}^l, \mathbf{w}) - \mathbf{t}^l\|^2 + \alpha \| \mathbf{w} \|^2$

- Calling the MLP a function **u(x,w)**, where **x** are the MLP inputs and **w** the MLP weights, training determines the MLP weights by minimising a cost function that includes a regularising functional to encourage smooth mappings.

3. Neural Network implementation

- PARMIO model is used to generate the training and the testing dataset for the Neural Networks

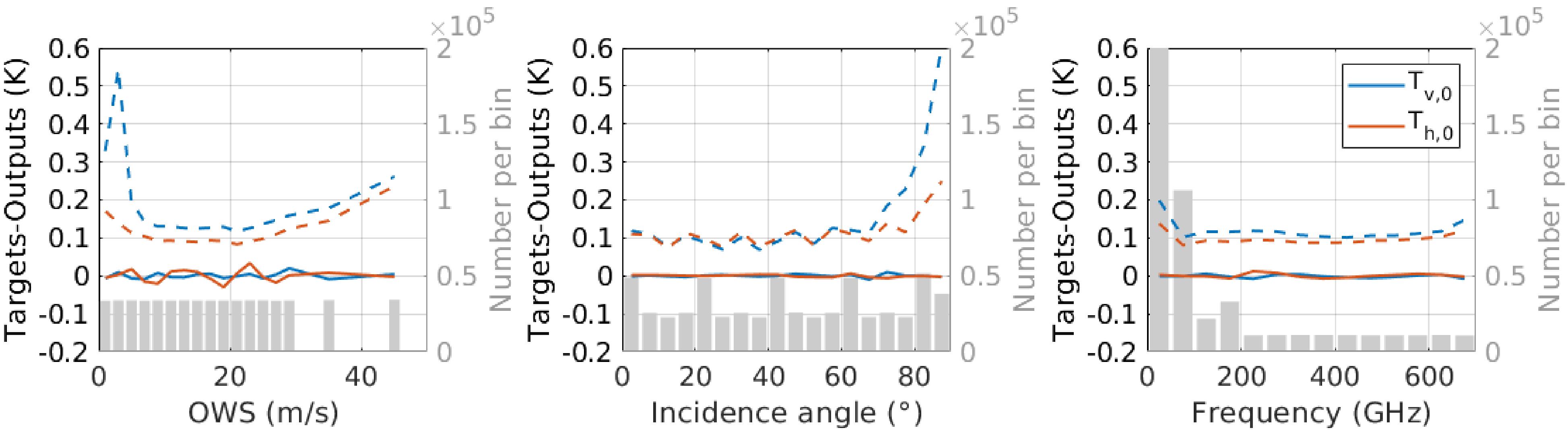
- For frequency, tighter steps between 500 MHz to 100 GHz, larger steps then up to 700 GHz
- For the incidence angles, the sampling is regular from 0 to 89 ◦ (each 4° with a supplementary point at 89°)
- For the SST and SSS, sampling each 4°C from -2 to 30°C, and each 10 psu from 0 to 40 psu (with an additional point at 35 psu)
- For OWS, the sampling is every 2 m/s from 0 to 30 m/s, with additional points at 40 and 50 m/s



4. Results of the Neural Networks

- After training the NNs with the training dataset, we evaluate the error of the NNs using the testing dataset
- A comparison between the outputs of the NNs and the targets which are the emissivities simulated with PARMIO is done.
- Here we expressed the error in terms of brightness temperatures TB=e*SST

