Exploring Statistical Insights coupled with Deep Neural Networks for the Inversion of the MTF

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OceanDataLab

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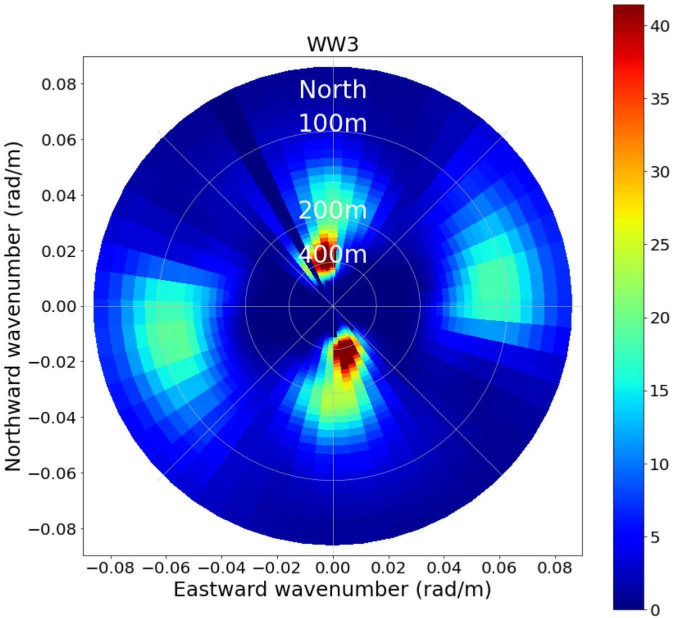
Context and Motivation

Modulation Transfer Function (MTF)

<u>MTF:</u> Relationship between wave directional spectra and measured modulation spectra

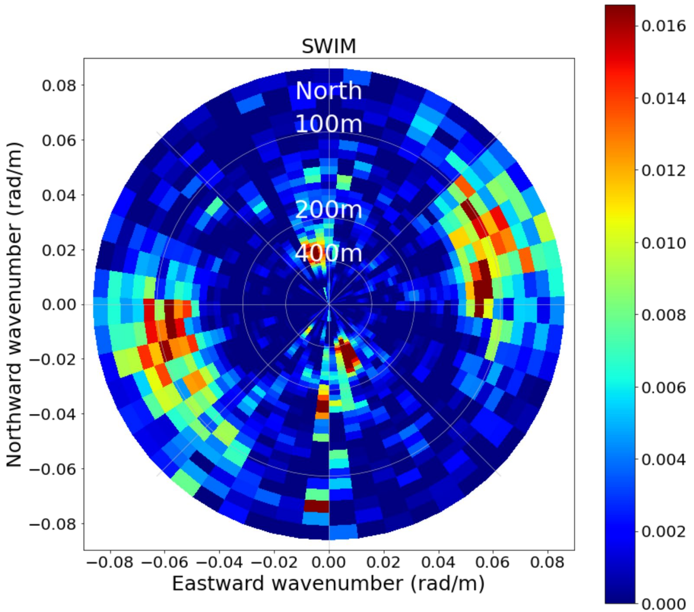


Wave directional spectra $F_m(k,\theta)$

(model with 180° ambiguity added)

MTF

$$P_m = MTF(F_m, k, ?)$$



Measured modulation spectra $P_m(k,\theta)$

Modulation Transfer Function (MTF)

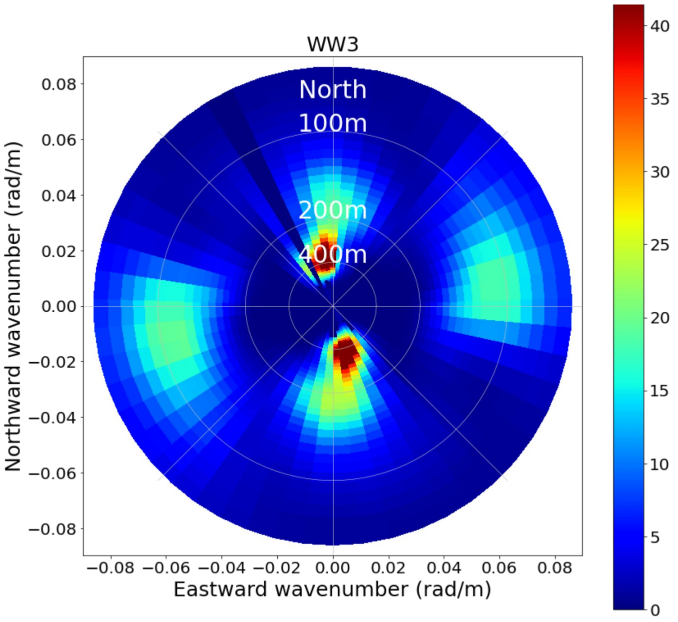
- **Current strategy:** MTF is theoretical (tilt effect, Jackson 1981) and parameterized with ancillary wind
  - Open questions:
    - *Impact of wave directional spread on MTF*
    - *Impact of range bunching especially at low incidence beams*
    - *Possible dependencies of the MTF on additional geophysical parameters*

- **Data-driven MTF inversion:** Exploiting available SWIM observations and model and/or in situ data to better understand, model and parameterize the MTF
  - Classical statistical approach: *understanding the relationship between SWIM and "ground truth" data, and use these insights to study the impact of beam angle, azimuth, wind, wave directional spread, etc.*
  - **Deep neural network approach: *Learn the MTF directly from SWIM data, coupled with model and/or in situ data (WaveWatch3, buoy data)***

Data-driven Inversion of the MTF

Objective: Learning the (inverse) MTF directly from data

$$\boxed{P_m = MTF(F_m, k, ?)}$$

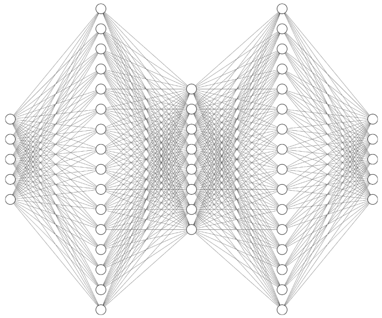


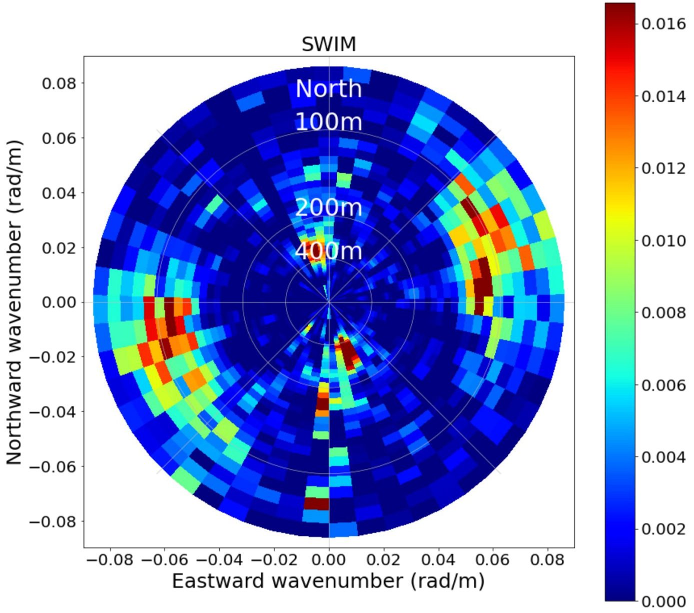
Wave directional spectra $F_m(k,\theta)$

(model with 180° ambiguity added)

MTF

Deep Neural Network (modeling MTF^{-1})





Measured modulation spectra $P_m(k,\theta)$

Implementation Details and Network Architecture

Dataset and Implementation Details

Dataset:

- Colocated SWIM/WW3 directional spectra (93482 pairs)
- 64/20/16 random split for train/test/validation datasets

Directional spectra:

- 10 degree incidence angle
- Linear directional sampling (52 directions)
- Logarithmic wavenumber sampling (60 *k* values)

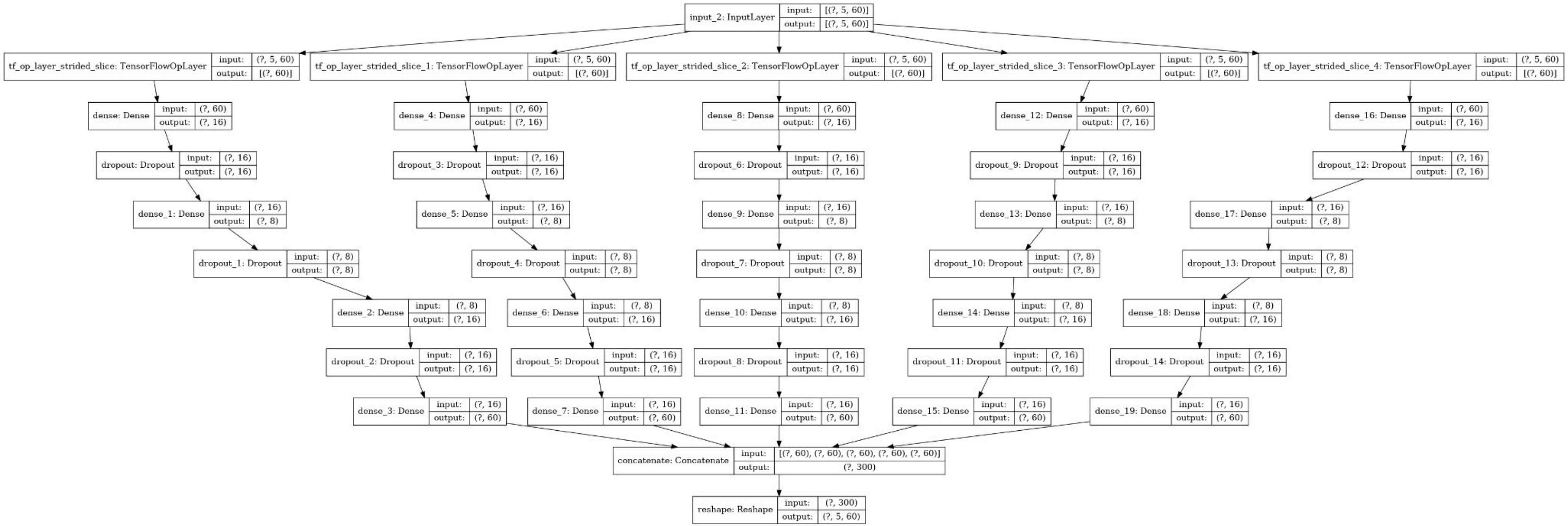
Dimensionality reduction:

- Directional Fourier decomposition, keeping the first 5 coefficients (buoy-like representation)
- Each coefficient is processed separately
- Reconstruction is obtained via MEM (Maximum Entropy)

Sea state classification (for result analysis):

- Swell: *Main (strongest) peak at* $\ell \in [350, 450]m$
- Wind sea: *Wave age < 1*
- Mixed sea states

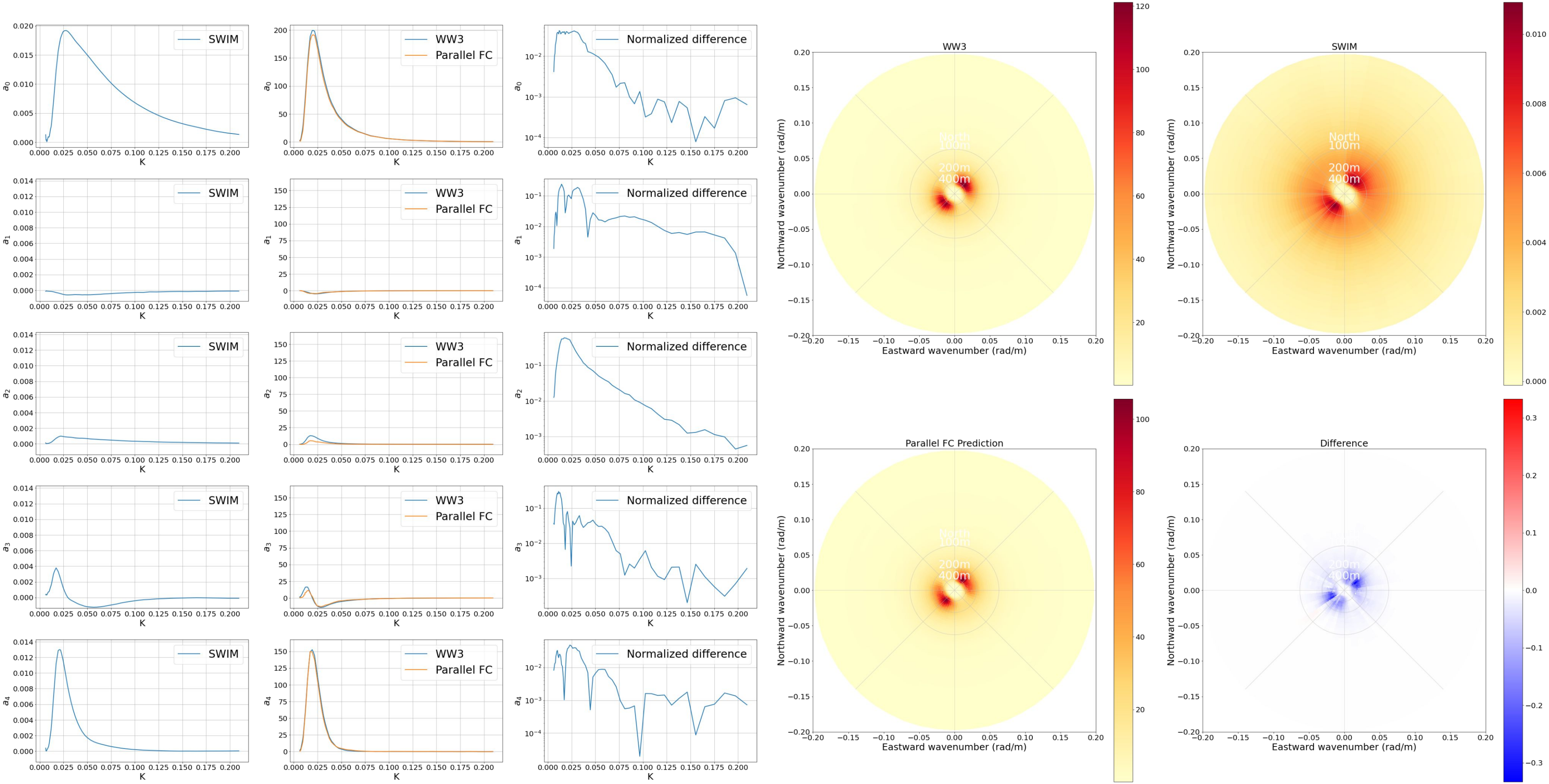
Network Architecture



- 11380 parameters (2276 per Fourier coefficient)
- Training dataset: 5631000 data points (18770 spectra, each with 5 Fourier coefficients evaluated at 60 *k* values)
- Parameters/data ratio : 0.0020

