RESEARCH PROGRAM

DIGITAL FOR EXASCALE

Workshop "Artificial Intelligence for HPC@Exascale"
Image Analysis/Scaling-up Data
& Data Analysis/Inferences
PARIS – Thursday October 3rd, 2024

Deep learning based approach in imaging radiometry by aperture synthesis: from the idea to the implementation

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The SMOS space mission

➢ *A long story*

1983-1984: statement of requirements
1983-1986: seek & explore solutions
1987-1988: theoretical solution
1988-1991: practical solution
1991-1997: mission proposal
1997-1999: mission acceptance & initialization
1999-2009: payload manufacturing, assembly & tests
2009-2010: launch (02-Nov-2009) & commissioning phase
2010-………: operational phase

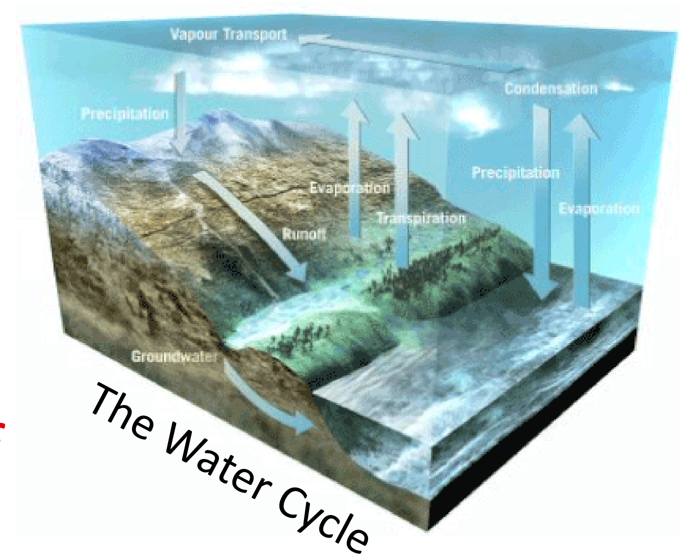
The SMOS space mission

➢ *The context*

ESA's Soil Moisture and Ocean Salinity (SMOS) mission has been designed to observe both soil moisture over the Earth's landmasses and salinity over the oceans from space.

SM data are urgently required for hydrological studies and data on OS are vital for improving our under-standing of ocean circulation patterns.

SMOS was a direct response to the current lack of global observations of SM and OS.



The Water Cycle

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The SMOS space mission

➢ *The concept*

A novel instrument has been especially developed with the objective to demonstrate the use of a Microwave Imaging Radiometer by Aperture Synthesis for imaging SM and OS by "capturing" images of emitted micro-wave radiation Tb in the "protected" L-band (1400-1427 MHz).

SMOS was the first attempt to apply to Earth remote sensing the concept of aperture synthesis initially developed by radio astronomers.

VLA (1970's)

The SMOS space mission

➢ *The concept*

A novel instrument has been especially developed with the objective to demonstrate the use of a Microwave Imaging Radiometer by Aperture Synthesis for imaging SM and OS by "capturing" images of emitted micro-wave radiation Tb in the "protected" L-band (1400-1427 MHz).

SMOS was the first attempt to apply to Earth remote sensing the concept of aperture synthesis initially developed by radio astronomers.

CBI (1990's)

The SMOS space mission

➢ *The concept*

A novel instrument has been especially developed with the objective to demonstrate the use of a Microwave Imaging Radiometer by Aperture Synthesis for imaging SM and OS by "capturing" images of emitted micro-wave radiation Tb in the "protected" L-band (1400-1427 MHz).

SMOS was launched on 2nd November 2009 and although designed for a five-year mission, it is still operational after more than 15 years in orbit.

SMOS (2000's)

The SMOS space mission

➢ *The instrument*

The single payload of SMOS is MIRAS, a Microwave Imaging Radiometer by Aperture Synthesis, operating in full-pol mode in the "protected" L-band (1400-1427 MHz).

MIRAS is a Y-shaped array equipped with 69 elementary antennas provides inter-ferometric measurements, 3 (of them) operating also as reference radio-meters to provide measurements of the average brightness temperature of the scene under observation.

SMOS (2000's)

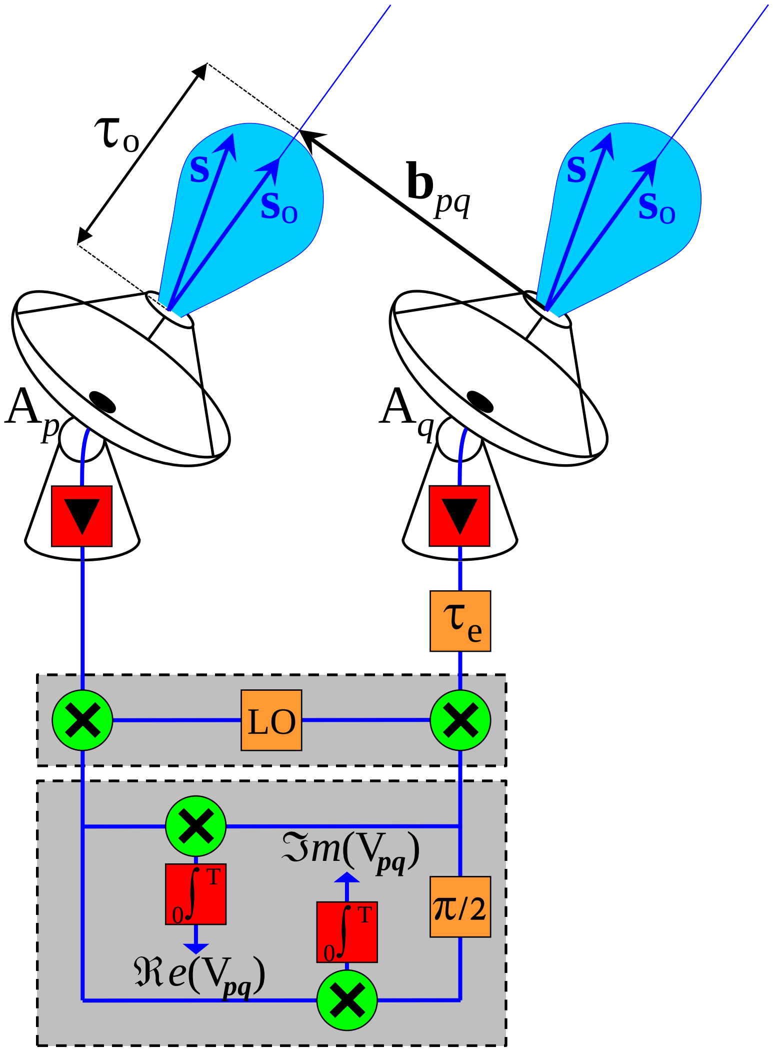
Aperture synthesis imaging

➢ *Arrays with connected antennas*

The radio signals received by the two antennas are sampled and directly transmitted via links to the correlation unit which combines them to produce interference fringes in real time.

Cosmic Background Imager

Very Large Array



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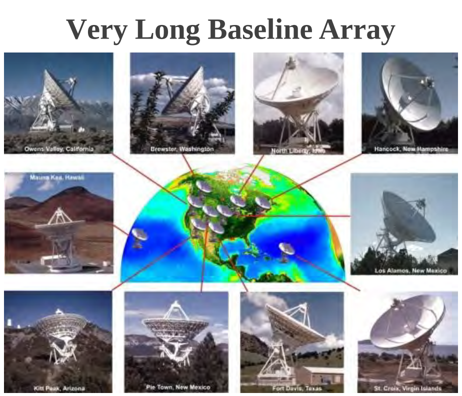
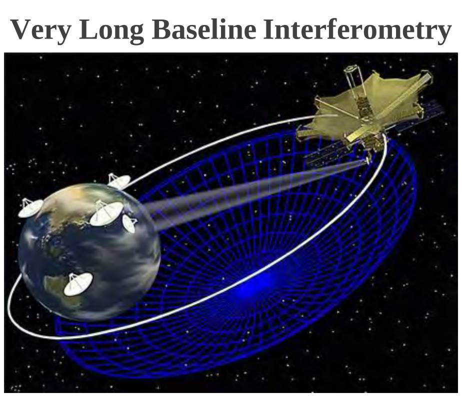
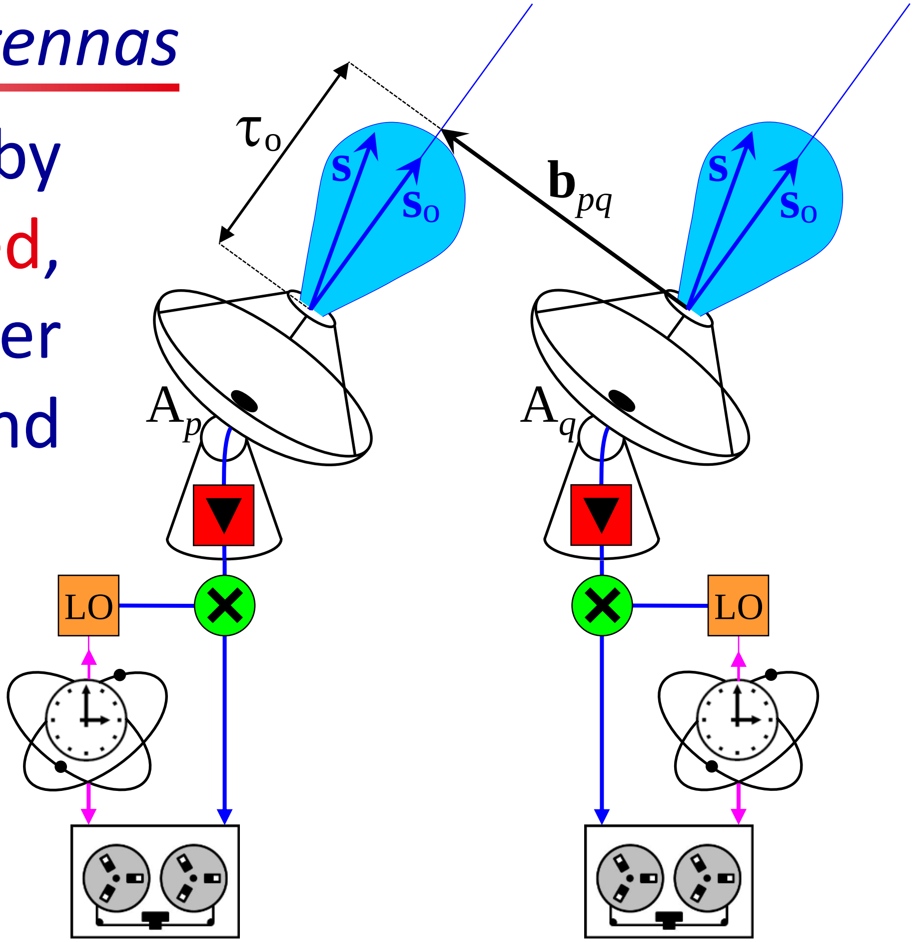
Aperture synthesis imaging