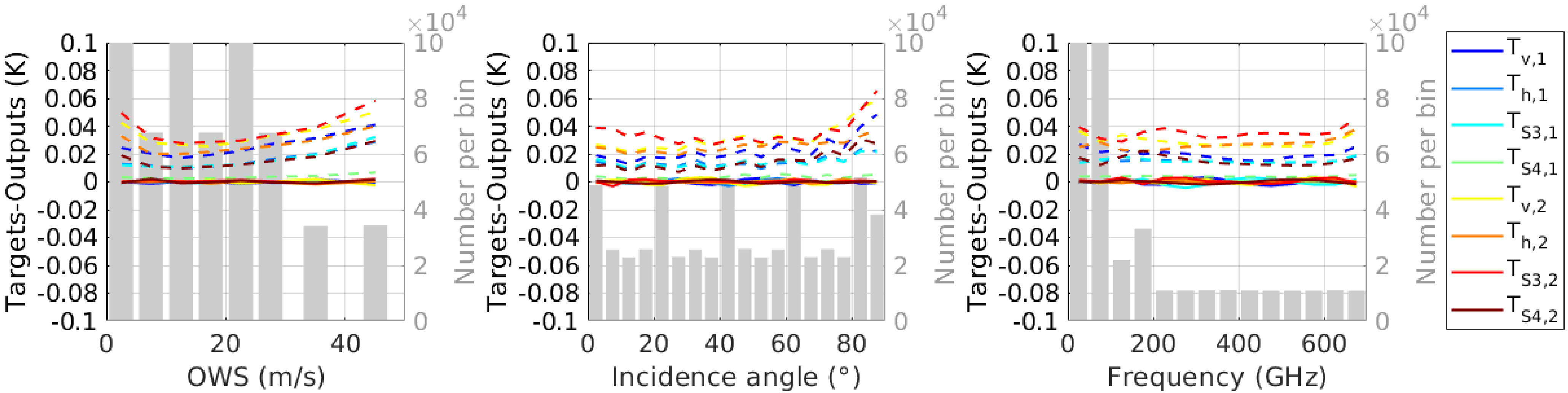
<u>Error for isotropic emissivities</u>



- Solid line=mean ; dashed line=StD
- The global precision of our NN is 0.22 K for $T_{v,0}$ and 0.13 K for $T_{h,0}$
- There is no bias with NN methods, the mean difference is very close to zero

4. Results of the Neural Networks

Error for anisotropic emissivities



- The global precision of our NN (dashed line) is :

0.025 K for $T_{v,1}$, 0.015 K for $T_{h,1}$, 0.015 K for $T_{S3,1}$, 0.003 K for $T_{S4,1}$,
0.035 K for $T_{v,2}$, 0.027 K for $T_{h,2}$, 0.038 K for $T_{S3,2}$, and 0.017 K for $T_{S4,2}$.

- Therefore the relative error of the NN for anisotropic emissivities is around 2%

5. Jacobians computation

- Analytical Jacobians have been computed to be implemented in the code of SURFEM-Ocean
- Derivation of the equations of the dielectric constant with Fresnel equations
- Derivation of the Neural Networks

$$\frac{de_p}{dX} = \frac{de_{p,flat}}{dX} + \frac{de_{p,0}}{dX} + \frac{de_{p,1}}{dX} cos(\phi) + \frac{de_{p,2}}{dX} cos(2\phi)$$

p= v or h

$$\frac{de_q}{dX} = \frac{de_{q,1}}{dX} sin(\phi) + \frac{de_{q,2}}{dX} sin(2\phi)$$

q=S3 or S4

X= SST, SSS and OWS

$$\frac{de_{p,flat}}{dX} = \frac{d(1 - R_{Fp})}{dX} = -\frac{dR_{Fp}}{d\epsilon} \times \frac{d\epsilon}{dX}$$

$$\frac{de_{p,i}}{dX} = J_N(e_{p,i}/X) + \frac{de_{p,i}}{de_{v,flat}} \times \frac{de_{v,flat}}{dX} + \frac{de_{p,i}}{de_{h,flat}} \times \frac{de_{h,flat}}{dX}$$