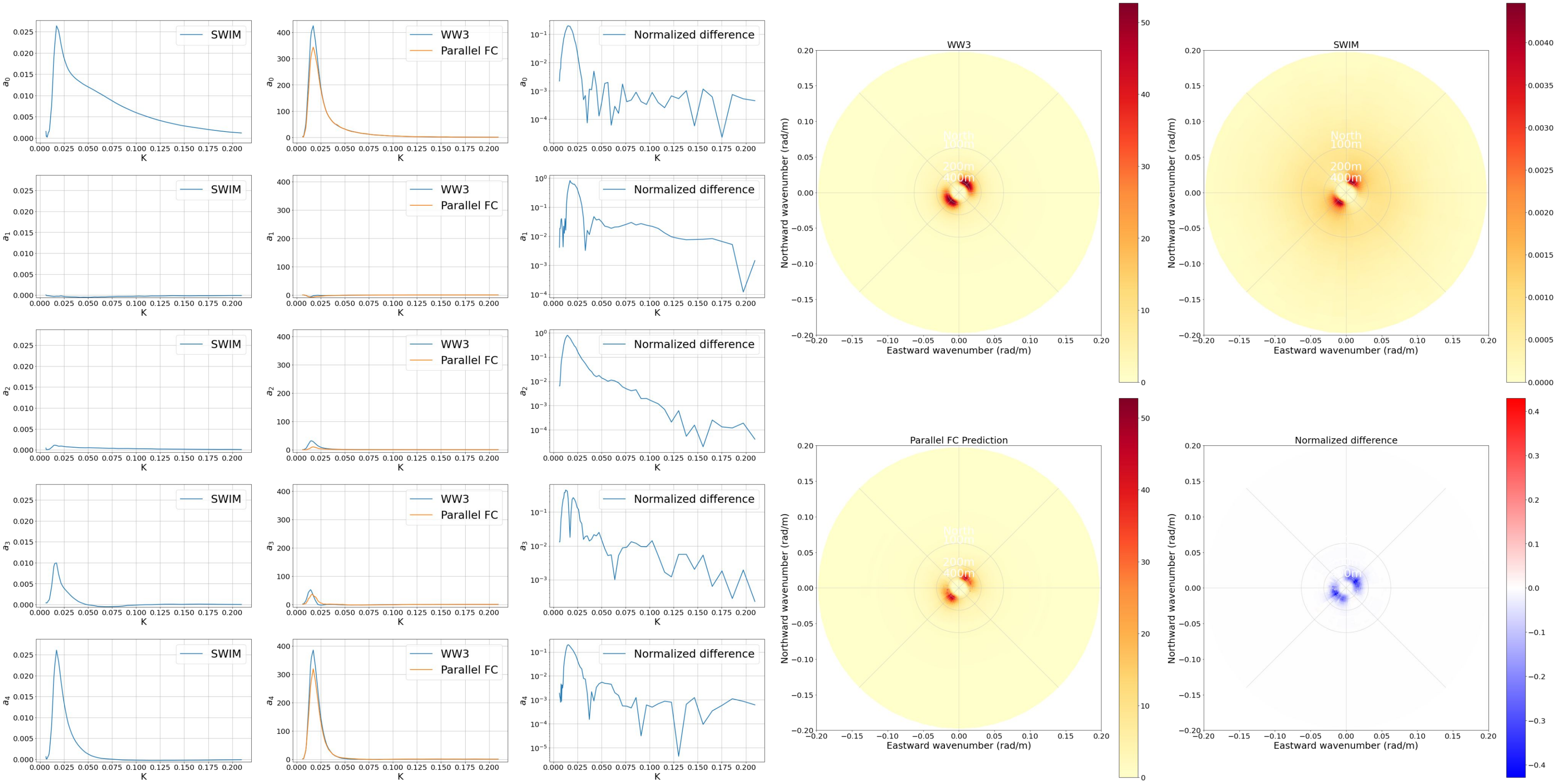
Global Mean Results

Global Mean Results

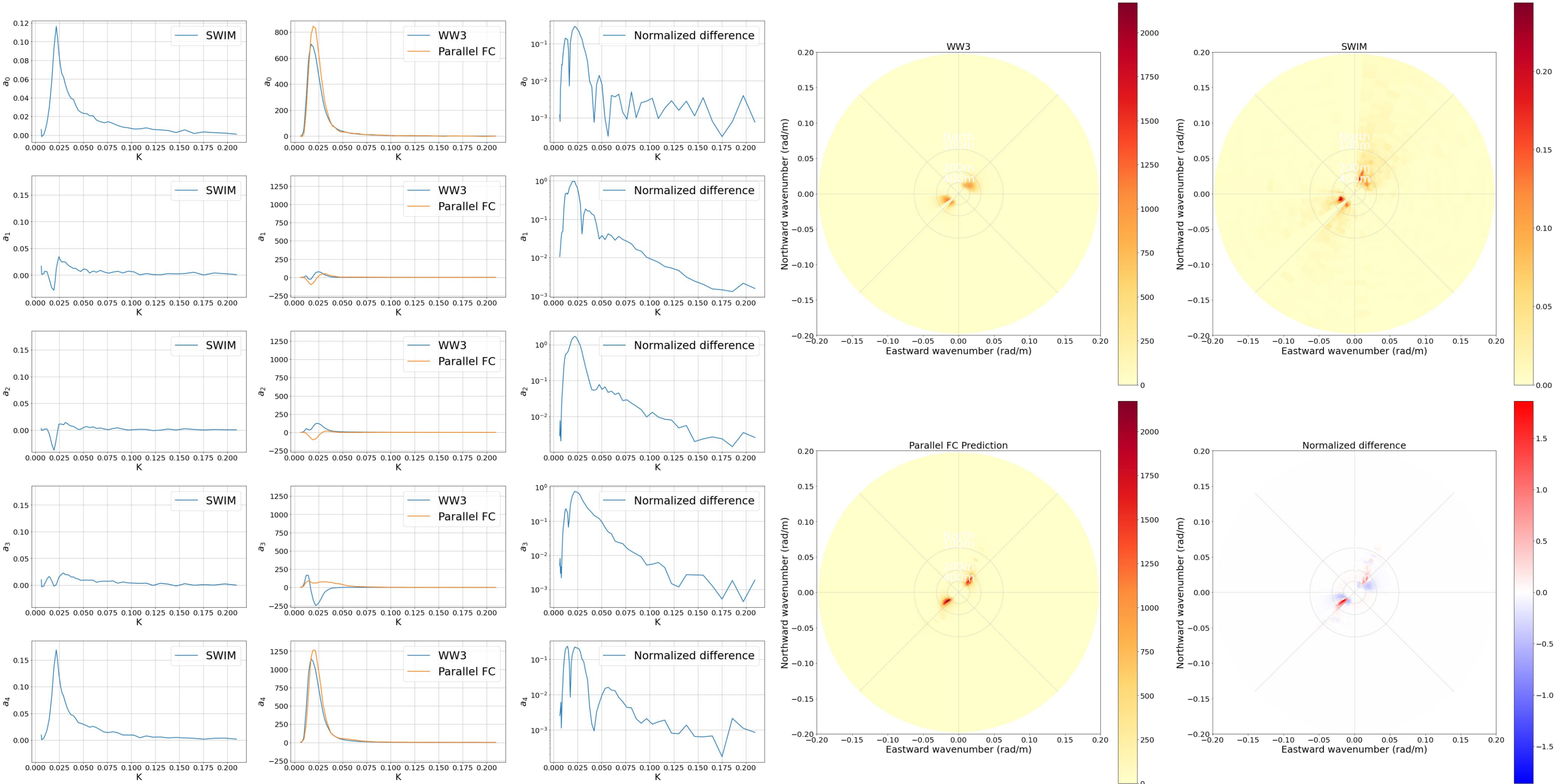


Results by Sea State Classification

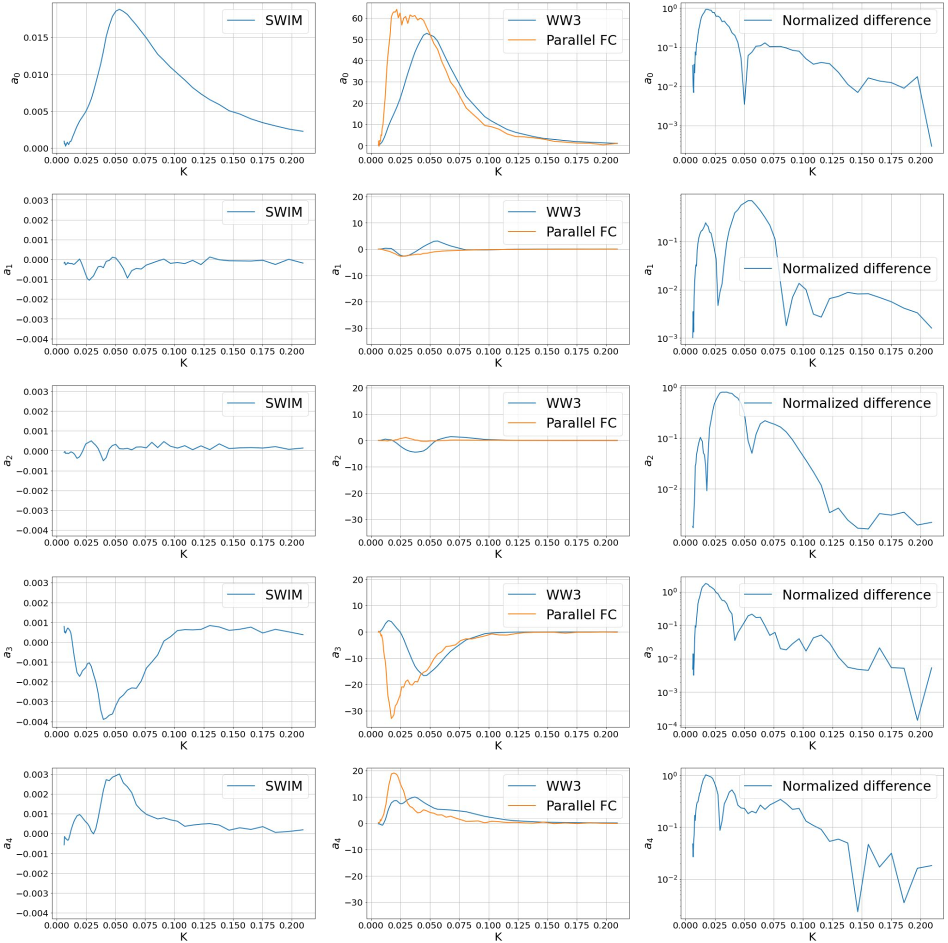
Swell: Mean results

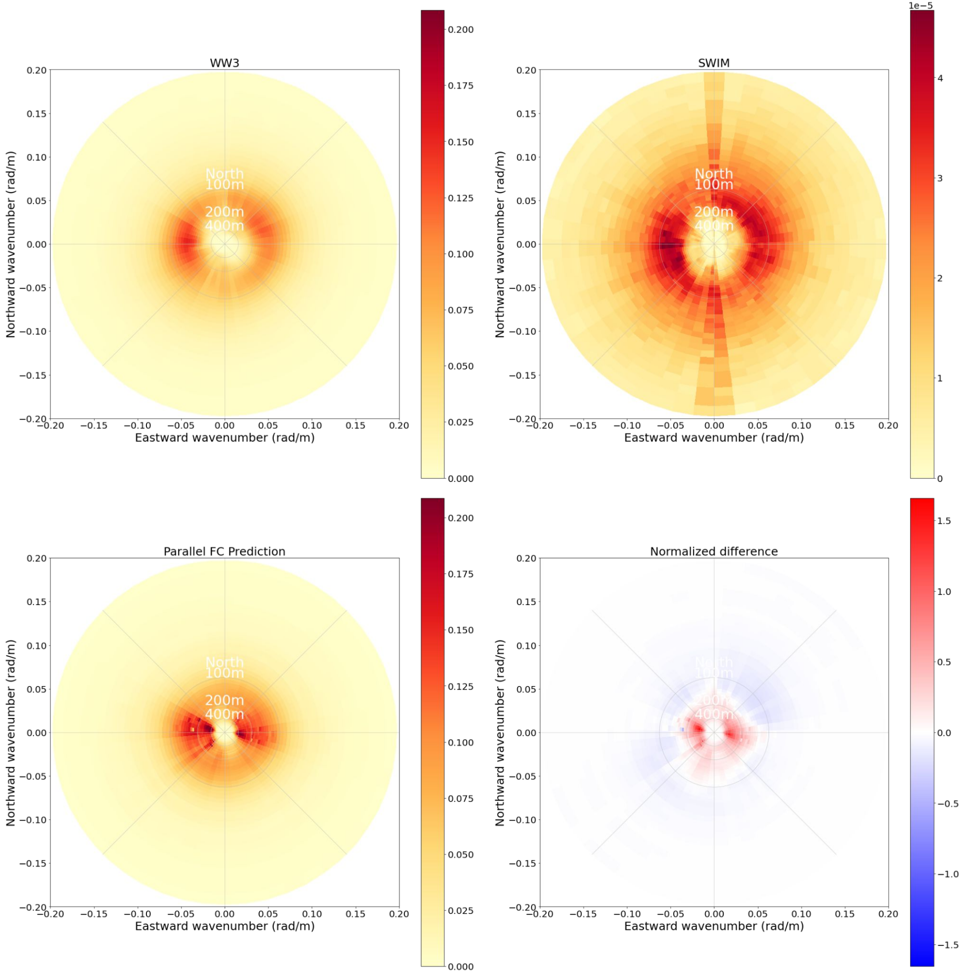


Swell: Single spectra example



Wind wave: Mean results





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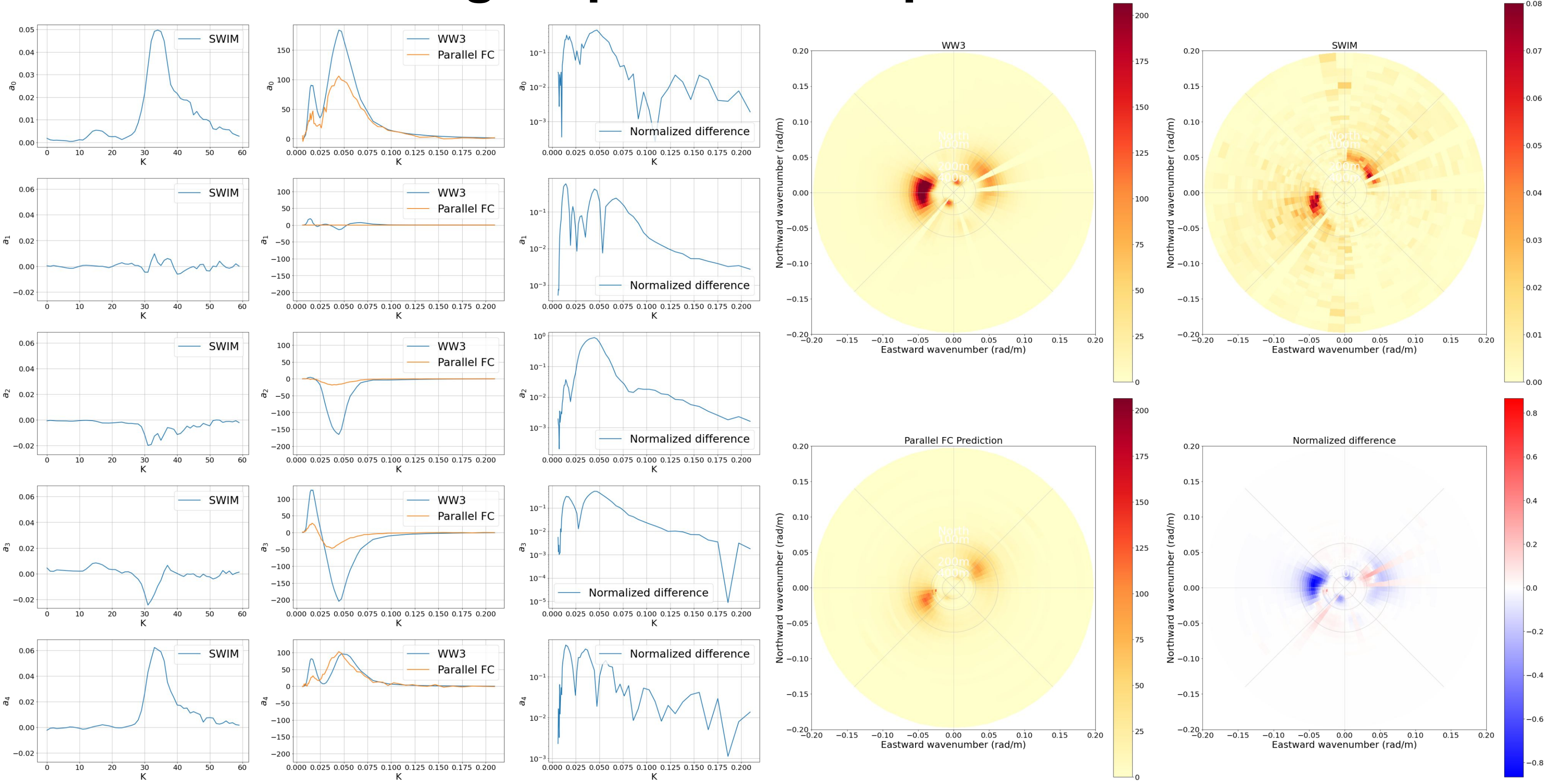
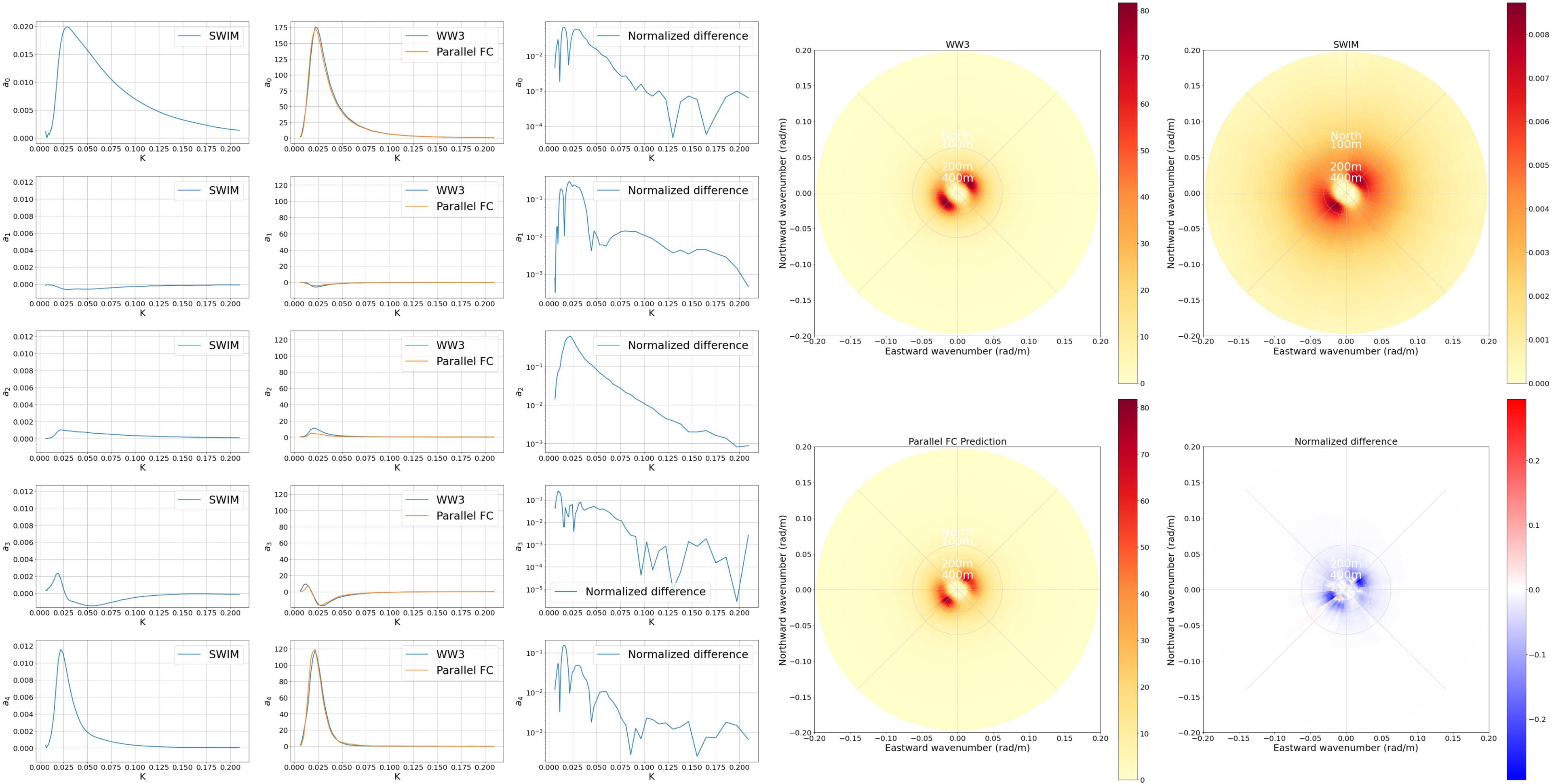


Mixed sea state: Mean results



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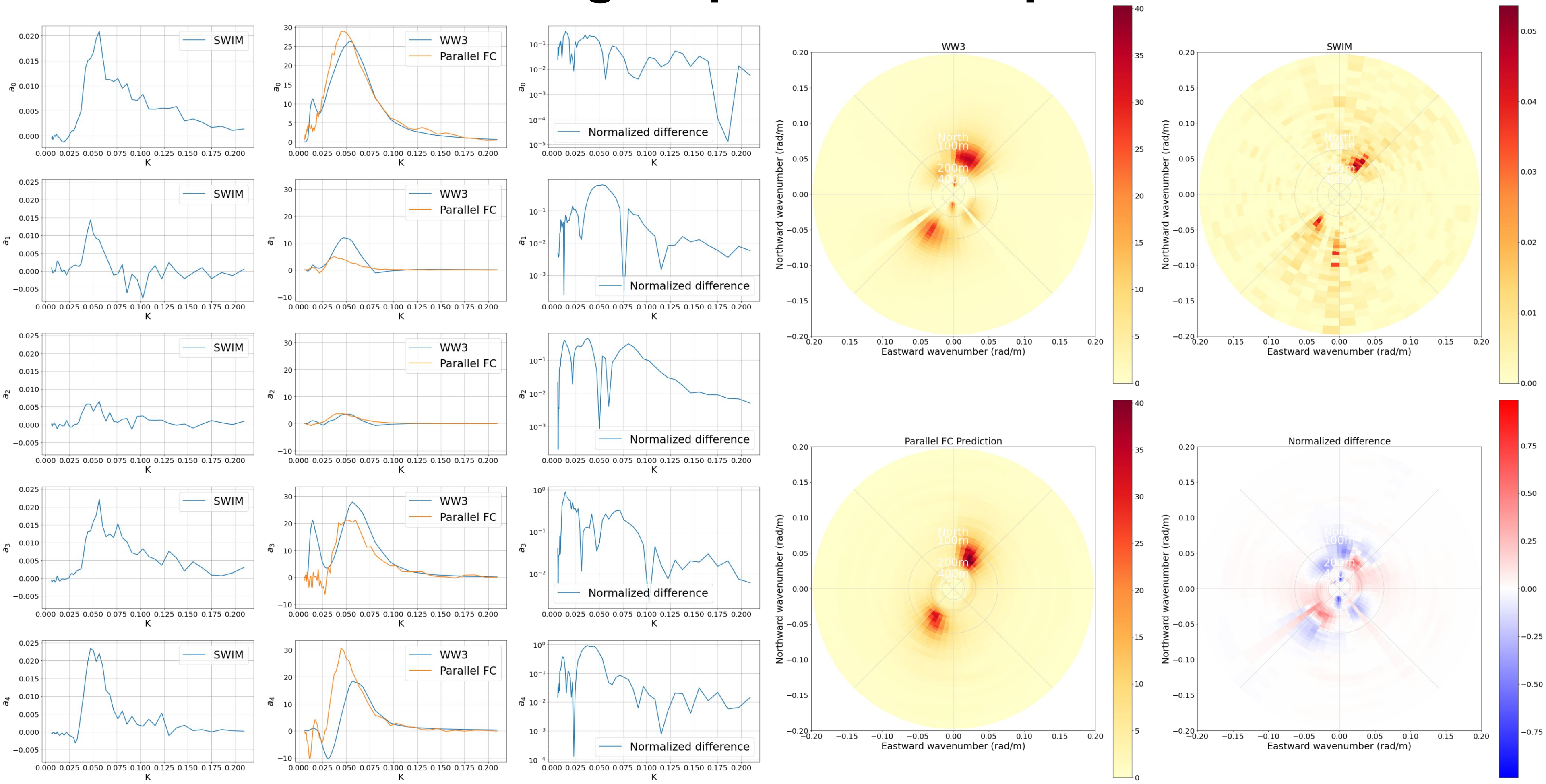

Discussion, Conclusions and Future Work

Deep neural networks for MTF Inversion

Preliminary results show **good mean performance**, but **per case performance is suboptimal** (more work is still needed)

Possible caveats:

- Network might be overfitting (experiment with different and/or shallower architectures)
- Training dataset might be biased (over-representation of some sea states, poor correspondence between SWIM and WW3, etc)
- Wave directional spread information might not be fully exploited (Add it explicitly as an input?)
- Fourier-based dimensionality reduction may not be the optimal choice (Other low-dimensional representations?)