➢ *Arrays with unconnected antennas*

1) The radio signals received by the two antennas are sampled, recorded alongside together with an accurate time base and then stored on a media…





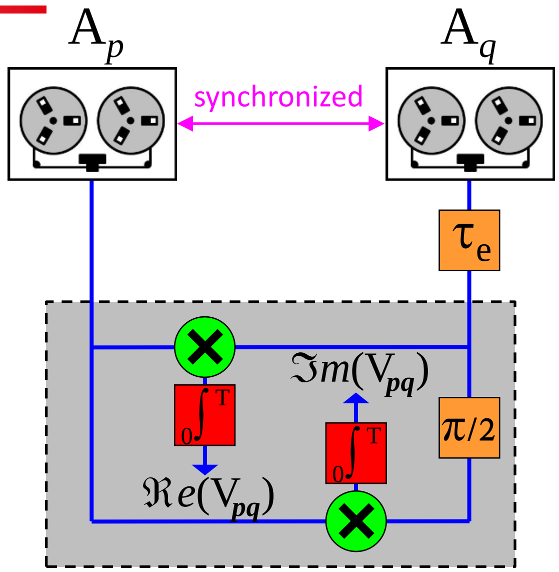


Aperture synthesis imaging

➢ *Arrays with unconnected antennas*

1) The radio signals received by the two antennas are sampled, recorded alongside together with an accurate time base and then stored on a media.

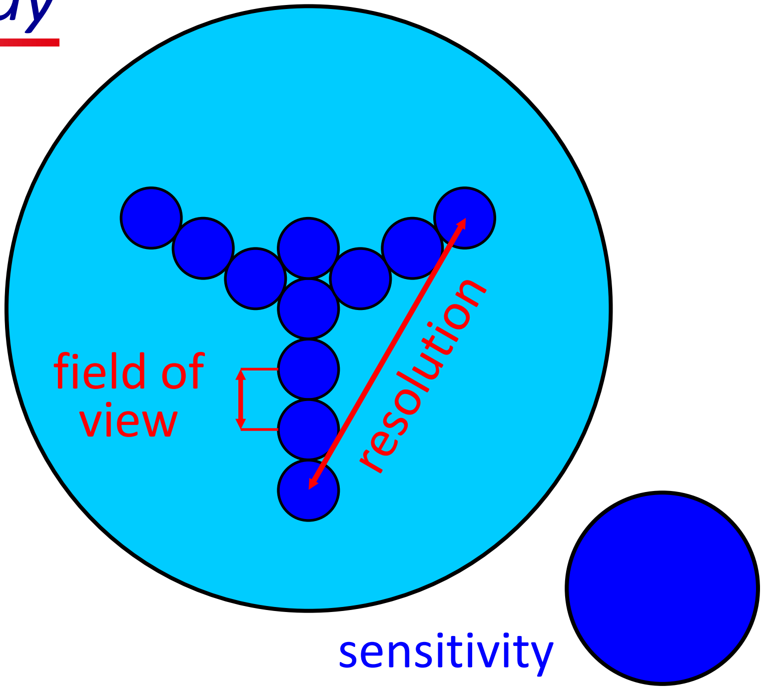
2) At a later time, at the location of a correlation unit, the data are synchronized, then played back together and combined just like if they were coming in real time from the two antennas.



VLBI correlation unit hosted by the Max Planck Institute for Radio Astronomy

Aperture synthesis imaging

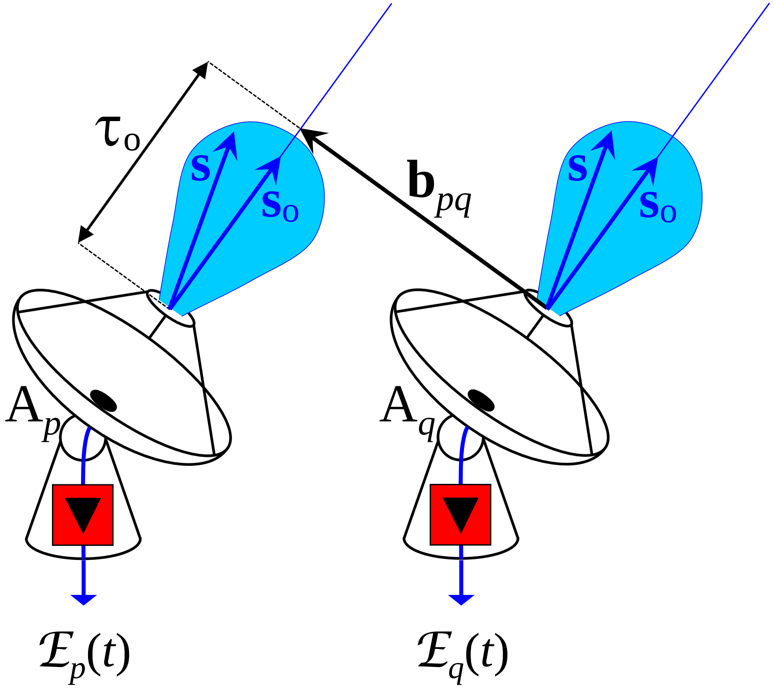
➢ *Key parameters of an antenna array*



1) Field of view: the extent of the observed scene that is synthesized by the instrument (with the aid of the computer).
2) Angular resolution: the ability to distinguish small details of the observed scene (estimated with Rayleigh / Schuster / Sparrow criterions of PSF, not of PSF2 !).
3) Radiometric sensitivity: the smallest temperature deviation that can be discerned by the instrument.

Aperture synthesis imaging

➢ *Complex visibilities*



Whether the antennas are connected or not, interferometer measurements are obtained by cross-correlating the signals $\mathcal{E}_p(t)$ and $\mathcal{E}_q(t)$ collected by pairs of spatially separated antennas A_p and A_q which have overlapping fields of view, yielding samples of the spatial coherence function V_{pq} (also termed complex visibilities) of the brightness temperature distribution T_b of the scene under observation for the angular frequency $\mathbf{u}_{pq} = \mathbf{b}_{pq}/\lambda_{\mathrm{o}}$.

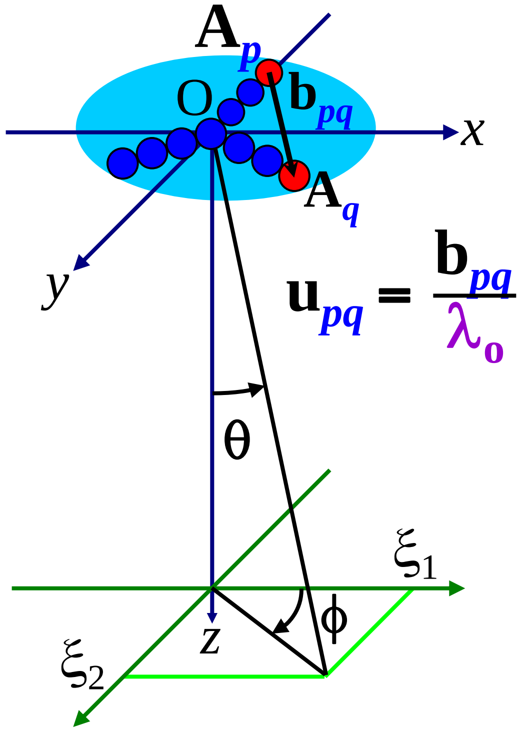
Instrument modelling

➢ *Van Cittert – Zernike theorem revisited*

$$\mathbf{V}_{pq} \propto \frac{1}{\sqrt{\Omega_p \Omega_q}} \iint_{\|\xi\| \leq 1} \mathcal{F}_p(\xi)\, \mathcal{F}_q^*(\xi)\, [\mathbf{T}_b(\xi) - \mathbf{T}_{rec}]\, \tilde{\mathbf{r}}_{pq}(t)\, \frac{e^{-2j\pi\, \mathbf{u}_{pq} \cdot \xi}}{\sqrt{1 - \|\xi\|^2}}\, d\xi$$

⬇

$$\mathbf{V} = \mathbf{G}\,\mathbf{T}$$



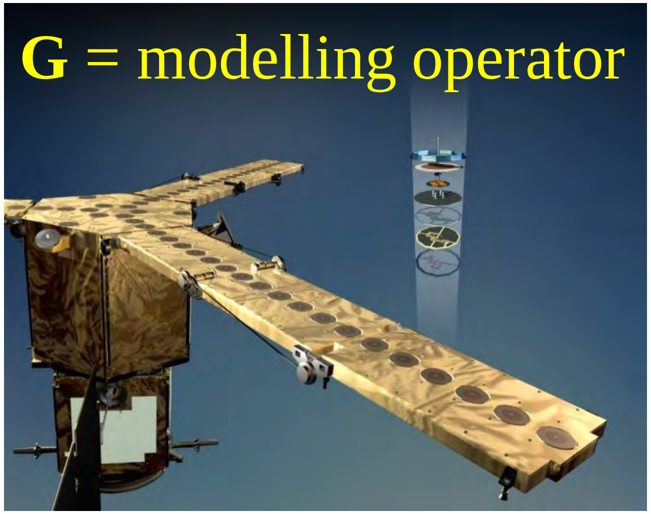
- $\mathcal{F}$: antenna voltage pattern
- $\mathbf{T}_{rec}$: receivers temperature
- $\tilde{\mathbf{r}}$: fringe washing function ($t = \mathbf{u}_{kl} \cdot \xi / f_o$)
- $\mathbf{V}$: complex visibilities
- $\mathbf{T}_b$: brightness temperature ($\mathbf{T}(\xi) = \mathbf{T}_b(\xi) - \mathbf{T}_{rec}$)