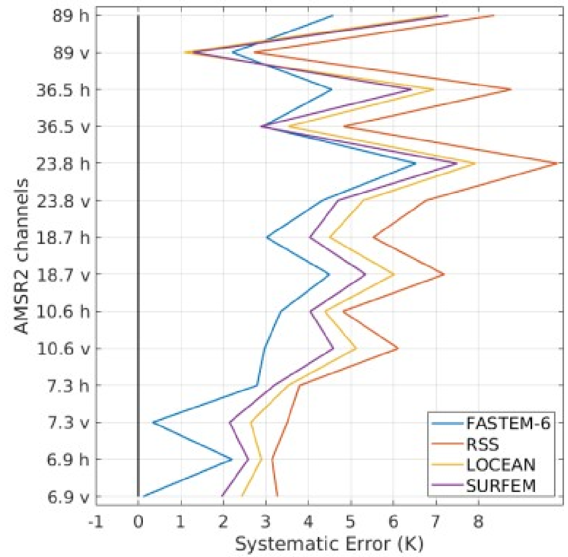
6. Evaluation

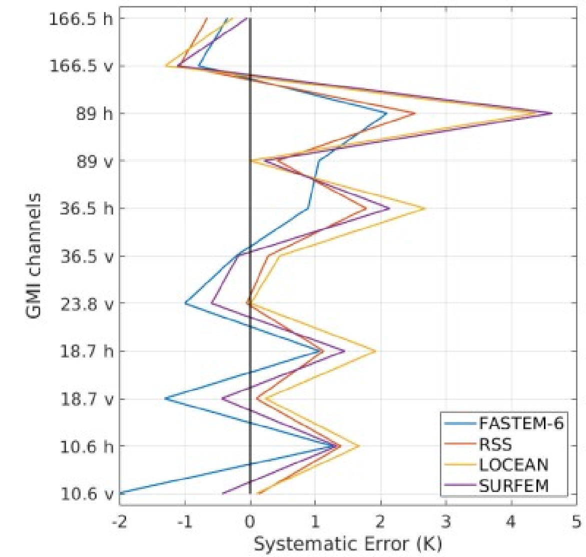
- Previous comparisons with SMAP, AMSR2, GMI and ATMS observations have been reproduced including SURFEM-Ocean
- ERA-5 geophysical data are collocated with observations to be used as input of the different ocean emissivity models
- Sea ice, coastal areas, and cloudy pixels are filtered out.

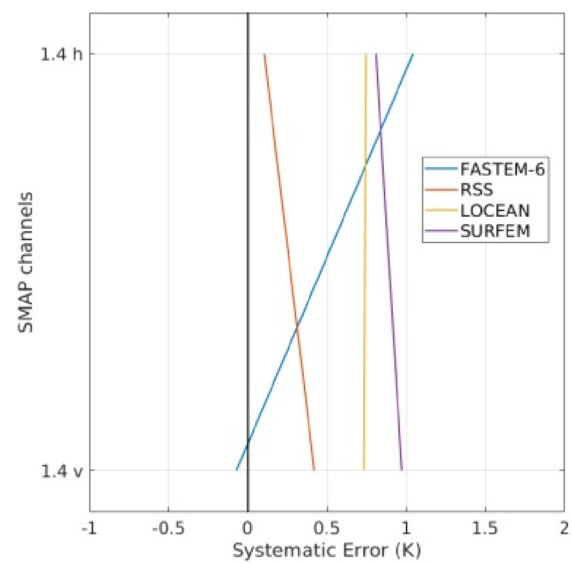
	Model type	Dielectric constant	Wave spectrum	Foam cover	Foam emissivity
LOCEAN Dinnat et al., 2003	Full physical model adjusted for L-band	Klein and Swift, 1977	Durden and Vesecky, 1985 with $a_0 \times 1.25$	Yin et al. 2016	Anguelova and Gaiser, 2013
FASTEM Liu et al., 2011	Parameterized and fast	Ellison et al., 1998 +Double Debye	Durden and Vesecky, 1985 with $a_0 \times 2$	Monahan and O'Muircheartaigh 1986	Kazumori et al., 2008 with Stogryn,1972
RSS Meissner and Wentz, 2012	Empirically fitted to observations	Meissner and Wentz, 2004 and 2012	Wind-induced emissivity fitted to observations Meissner and Wentz, 2012 Meissner et al., 2014		
SURFEM-Ocean Kilic et al.	Fast using neural networks	Meissner and Wentz, 2004 and 2012	Wind-induced emissivity fitted to PARMIO model with neural networks		