Improvements to be explored:

- Different network architectures (Convolutional, Locally-connected, Recurrent, etc)
- Explore other low-dimensional representations
- Consider additional, physically-informed constraints (network architecture, cost function, etc)
- Network pre-training on synthetic datasets
- Data augmentation
- Transfer learning
- Data fusion (Consider multiple incidence angles, use in situ (buoy) measurements, etc)

Thank you for your attention

Global Mean Results

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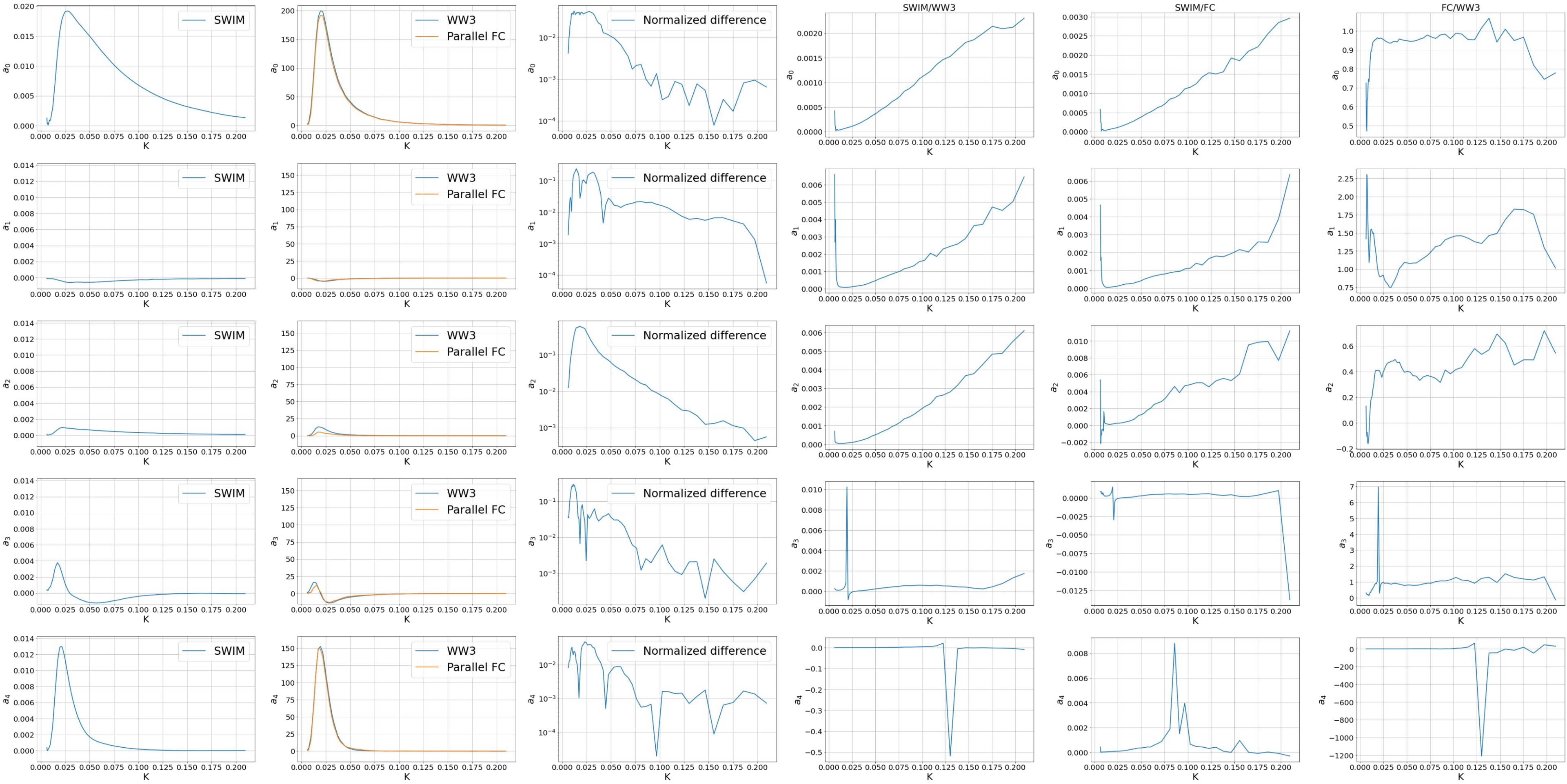

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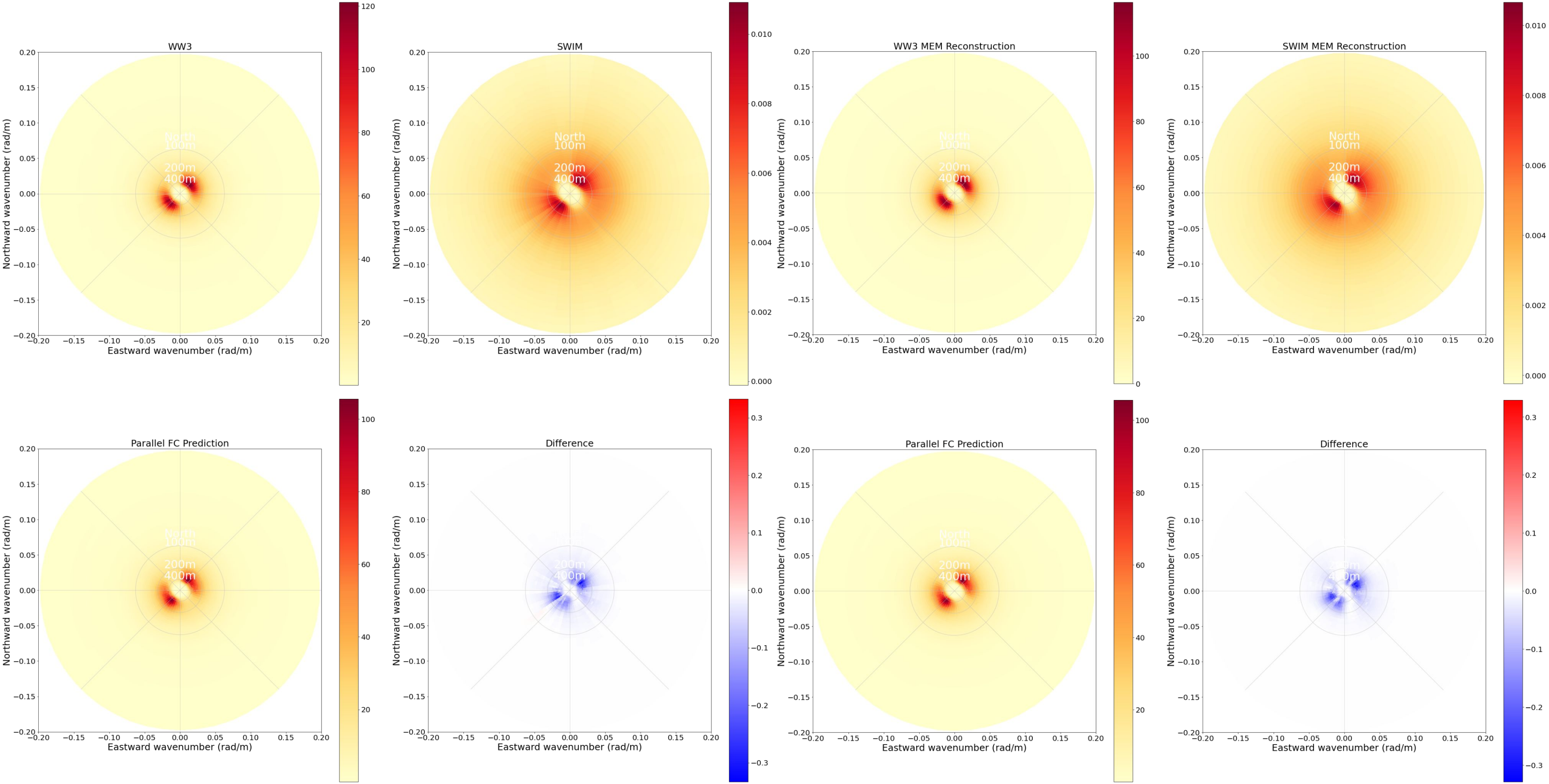

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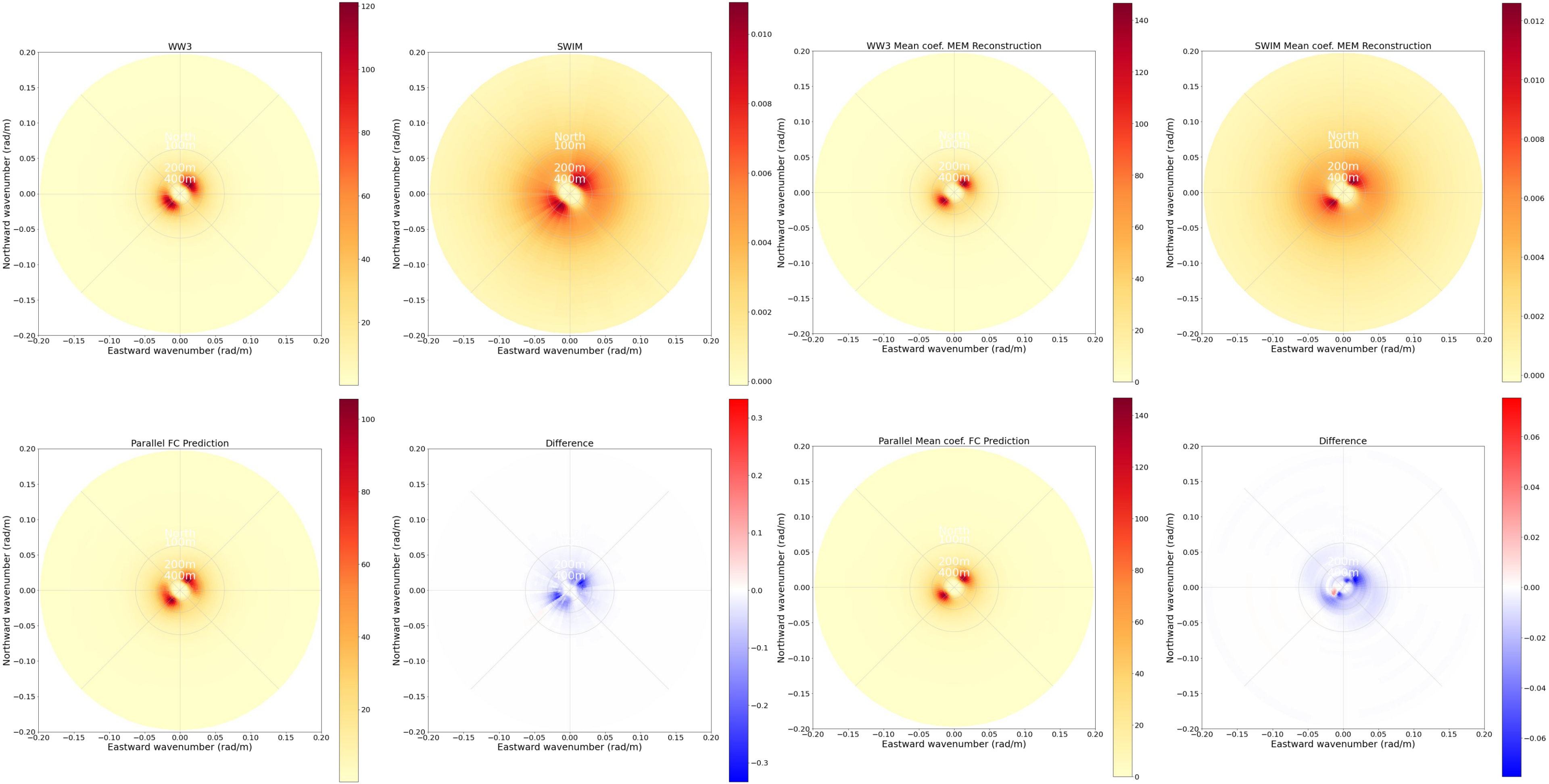