Instrument modelling

➢ *Van Cittert – Zernike theorem revisited*

$$\mathbf{V}_{pq} \propto \frac{1}{\sqrt{\Omega_p \Omega_q}} \iint_{\|\xi\| \leq 1} \mathcal{F}_p(\xi)\, \mathcal{F}_q^*(\xi)\, [\mathbf{T}_b(\xi) - \mathbf{T}_{rec}]\, \tilde{\mathbf{r}}_{pq}(t)\, \frac{e^{-2j\pi\, \mathbf{u}_{pq} \cdot \xi}}{\sqrt{1 - \|\xi\|^2}}\, d\xi$$

$$\mathbf{V} = \mathbf{G}\, \mathbf{T}$$



Instrument modelling

➢ *Dual polarization*

$$\mathbf{V}_{pq}^{x} \propto \frac{1}{\sqrt{\Omega_p \Omega_q}} \iint_{\|\xi\|\leq 1} \Big[\mathbf{C}_p^{x}(\xi)\, \mathbf{C}_q^{x*}(\xi)\, [\mathbf{T}_b^{x}(\xi) - \mathbf{T}_{rec}] + \mathbf{X}_p^{x}(\xi)\, \mathbf{X}_q^{x*}(\xi)\, [\mathbf{T}_b^{y}(\xi) - \mathbf{T}_{rec}] \Big]\, \tilde{\mathbf{r}}_{pq}(t)\, \frac{e^{-2j\pi \mathbf{u}_{pq}\cdot\xi}}{\sqrt{1-\|\xi\|^2}}\, d\xi$$

$$\mathbf{V}_{pq}^{y} \propto \frac{1}{\sqrt{\Omega_p \Omega_q}} \iint_{\|\xi\|\leq 1} \Big[\mathbf{X}_p^{y}(\xi)\, \mathbf{X}_q^{y*}(\xi)\, [\mathbf{T}_b^{x}(\xi) - \mathbf{T}_{rec}] + \mathbf{C}_p^{y}(\xi)\, \mathbf{C}_q^{y*}(\xi)\, [\mathbf{T}_b^{y}(\xi) - \mathbf{T}_{rec}] \Big]\, \tilde{\mathbf{r}}_{pq}(t)\, \frac{e^{-2j\pi \mathbf{u}_{pq}\cdot\xi}}{\sqrt{1-\|\xi\|^2}}\, d\xi$$

⬇

$$\mathbf{V} = \mathbf{G}\,\mathbf{T}$$

$$\mathbf{V} = \begin{pmatrix} \mathbf{V}^{x} \\ \mathbf{V}^{y} \end{pmatrix} \qquad \mathbf{G} = \begin{pmatrix} \mathbf{G}^{xx} & \mathbf{G}^{xy} \\ \mathbf{G}^{yx} & \mathbf{G}^{yy} \end{pmatrix} \qquad \mathbf{T} = \begin{pmatrix} \mathbf{T}^{x}(\xi) \\ \mathbf{T}^{y}(\xi) \end{pmatrix} = \begin{pmatrix} \mathbf{T}_b^{x}(\xi) - \mathbf{T}_{rec} \\ \mathbf{T}_b^{y}(\xi) - \mathbf{T}_{rec} \end{pmatrix}$$

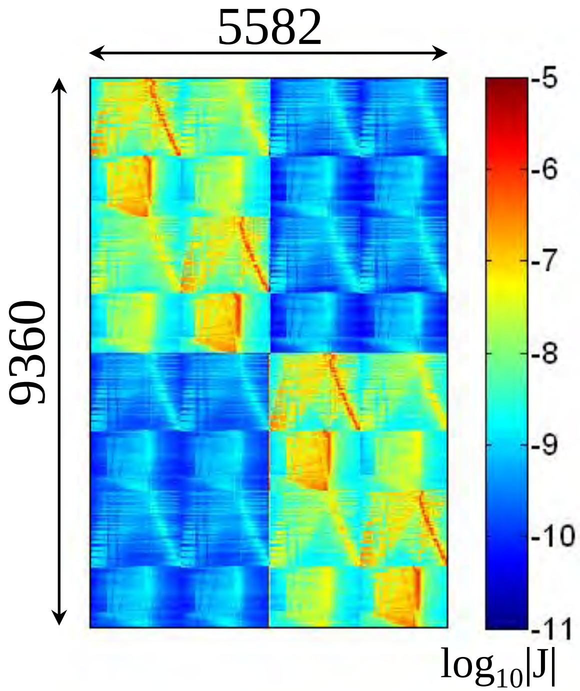
Regularized inversion

Dual polarization

$$\begin{pmatrix} T_r^x \\ T_r^y \end{pmatrix} = \begin{pmatrix} U^*Z & 0 \\ 0 & U^*Z \end{pmatrix} \begin{pmatrix} J^{xx} & J^{xy} \\ J^{yx} & J^{yy} \end{pmatrix}^+ \left[\begin{pmatrix} V^x \\ V^y \end{pmatrix} - \begin{pmatrix} G^{xx} & G^{xy} \\ G^{yx} & G^{yy} \end{pmatrix} \begin{pmatrix} \tilde{T}^x \\ \tilde{T}^y \end{pmatrix} \right] + \begin{pmatrix} \tilde{T}^x \\ \tilde{T}^y \end{pmatrix}$$

numerical implementation in ground segment

69 antennas
dual polarisation
(**J** ~ 400 Mbytes)



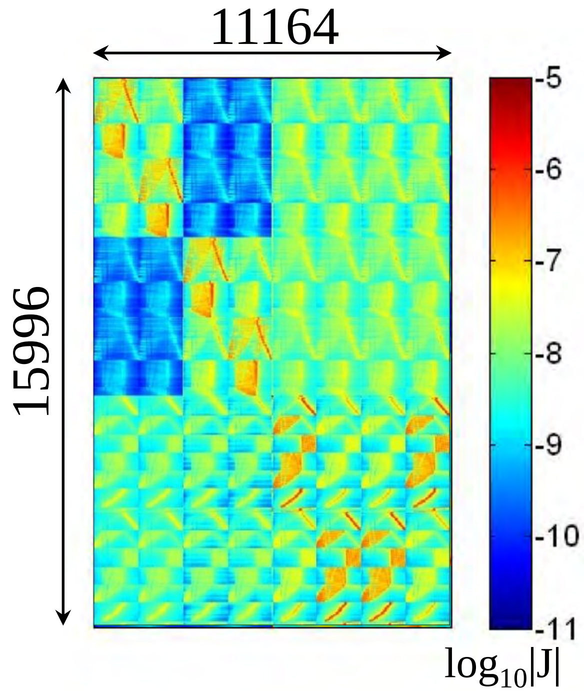
Regularized inversion

➢ *Full polarization*

$$\begin{pmatrix} \mathbf{T}_{\mathbf{r}}^{x} \\ \mathbf{T}_{\mathbf{r}}^{y} \\ \mathbf{T}_{\mathbf{r}}^{3} \\ \mathbf{T}_{\mathbf{r}}^{4} \end{pmatrix} = \cdots \begin{pmatrix} \mathbf{V}^{x} \\ \mathbf{V}^{y} \\ \mathbf{V}^{xy} \end{pmatrix} \cdots$$

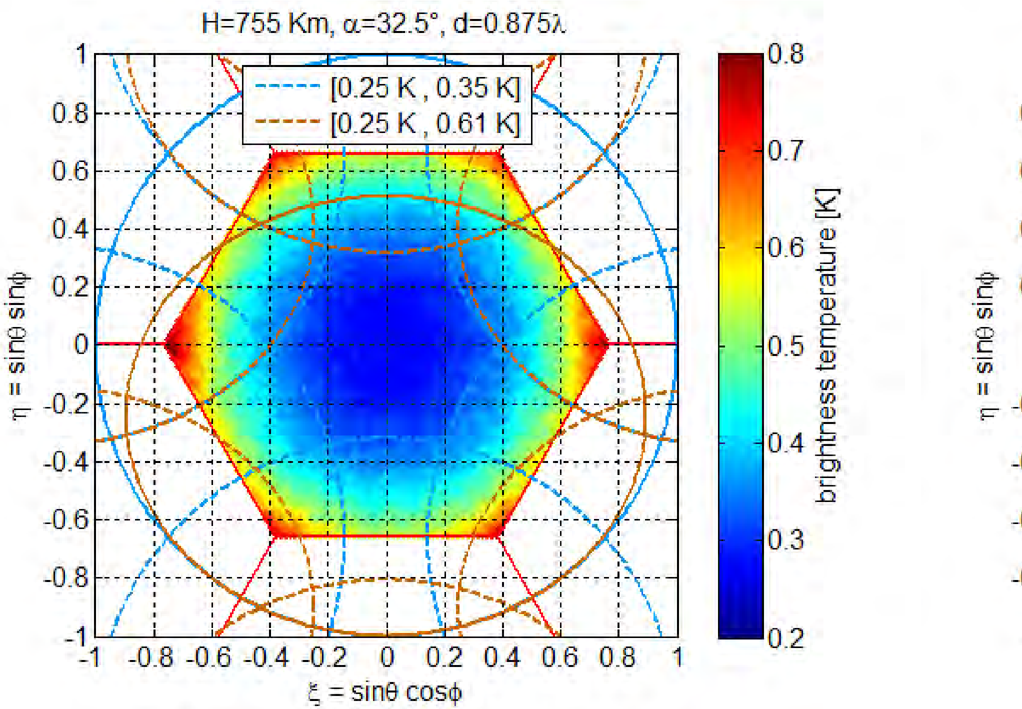
numerical implementation in ground segment