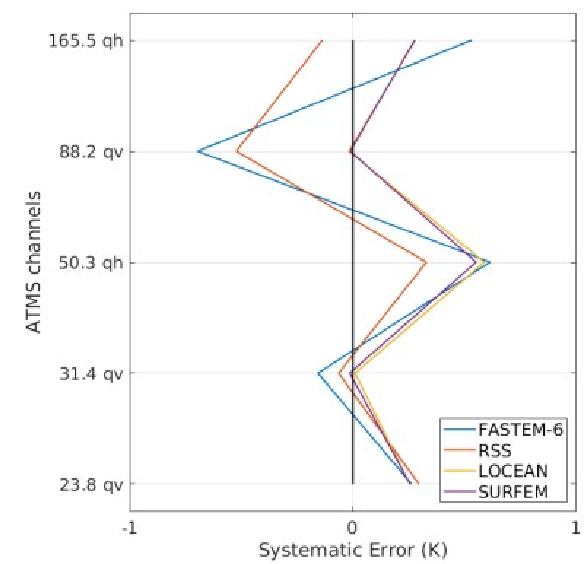
6. Evaluation

- Biases/systematic errors are estimated between each instrument and model
- We found similar biases with SURFEM than with the other ocean emissivity models



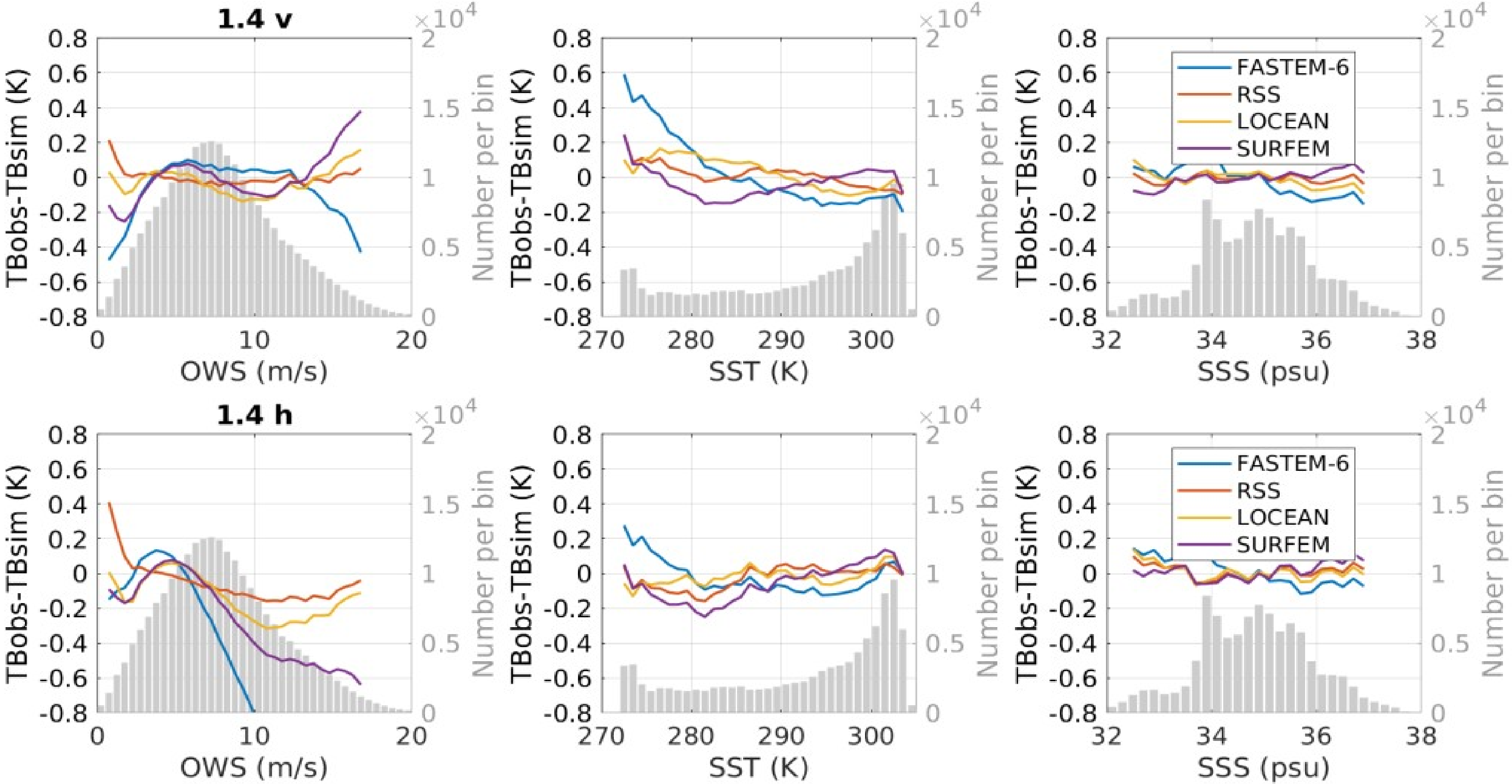






6. Evaluation

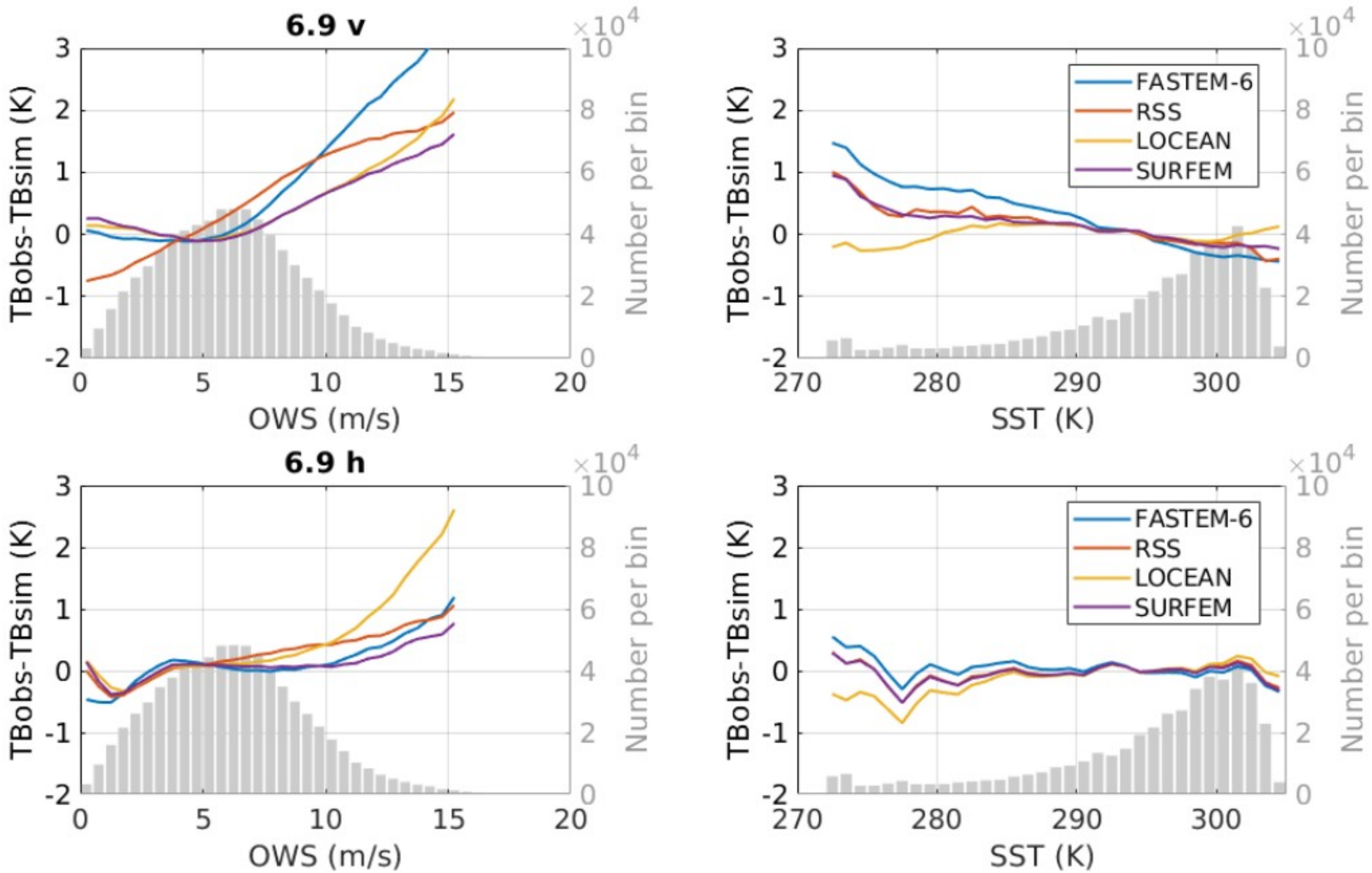
Comparison with SMAP as a function of the different parameters