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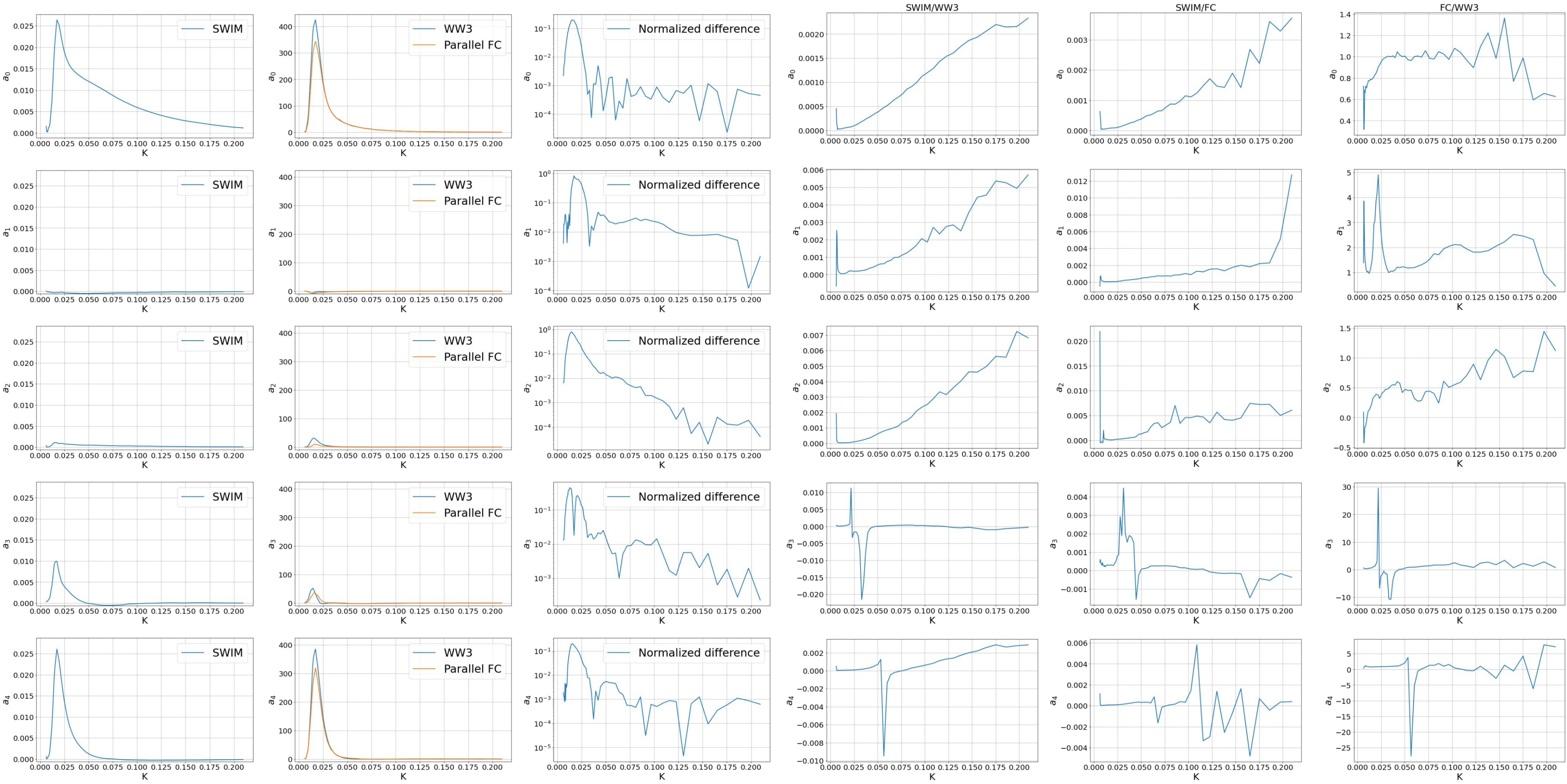

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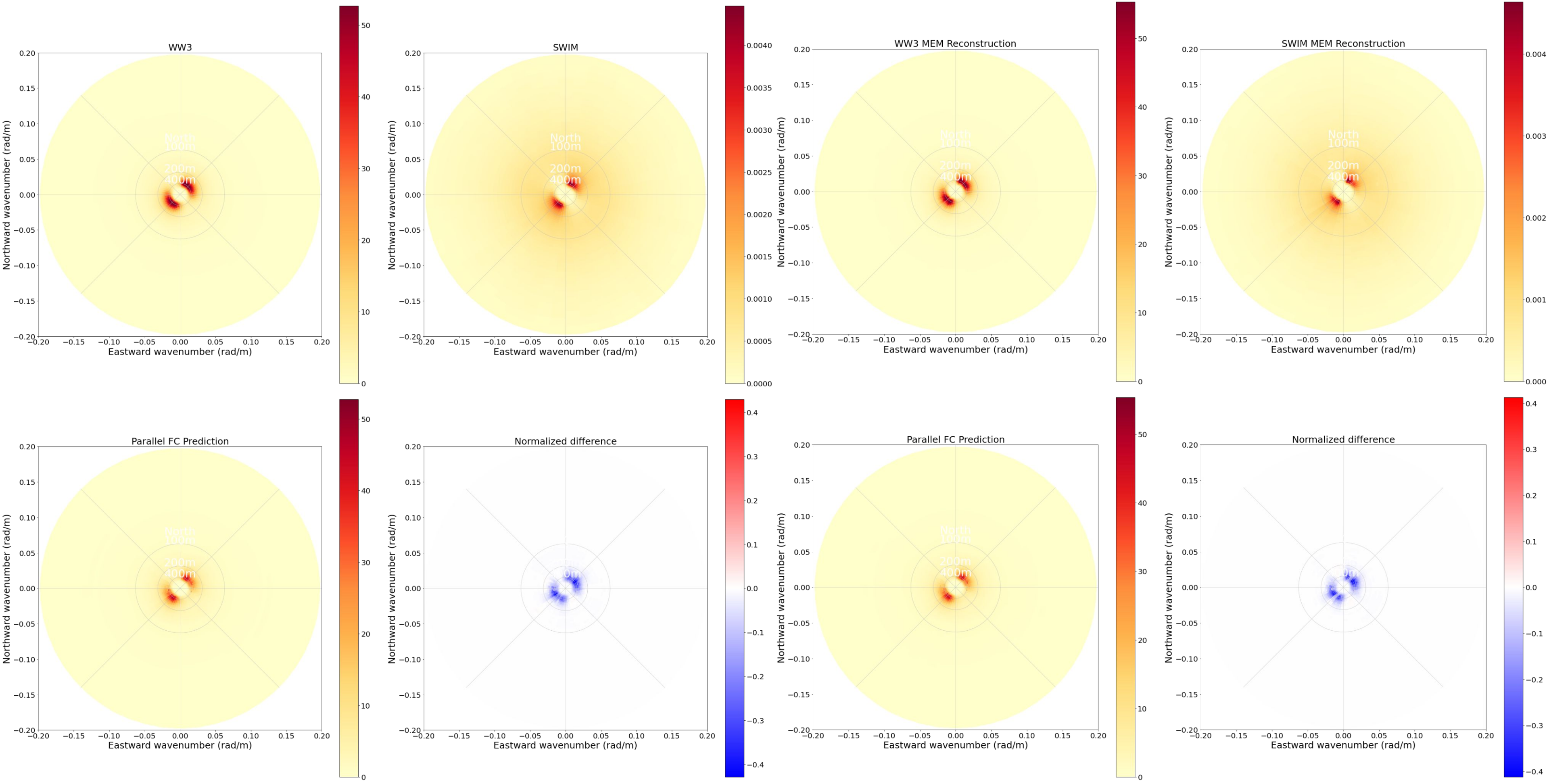

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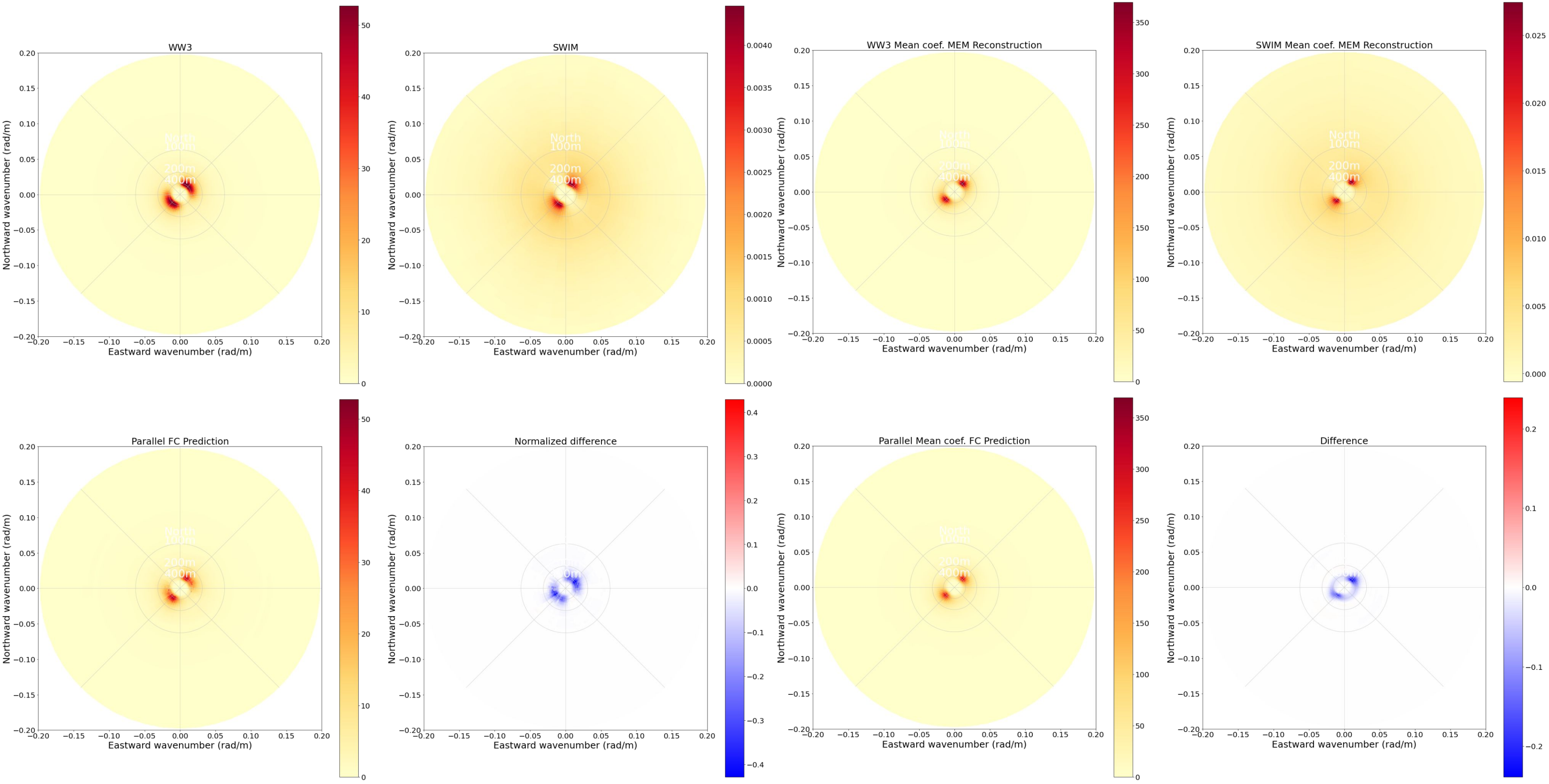

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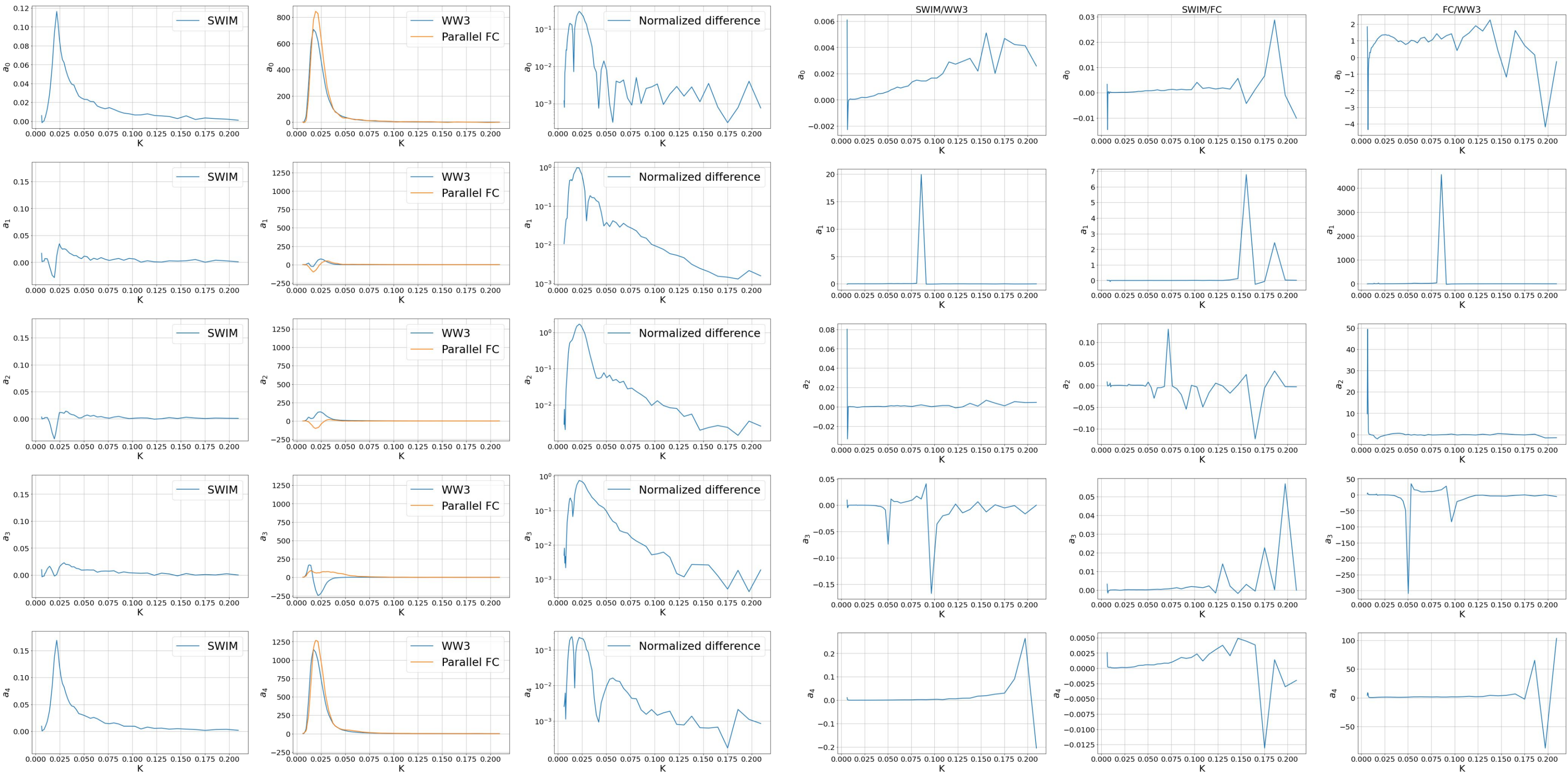