69 antennas
full polarisation
(**J** ~ 1.3 Gbytes)



Illustrations & performances

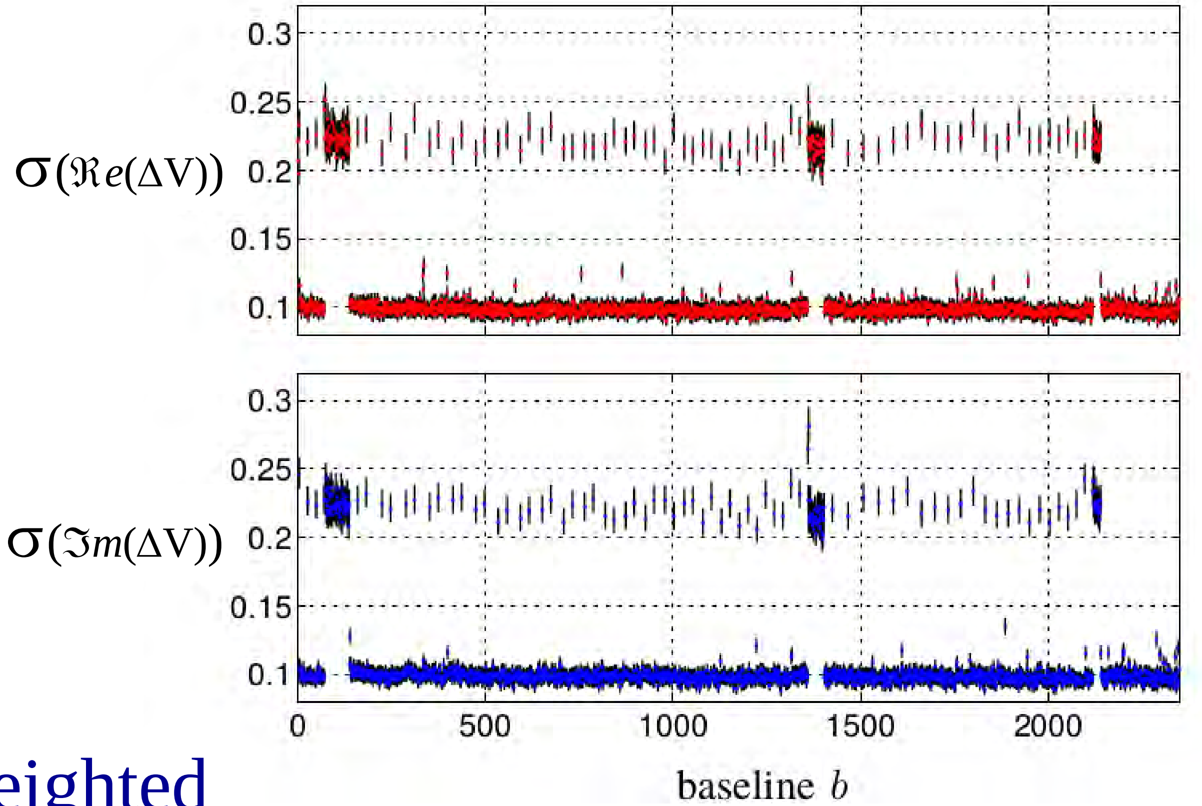
➢ *Noise propagation: $\Delta V = N(0,\sigma^2)$ with $\sigma = 0.01$ K*



Amplification factor: ×25 (num. simul.)
(boresight) ×25 (radio. theory)

Illustrations & performances

➢ *Noise statistics: heteroscedastic vs. homoscedastic*

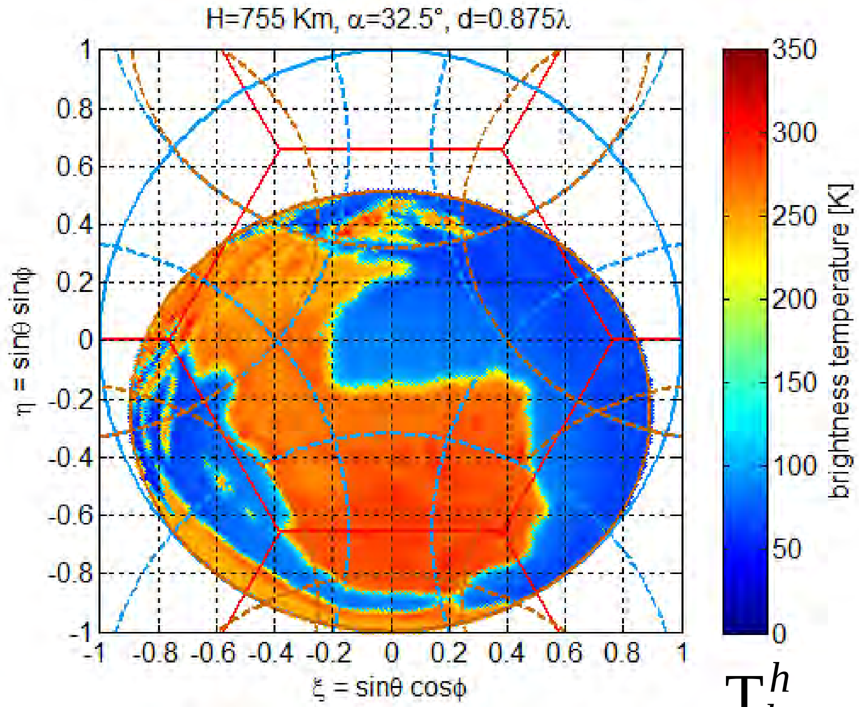


0.1 K error on T_b may induce 0.2-0.3 PSU error in retrieved SSS

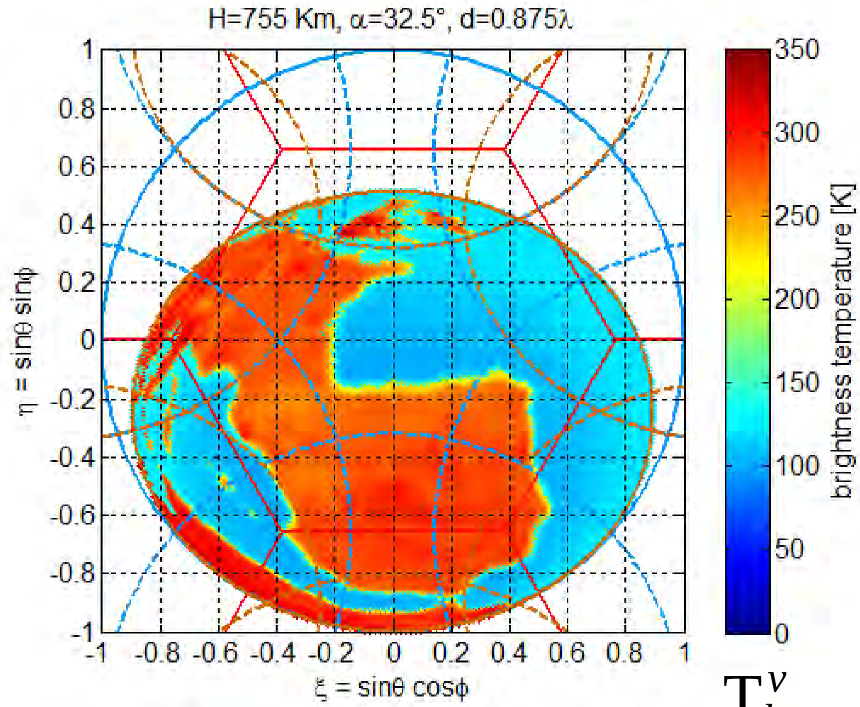
Weighted *vs.* Standard inversion ⇒ radiometric sensitivity: 2.3 K *vs.* 2.5 K (–8%)