- SURFEM shows lower accuracy at 1.4GHz than models that are specifically designed for this frequency (LOCEAN/ RSS roughness for 1.4 GHz)
- But it shows improved results compared to FASTEM.

6. Evaluation

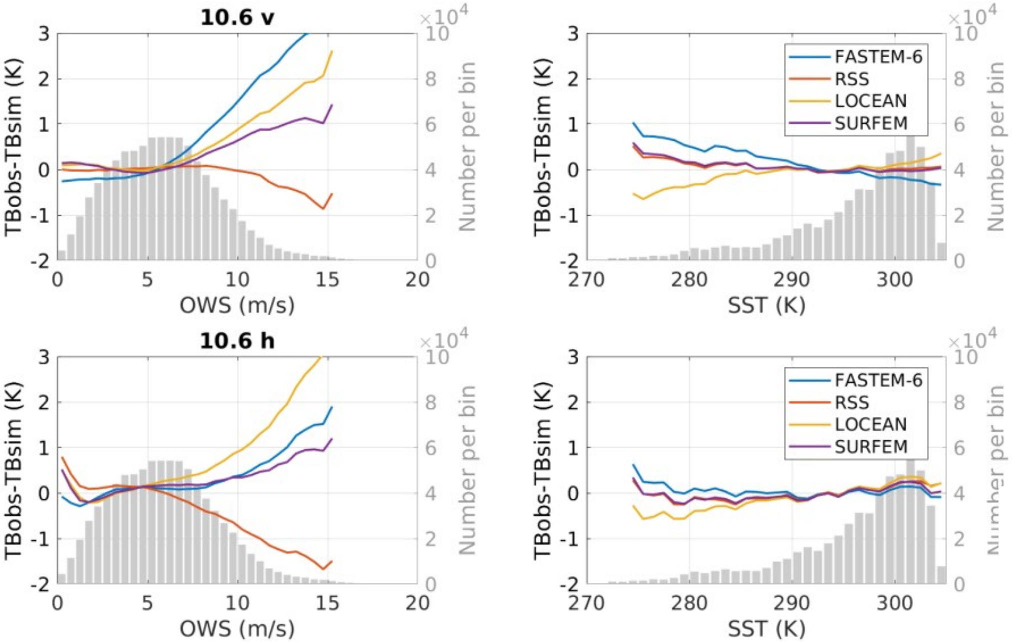
Comparison with AMSR2 as a function of the different parameters