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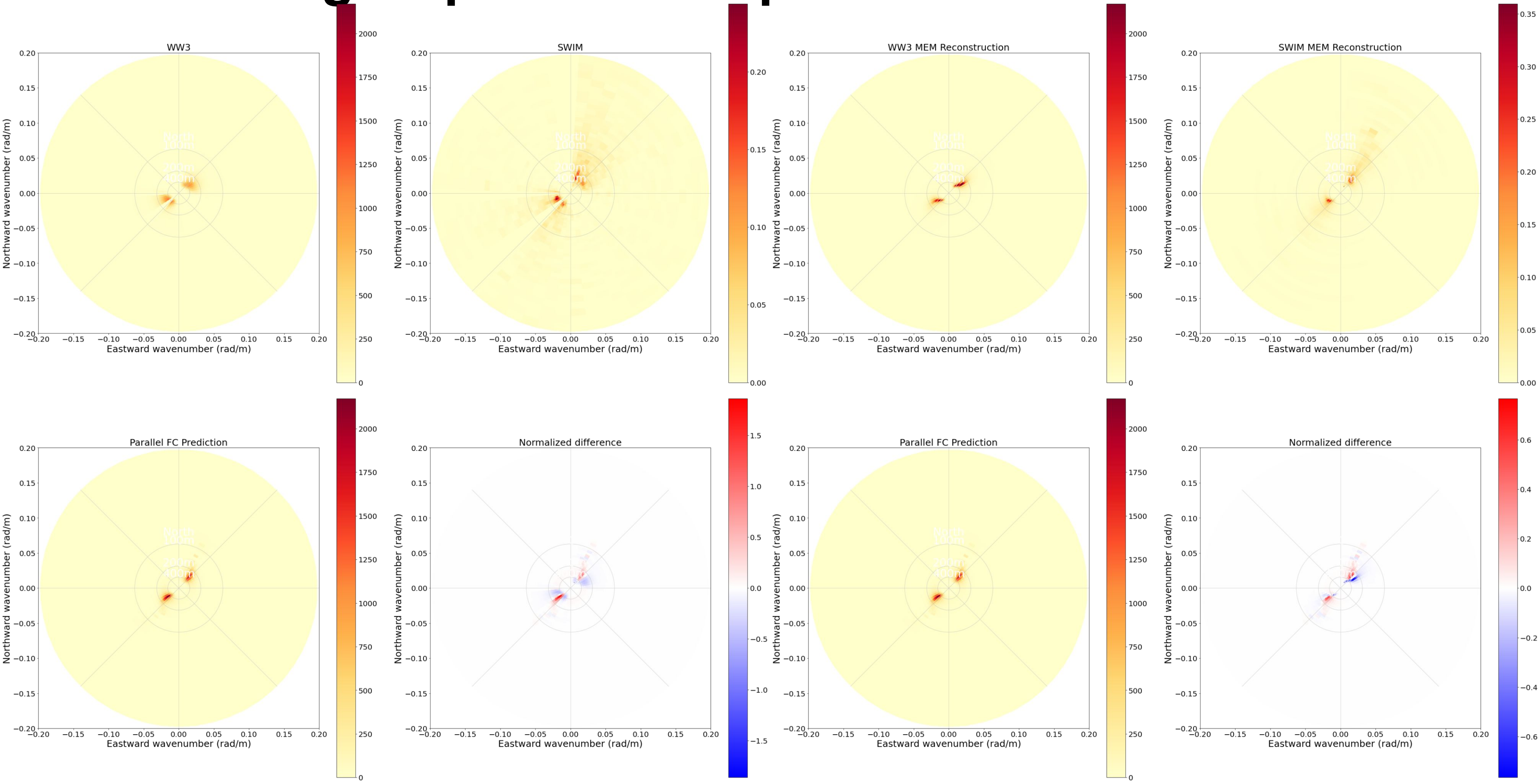
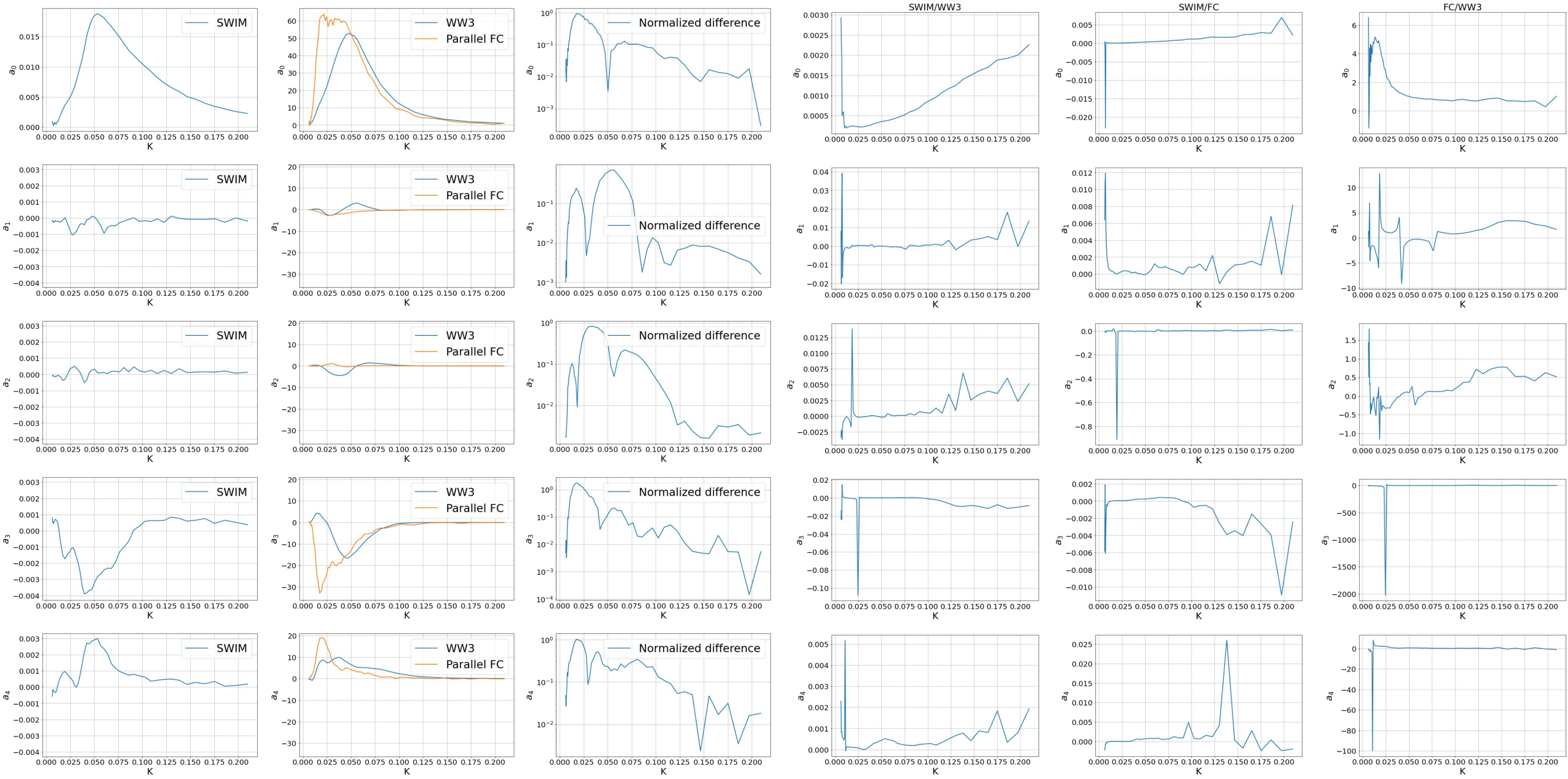


Wind wave: Mean results



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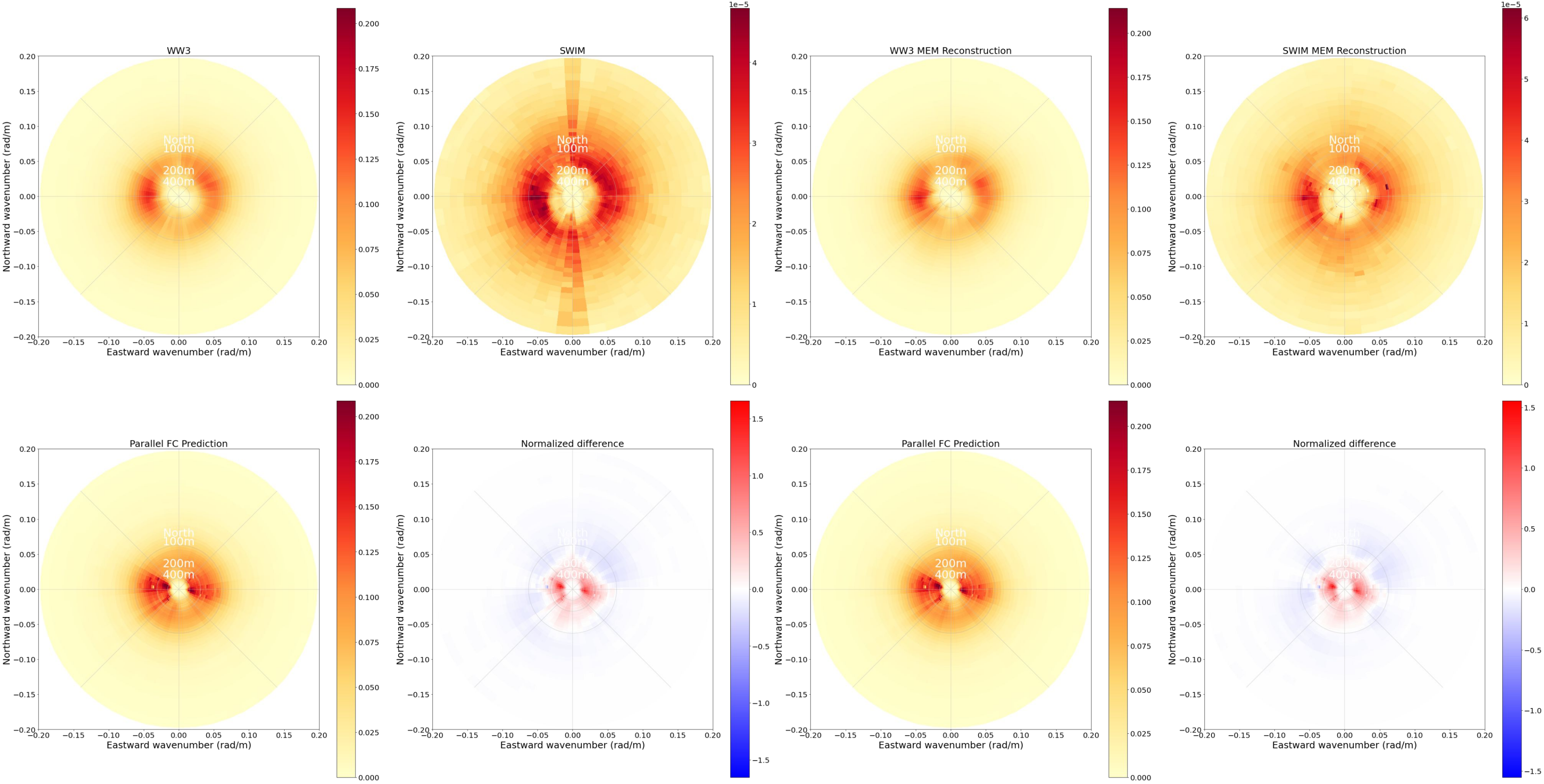