Illustrations & performances

➢ *Observed scene: H & V*



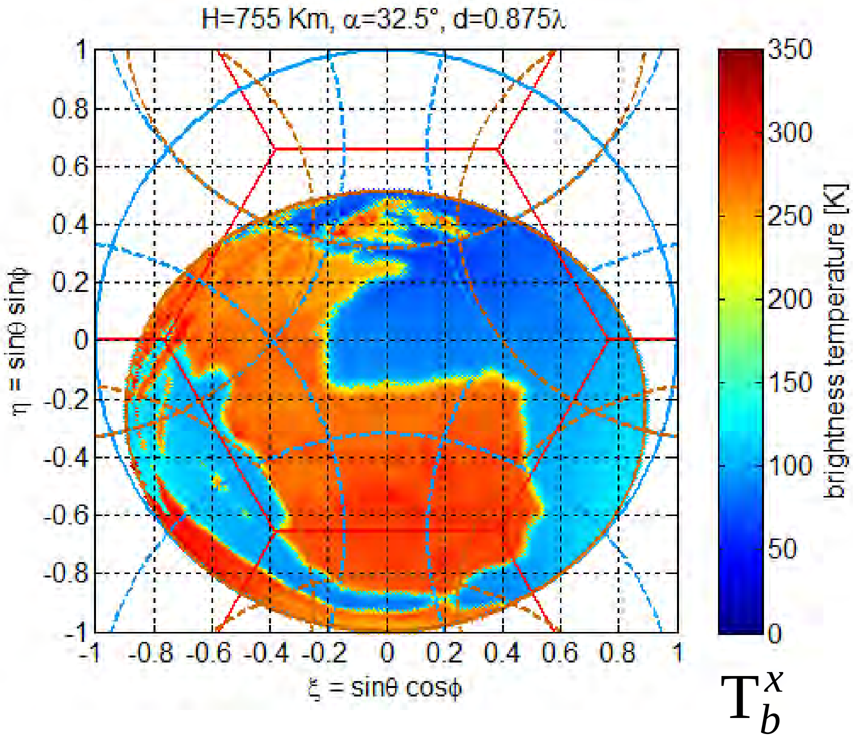
T_b^h

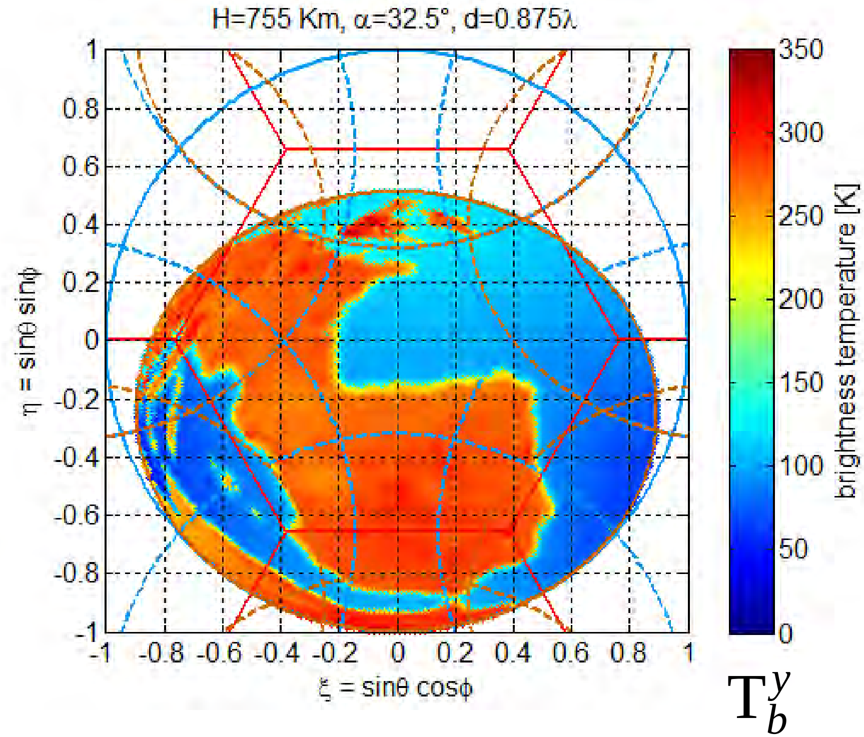


T_b^v

Illustrations & performances

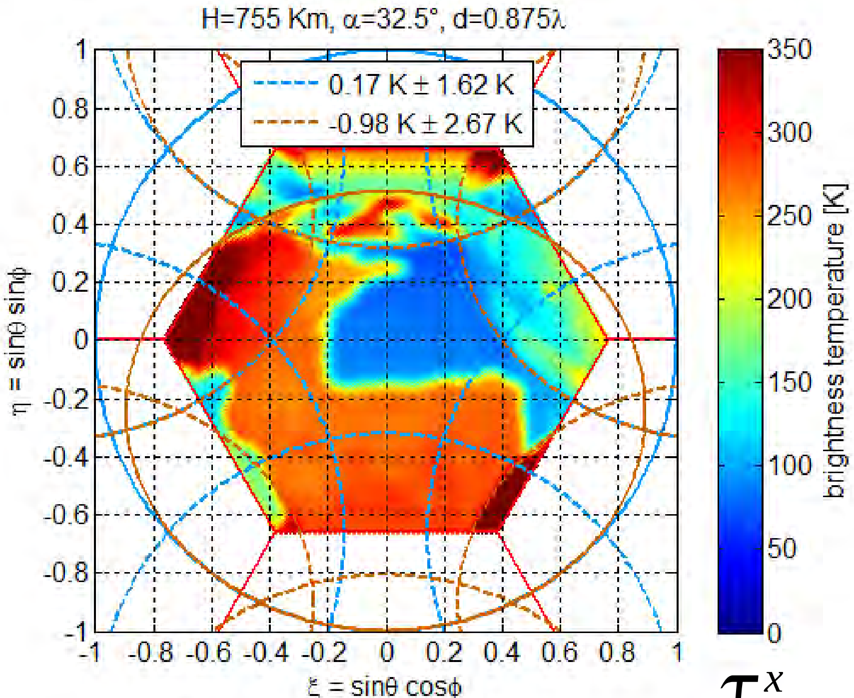
➢ *Observed scene: X & Y*



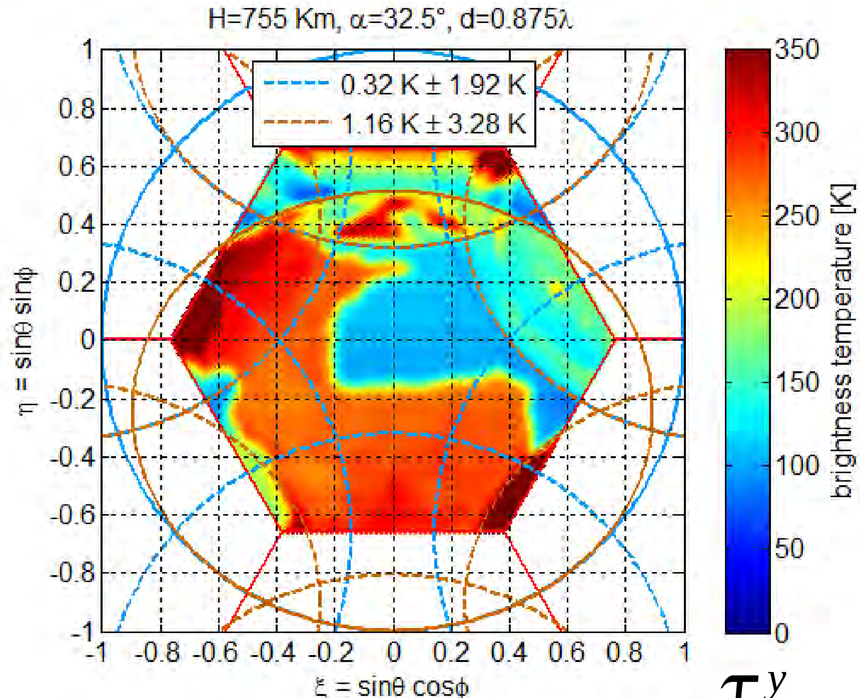


Illustrations & performances

➢ *Standard inversion*



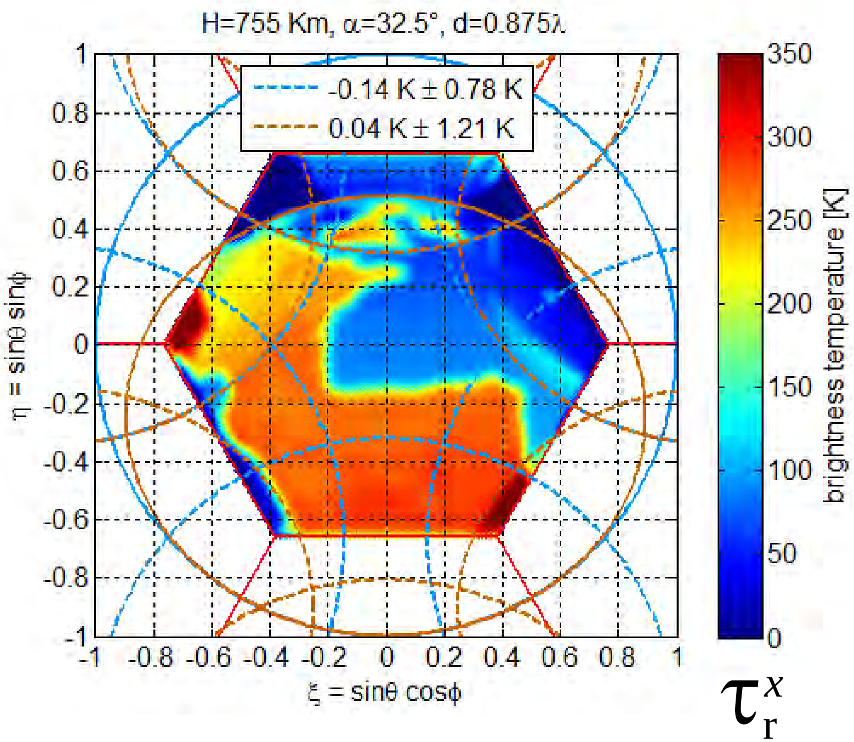
τ_{r}^{x}

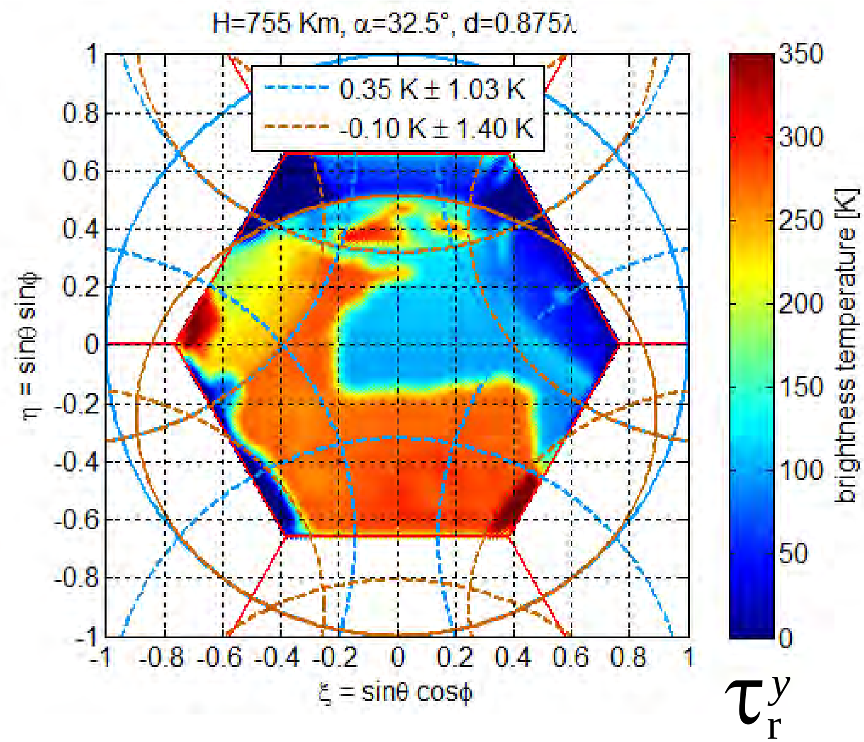


τ_{r}^{y}

Illustrations & performances

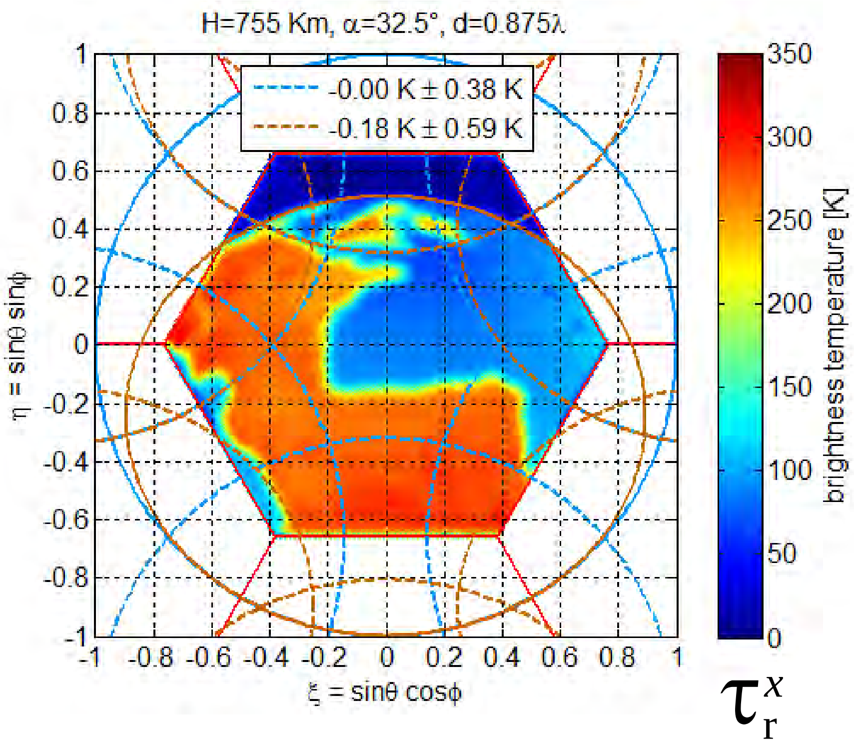
➢ *Differential inversion with $\tilde{T}(t_{sky}, t_{earth})$*

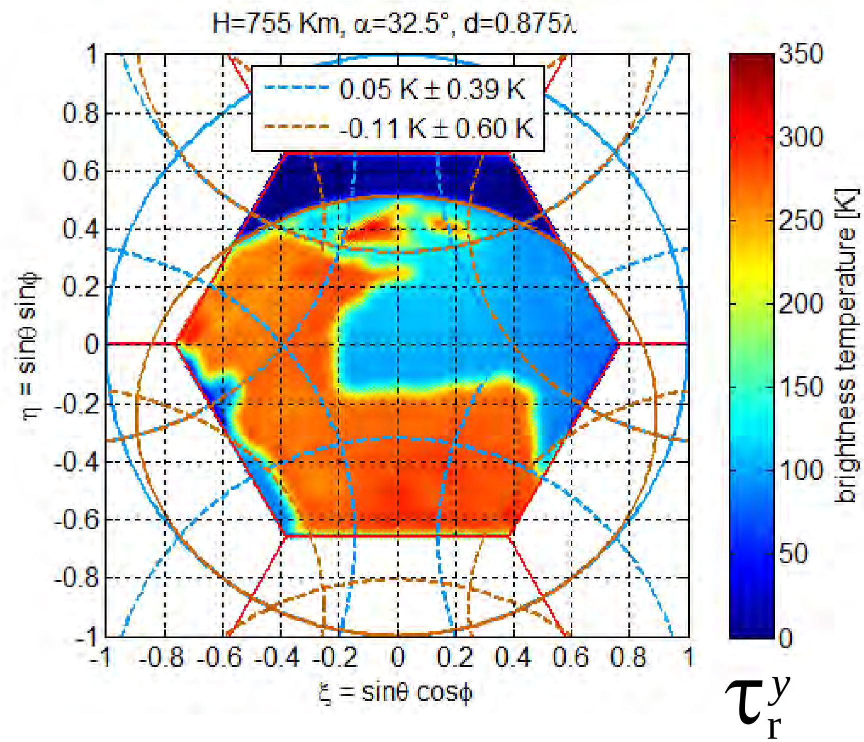




Illustrations & performances

➢ *Differential inversion with $\tilde{T}(t_{sky}, t_{land}, t_{ocean})$*





A co-design approach

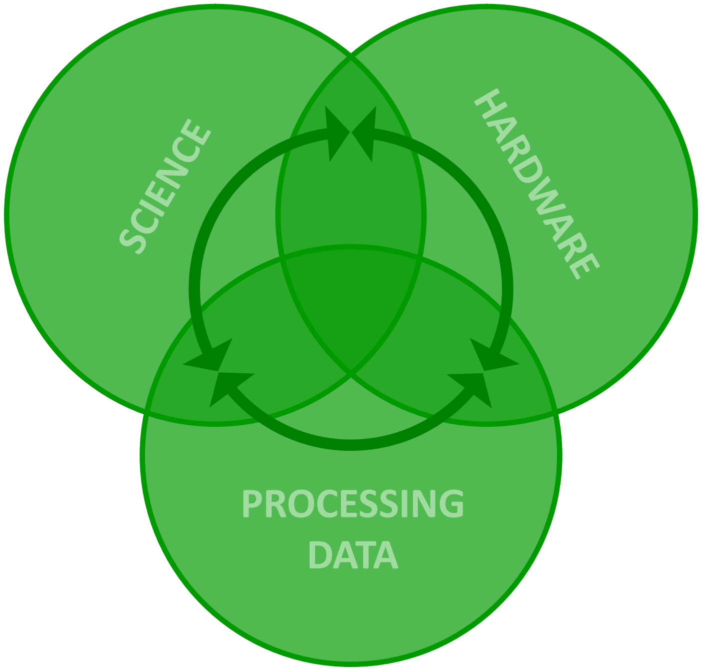