- Improved results with SURFEM as a function of OWS for OWS >7m/s compared to the other models
- Results similar to RSS as a function of SST as it uses the same dielectric constants

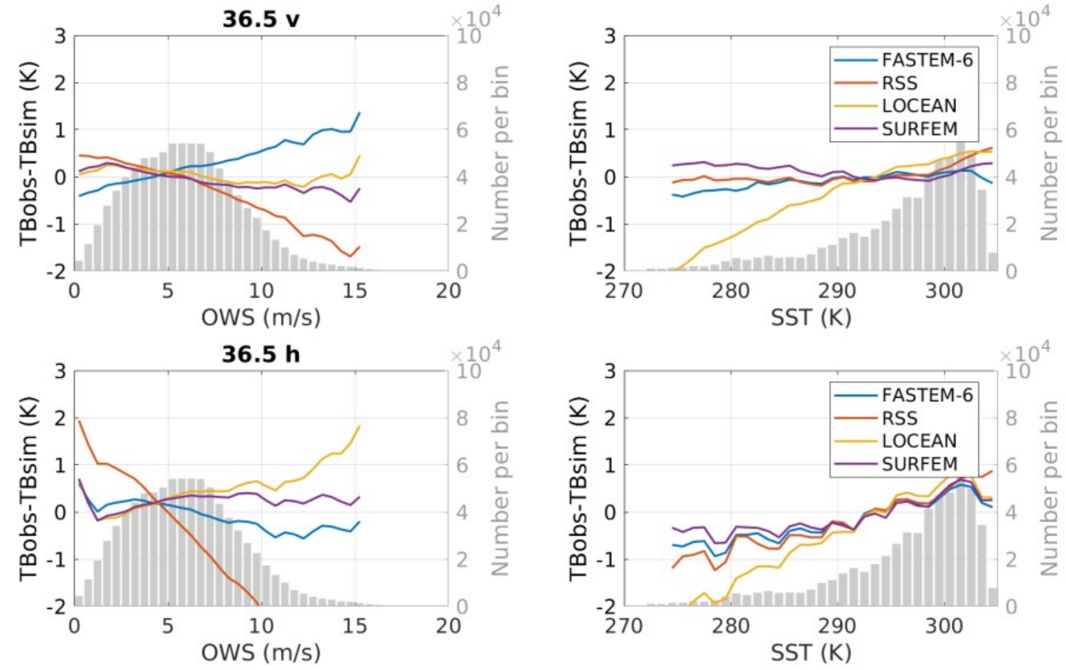
6. Evaluation

Comparison with GMI as a function of the different parameters



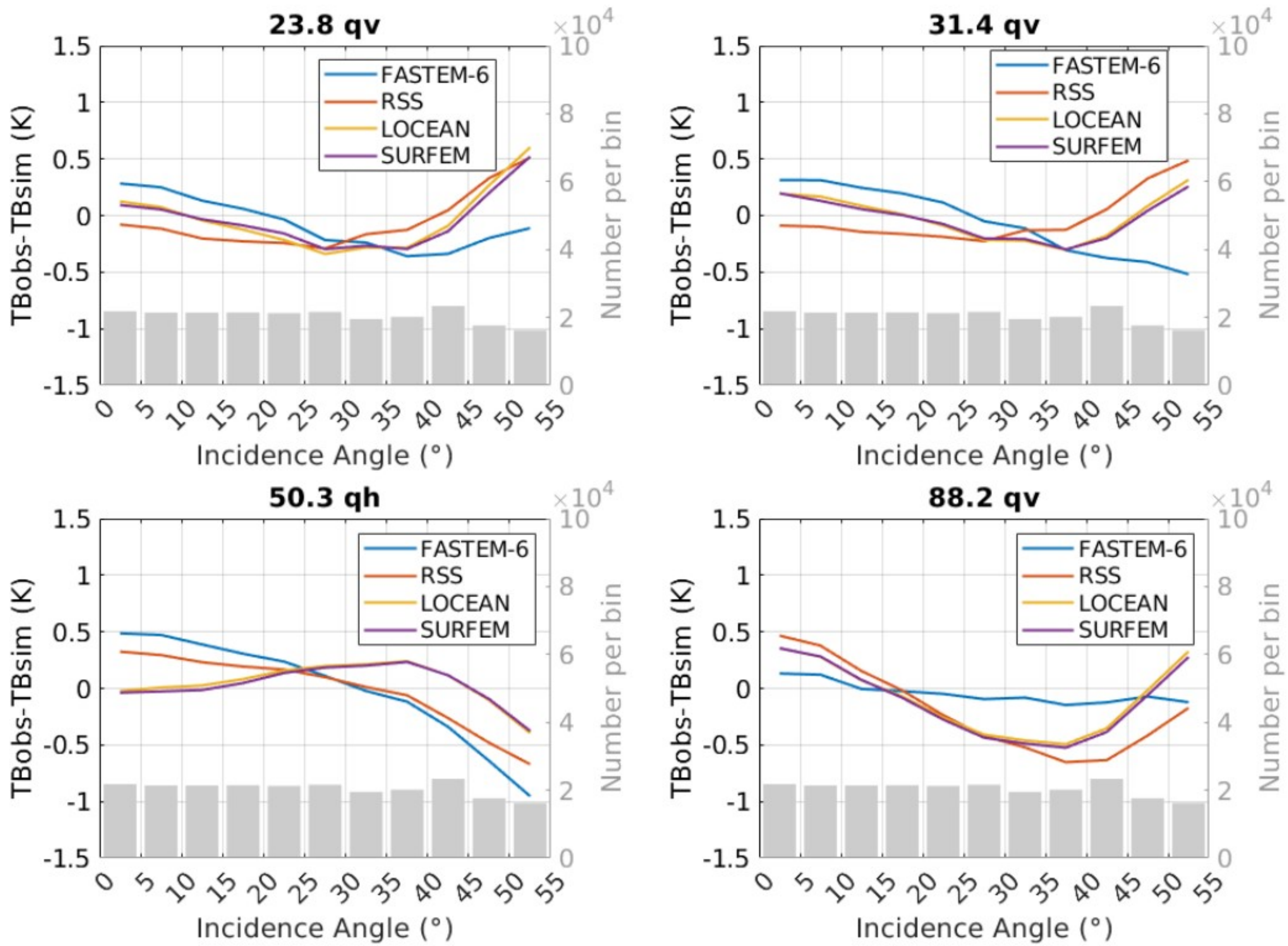
- Better results with SURFEM as a function of OWS

- SURFEM results similar to RSS as function of SST



6. Evaluation

Comparison with ATMS as a function of the incidence angle



- The dependence as a function of the incidence angle is similar to the other models and less than 0.5 K
- It is the same than LOCEAN model as the same wave spectrum is used.

7. Conclusion

- SURFEM-Ocean has been developed based on the community model PARMIO using Neural Network methods.
- Configuration of PARMIO has been updated for an improved agreement with satellite observations over a large frequency range from 500 MHz to 700 GHz, and for cold SST and high OWS.
- The precision of the NNs used in SURFEM-Ocean is better than 0.2 K globally.
- SURFEM-Ocean provides the emissivities for the 4 polarizations along with the jacobians.
- SURFEM-Ocean covers frequencies from 500 MHz to 700 GHz, OWS from 0 to 50 m/s, SST from -2 to 30°C, and SSS from 0 to 40 psu, for all incidence angles, and wind directions.
- SURFEM-Ocean will be implemented in RTTOV in replacement to FASTEM.