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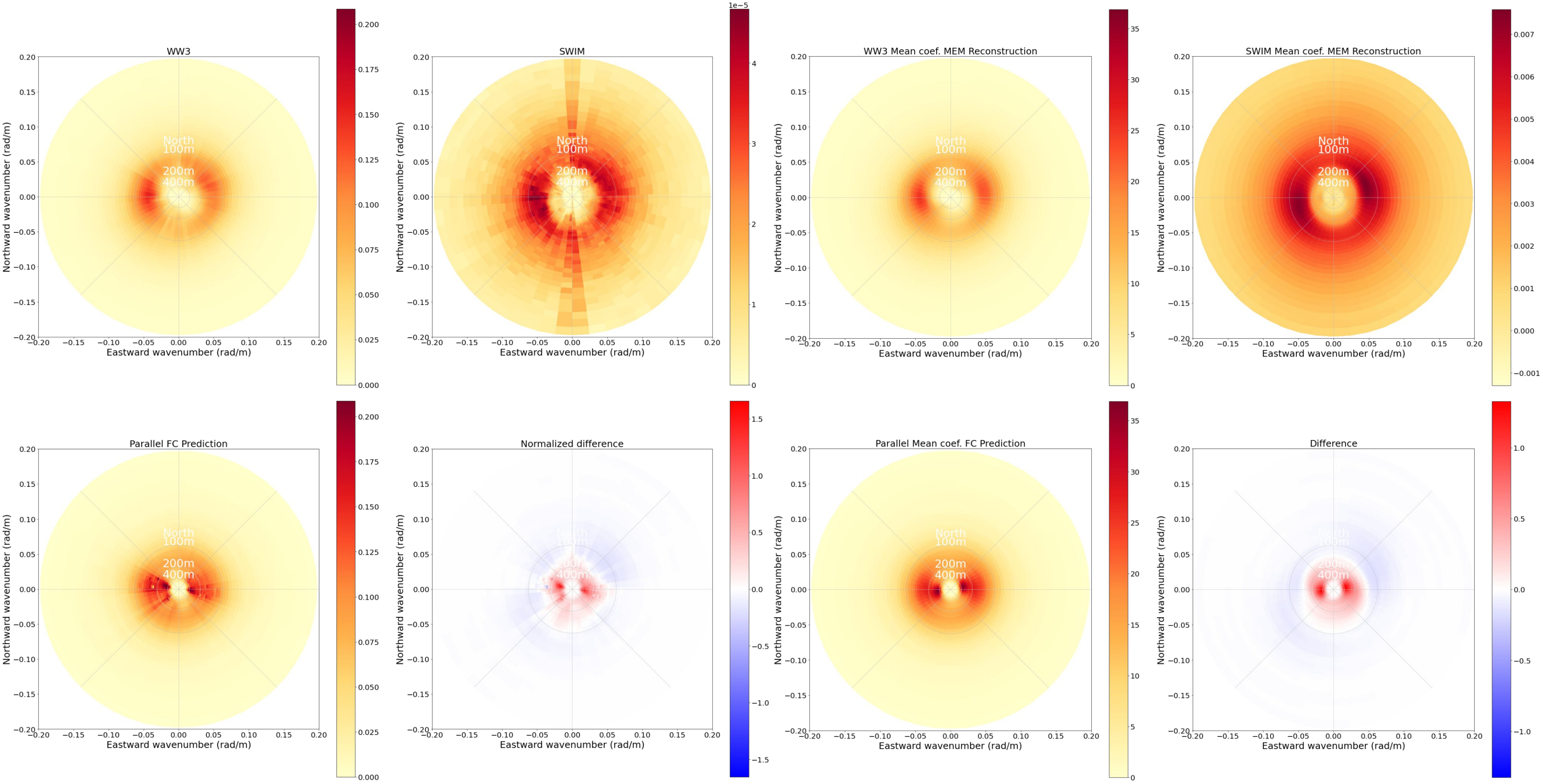

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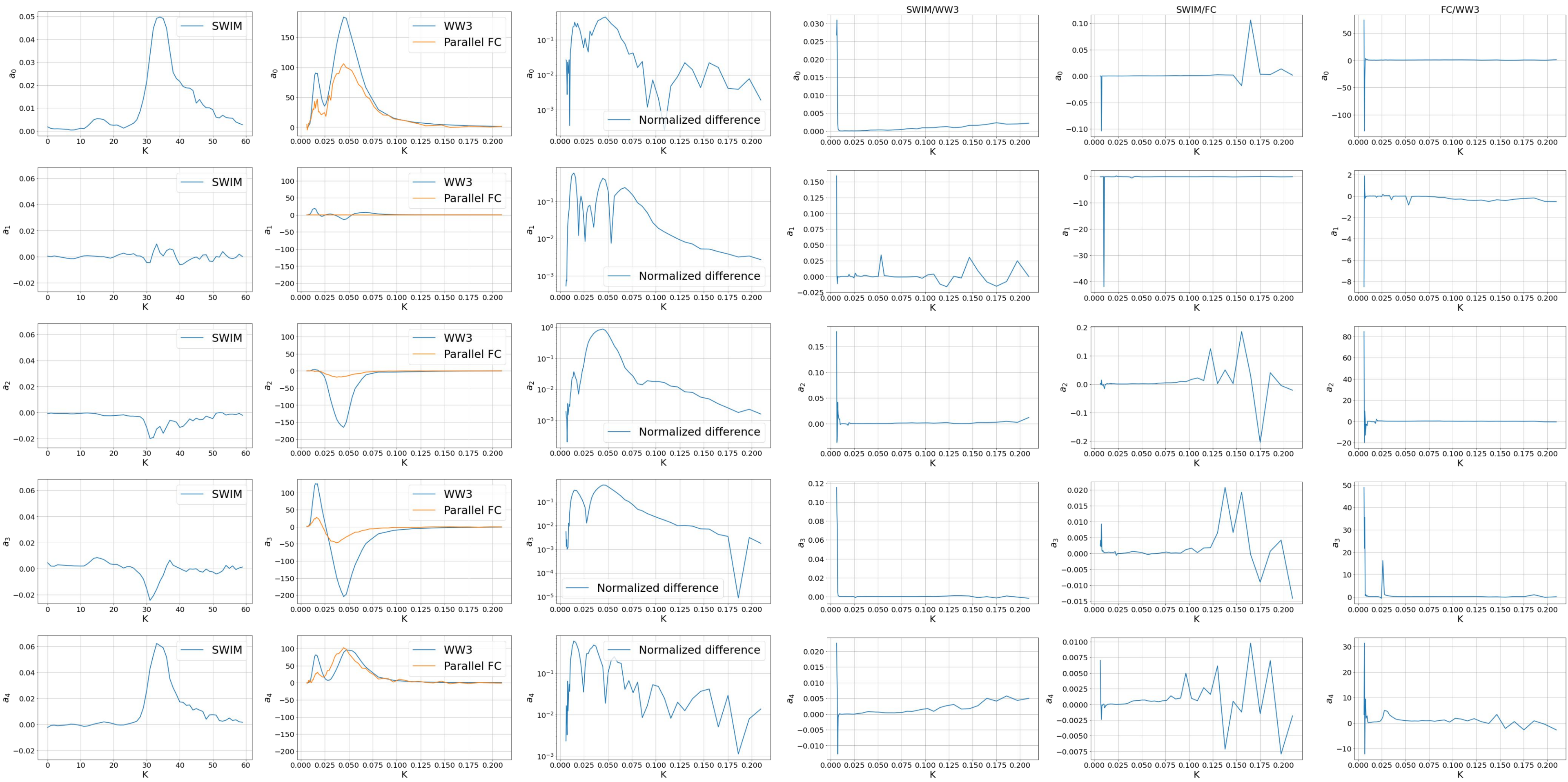

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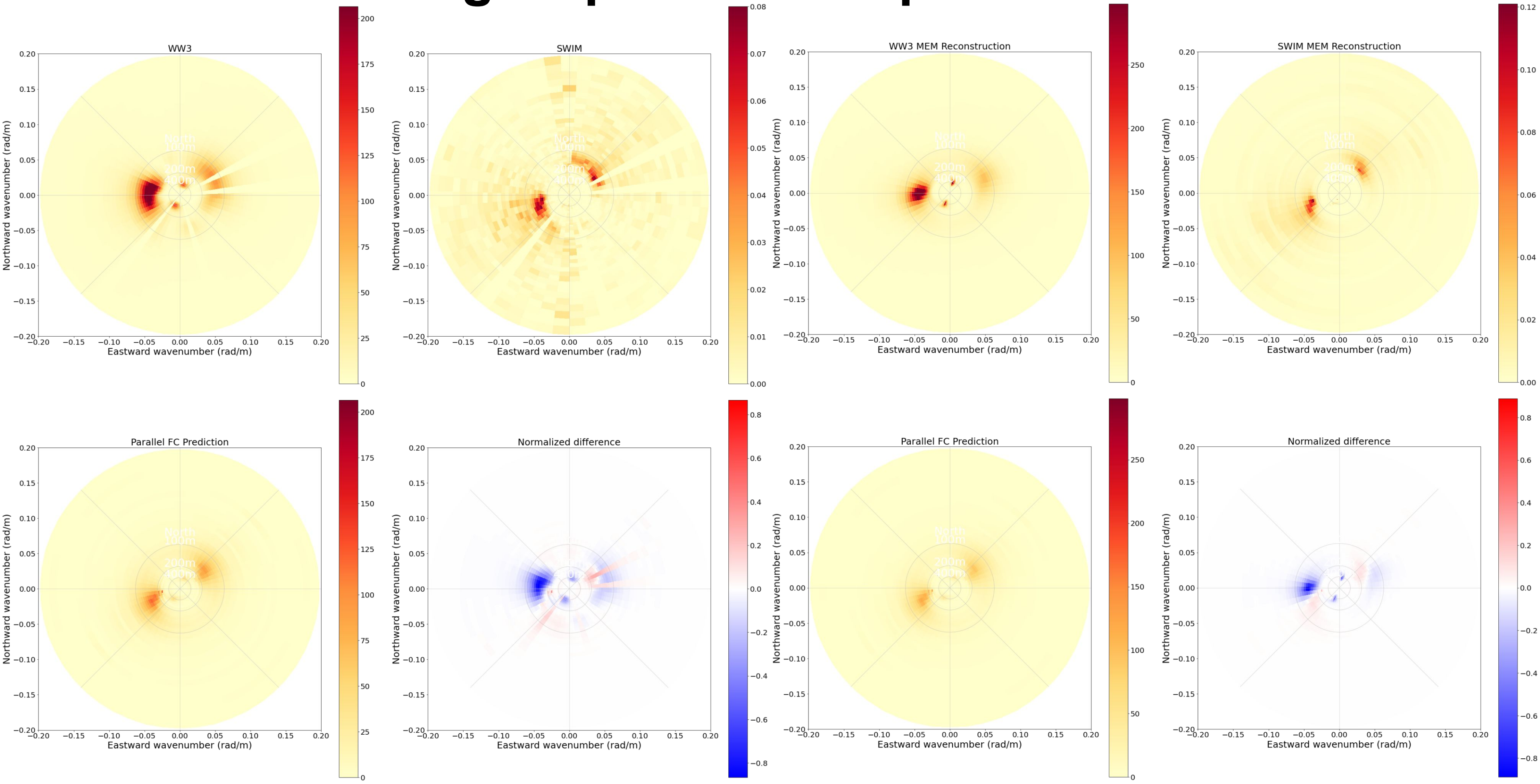
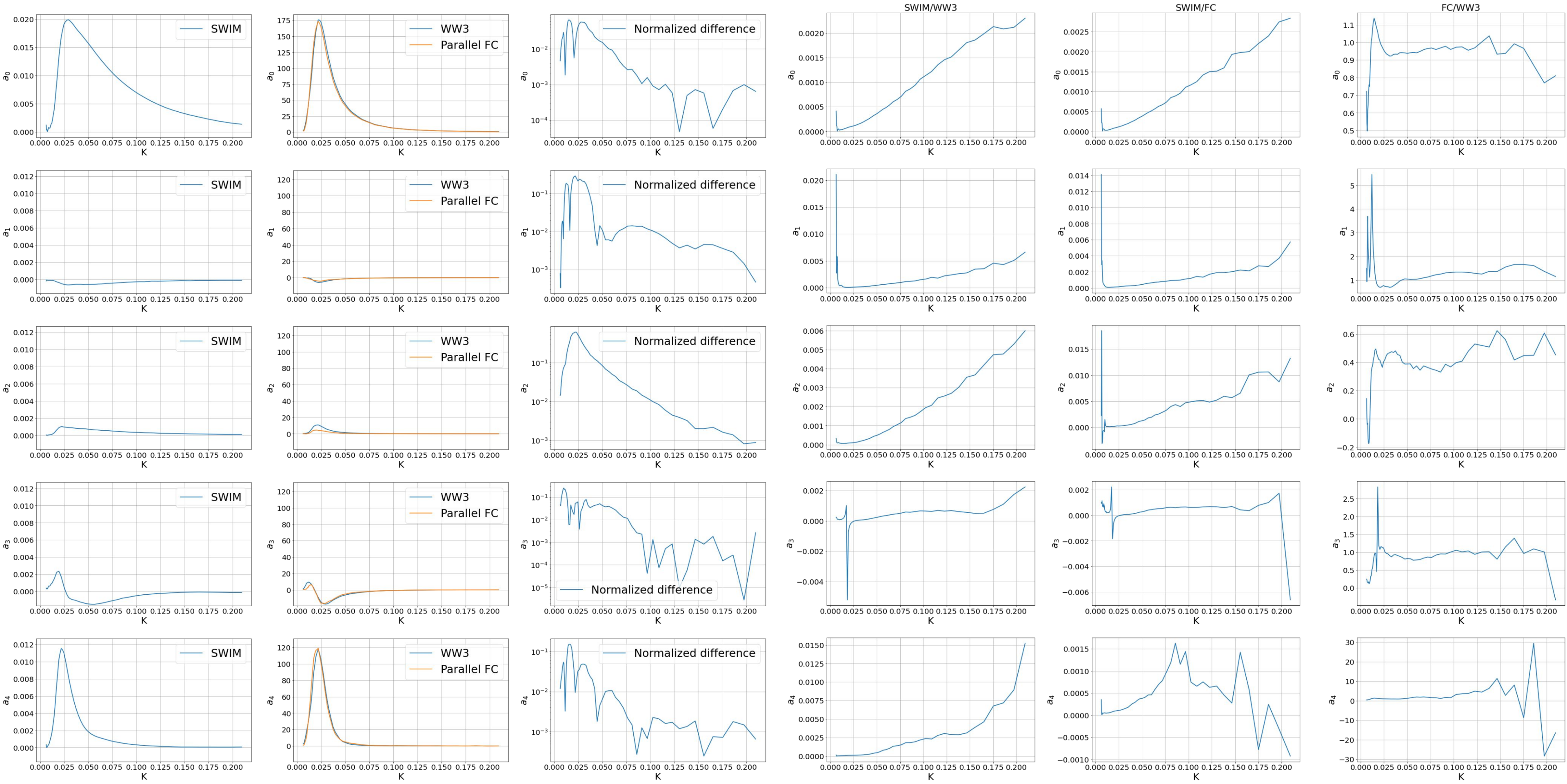