➢ *Participatory design (from Scandinavia)*

Co-design (or co-operative design) is an approach to design attempting to actively involve all stakeholders (e.g. employees, partners, customers, citizens, end-users) in the design process to help ensure the result meets their needs and is usable and marketable. All the participants are invited to cooperate during the several stages of an innovation process.

A co-design approach

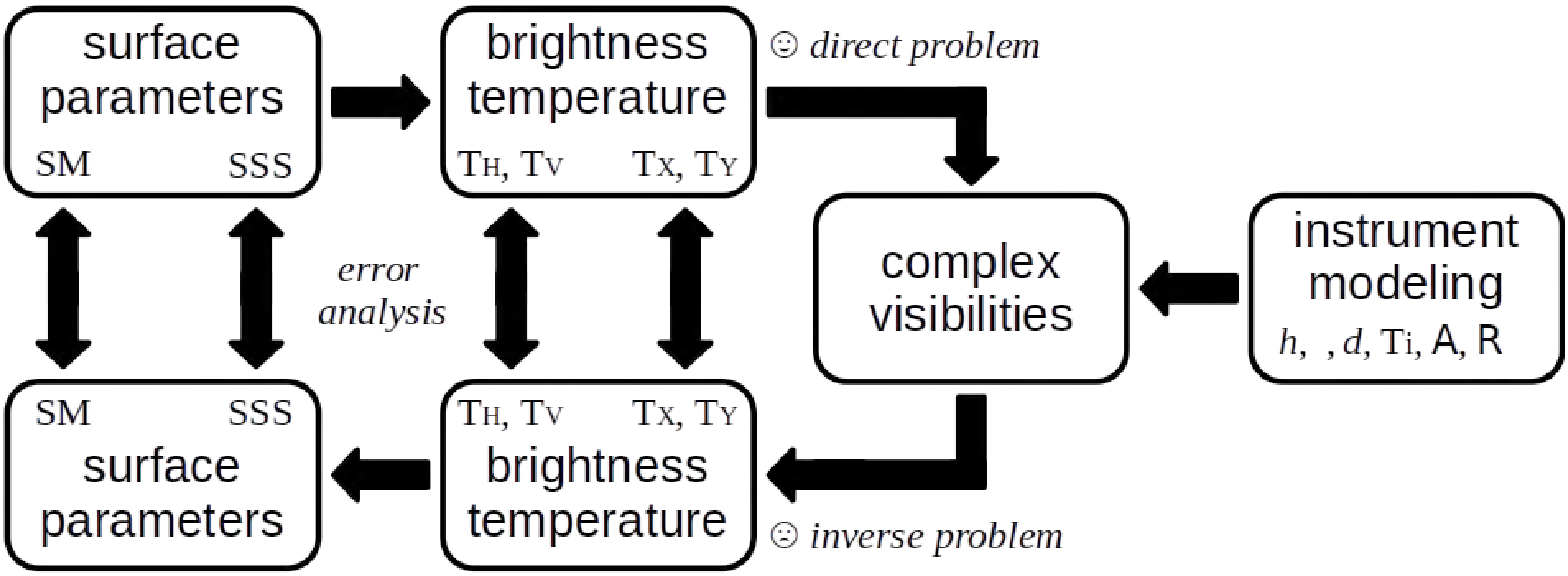
➢ *Participatory design (in scientific instrumentation)*

Time consuming end-to-end simulations involving engineers, scientists and end-users actively collaborating are playing an ongoing role for assessing the sensitivity and the robustness of mission performances to driving parameters, to instrument errors and noises as well as to data processing and analysis.