Mixed sea state: Mean results



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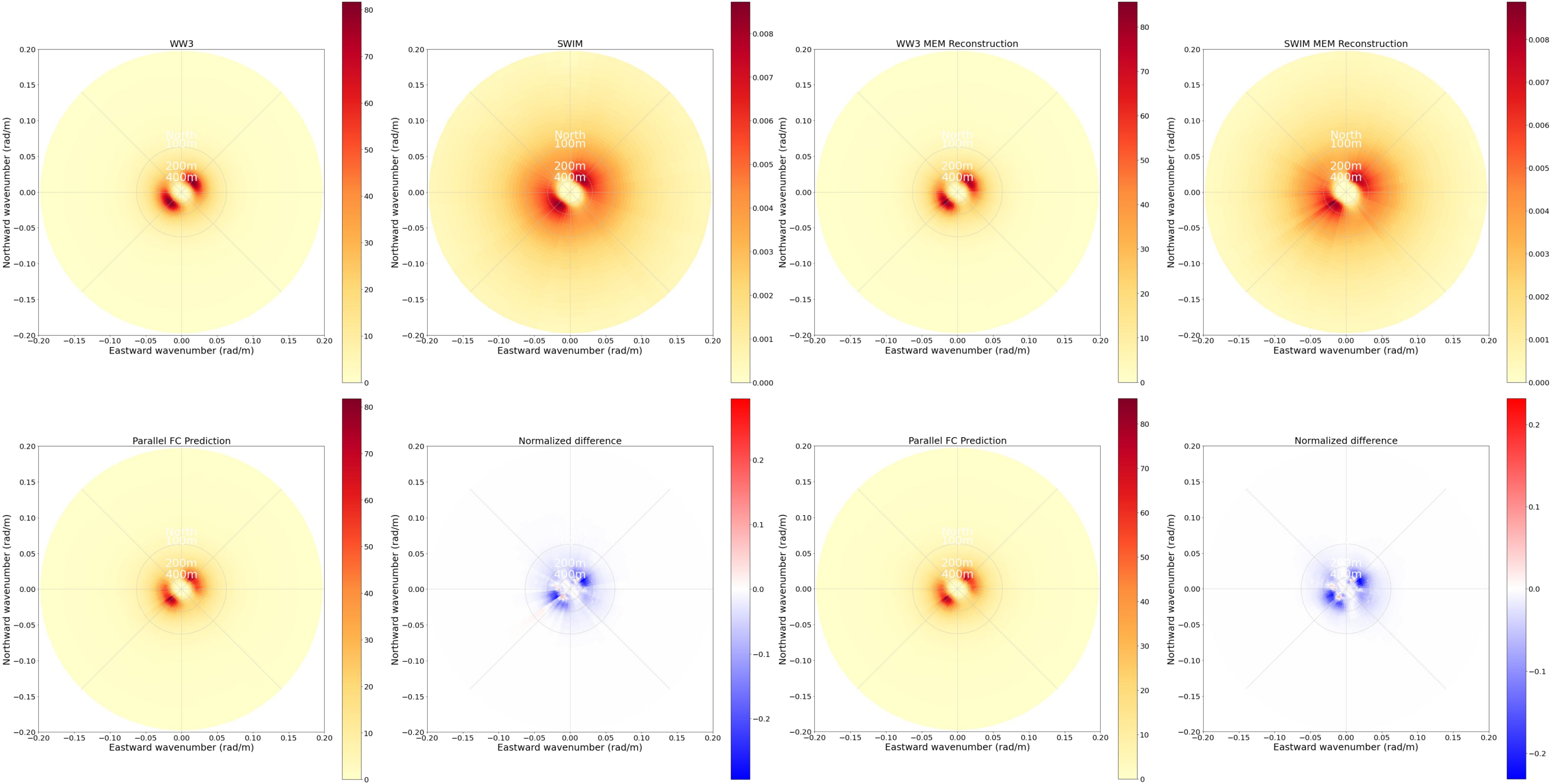

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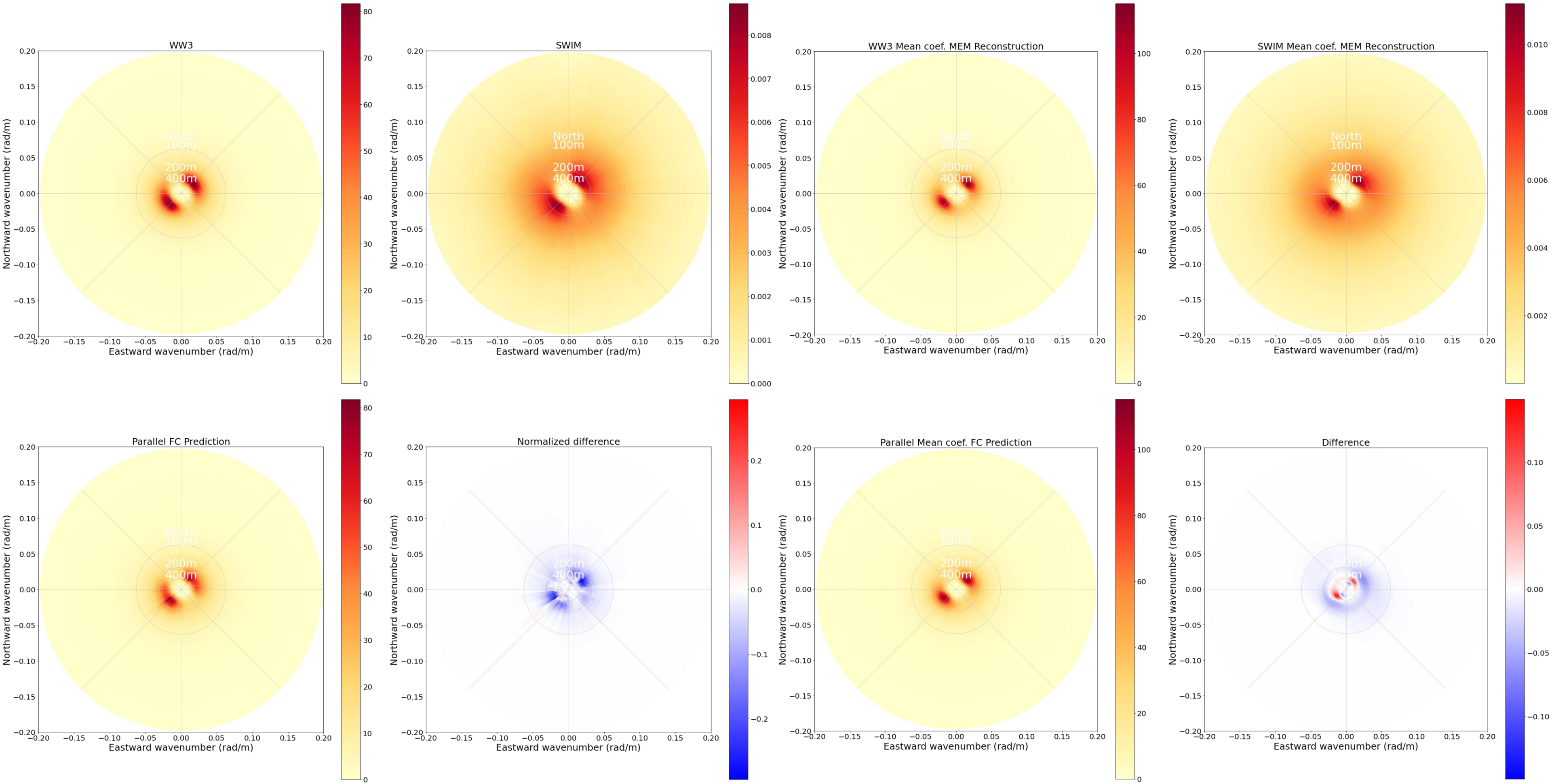

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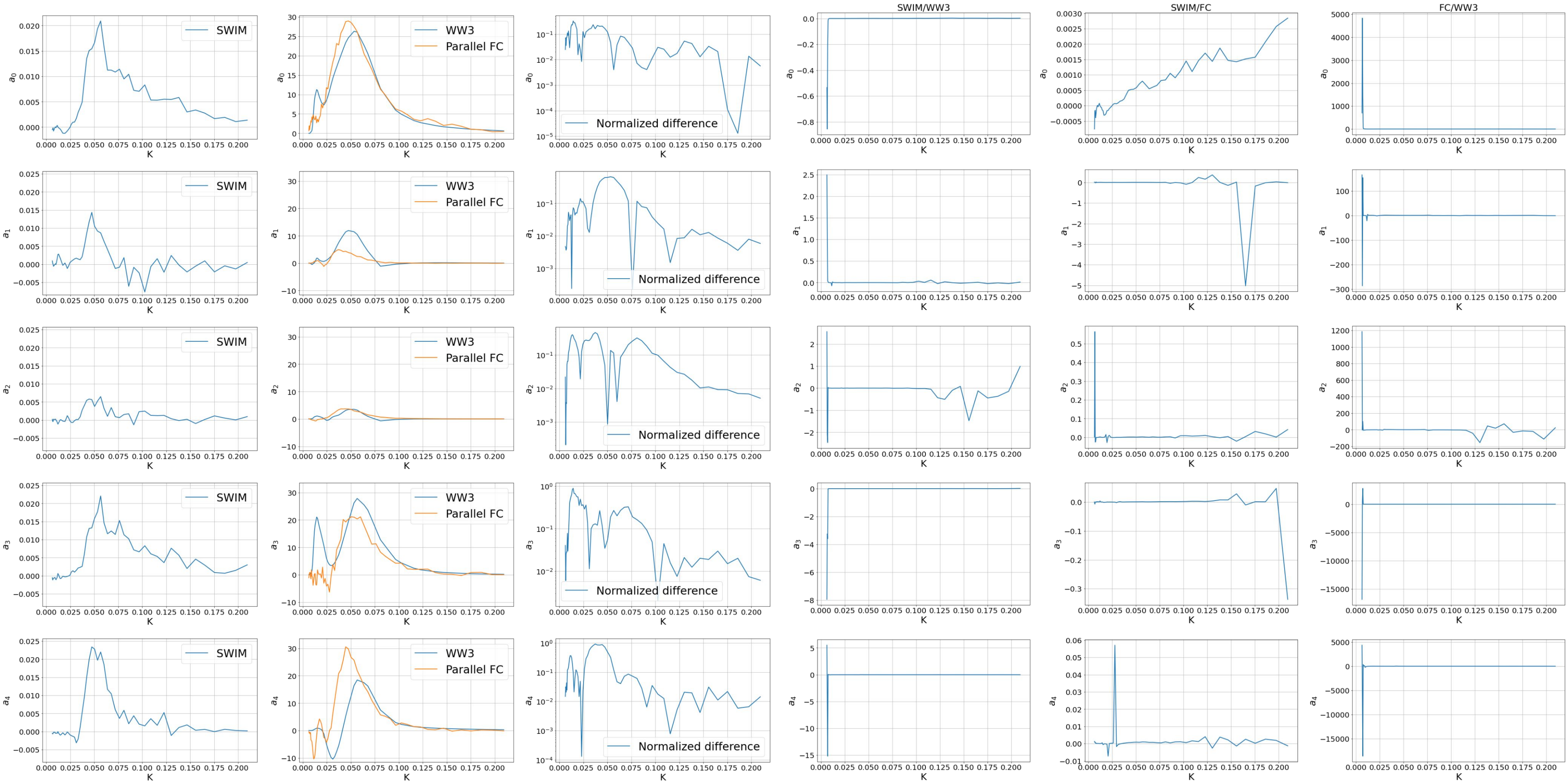

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