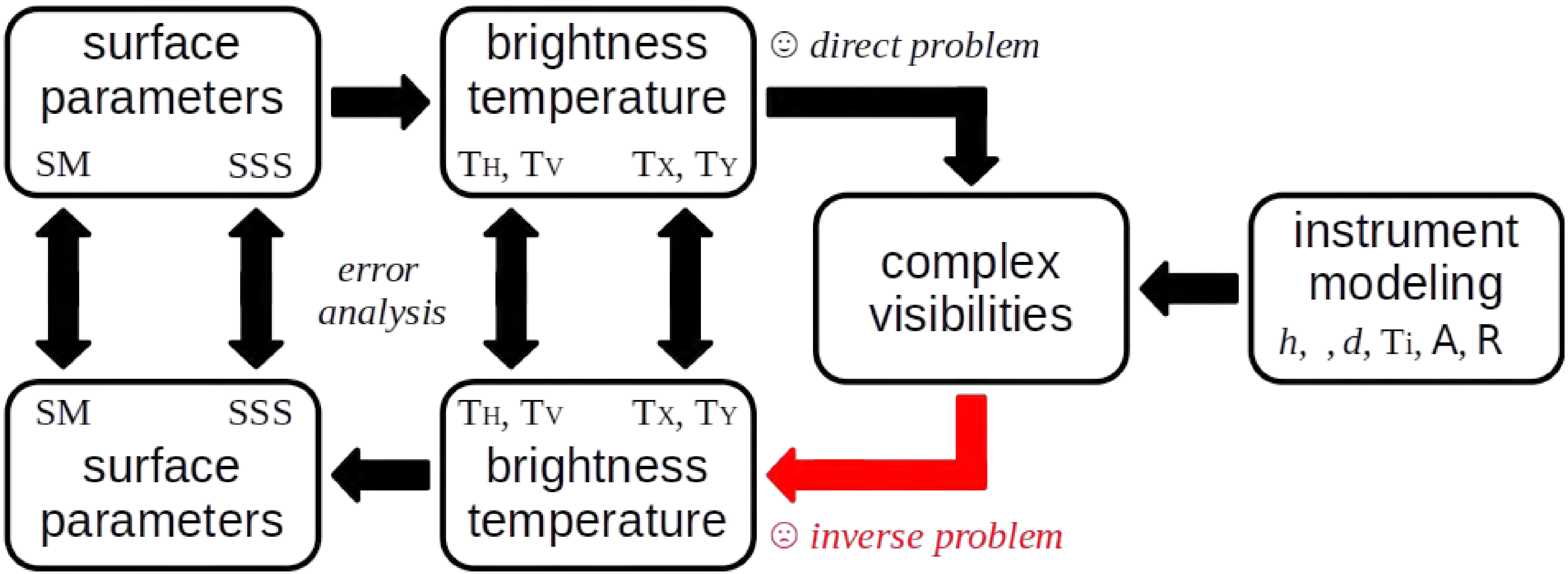
A co-design approach

➢ *An end-to-end simulator for participatory design*



A co-design approach

➢ *An end-to-end simulator for participatory design*



A deep-learning approach

➤ *Building dataset: numerical simulations*

Dual-polarization {T,V} simulated from monthly SMOS L3.

One snapshot {T,V} = 34087 $T_{i\,j}$ (23042 earth + ~~11045 sky~~)

+ 4695 V_{pq} (69×(69-1)+3)

Only 1 snapshot every 12 sec, first 3 days of every 12 months,

Year 2012 {T,V} = 332791 snapshots (166557 ↑ + 166234 ↓)

≈ 70 Gbytes per polarization

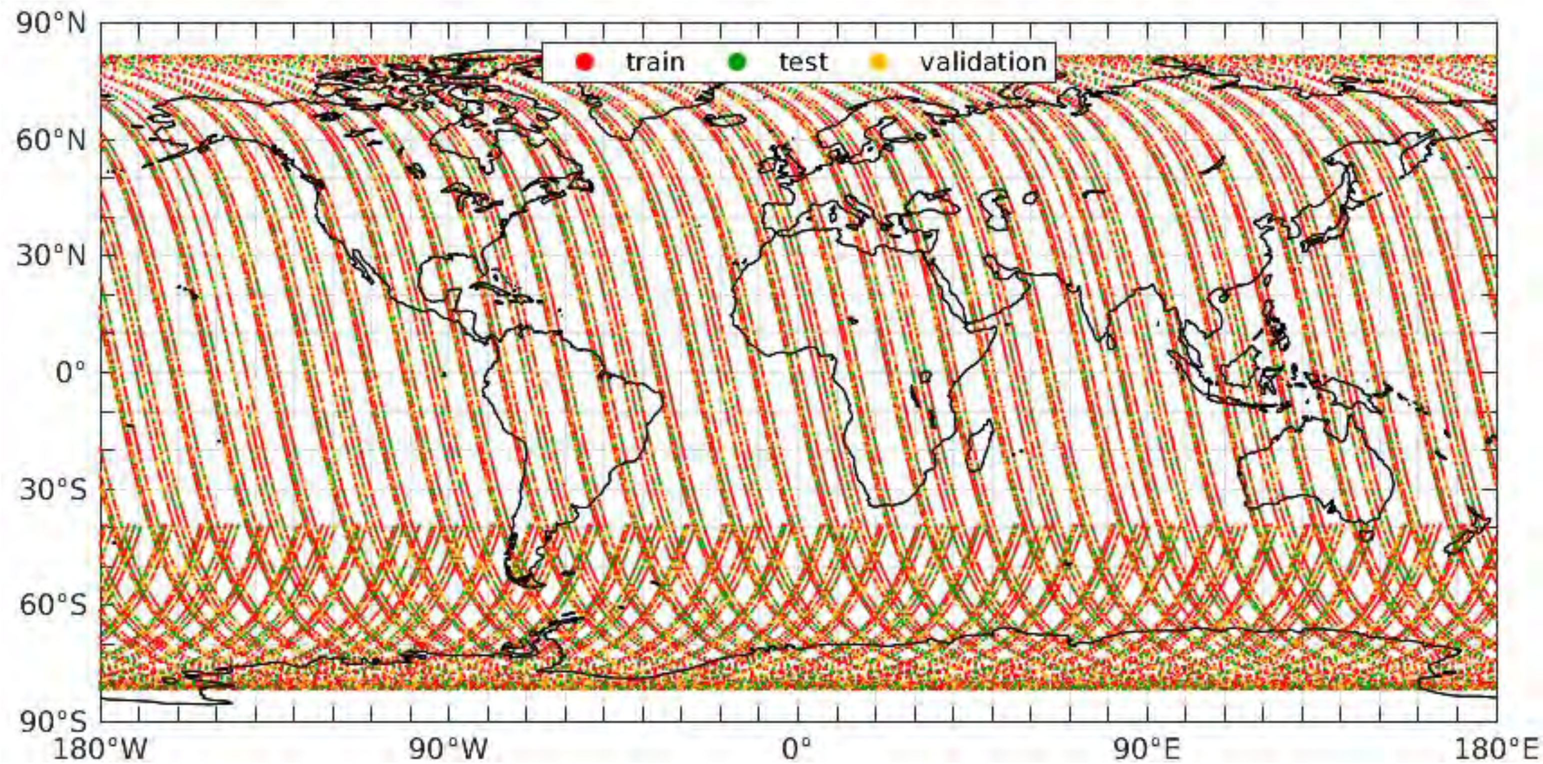
{T,V} dataset ≈ 140 Gbytes

⇒ only ↑ snapshots in X-polarization (≈ 35 Gbytes)

A deep-learning approach

➢ *Splitting dataset*

60% (training) + 20% (validation) + 20% (testing)

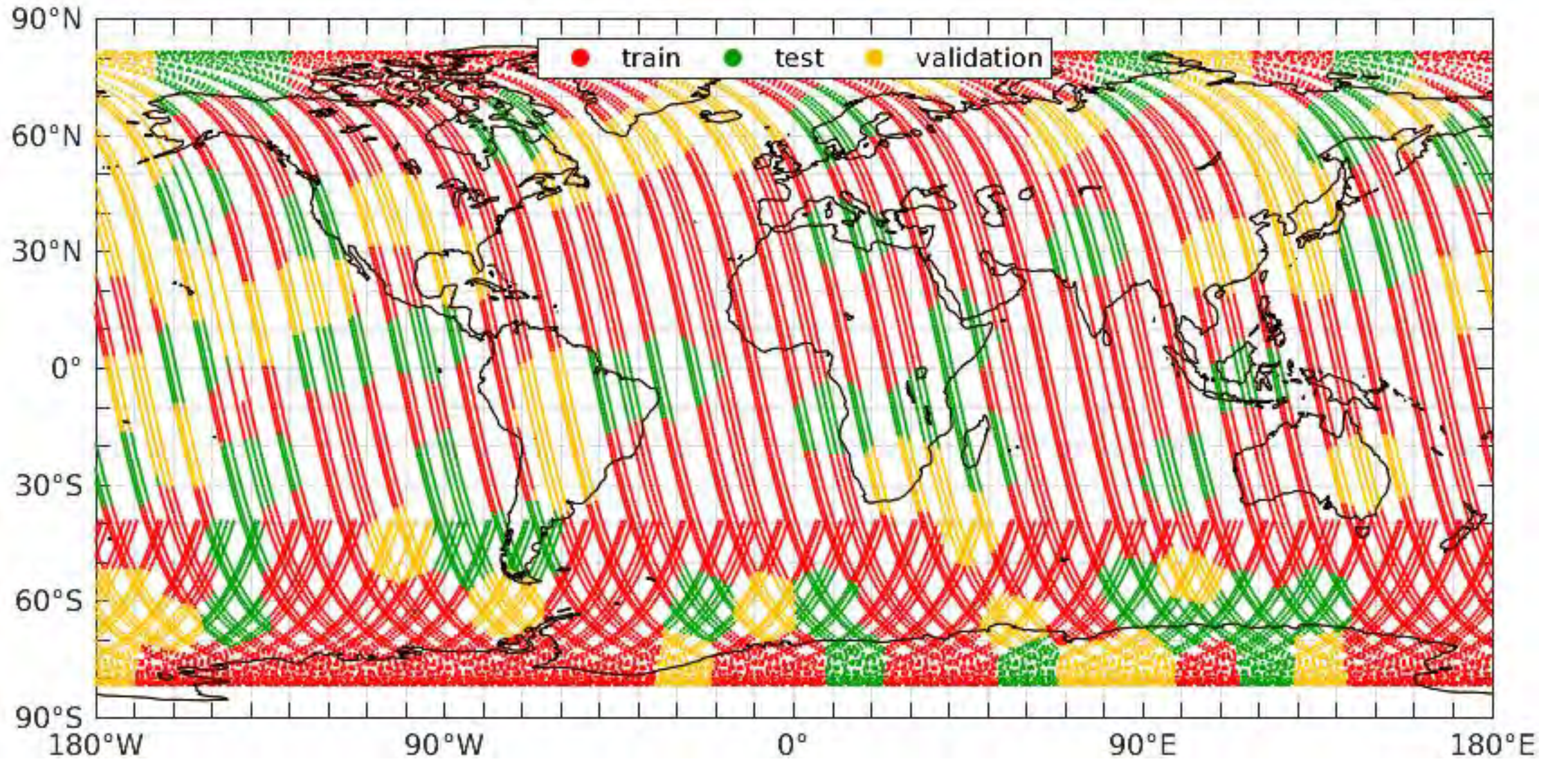


random split (risk of similar {T,V} for train/valid/test)

A deep-learning approach

➢ *Splitting dataset*

60% (training) + 20% (validation) + 20% (testing)



K-means split (over-training risk reduced)

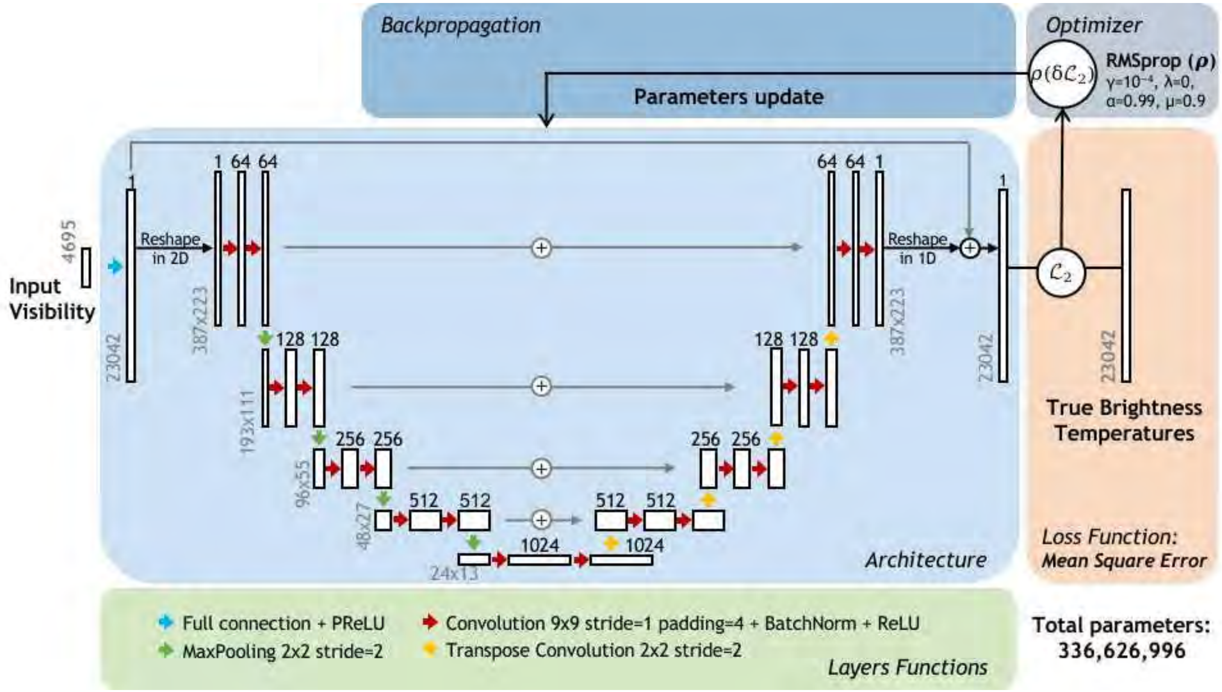
A deep-learning approach

➢ DNN architecture

The result of several trials…

Loss function: MSE.

A total of 336 million parameters.

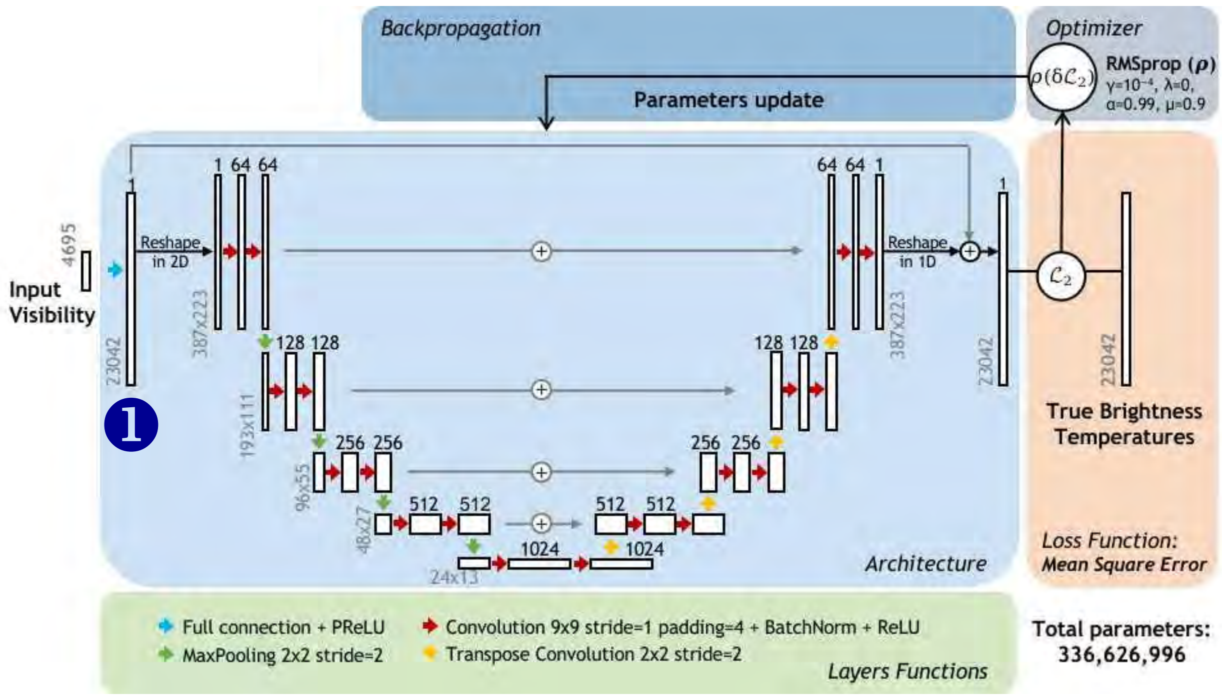


A deep-learning approach

➢ DNN architecture

❶ fully connected layer: raw inversion of visibilities

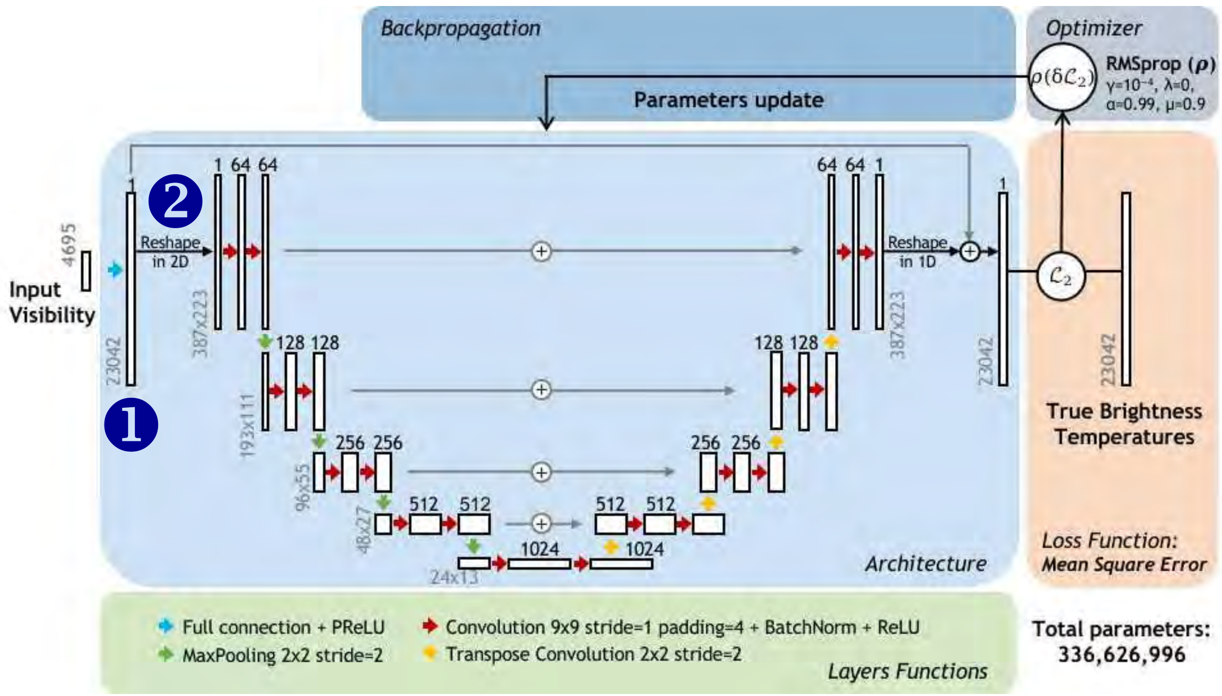
$$4695\ V_{pq} \rightarrow 23042\ T_{i\,j}$$



A deep-learning approach

➢ DNN architecture

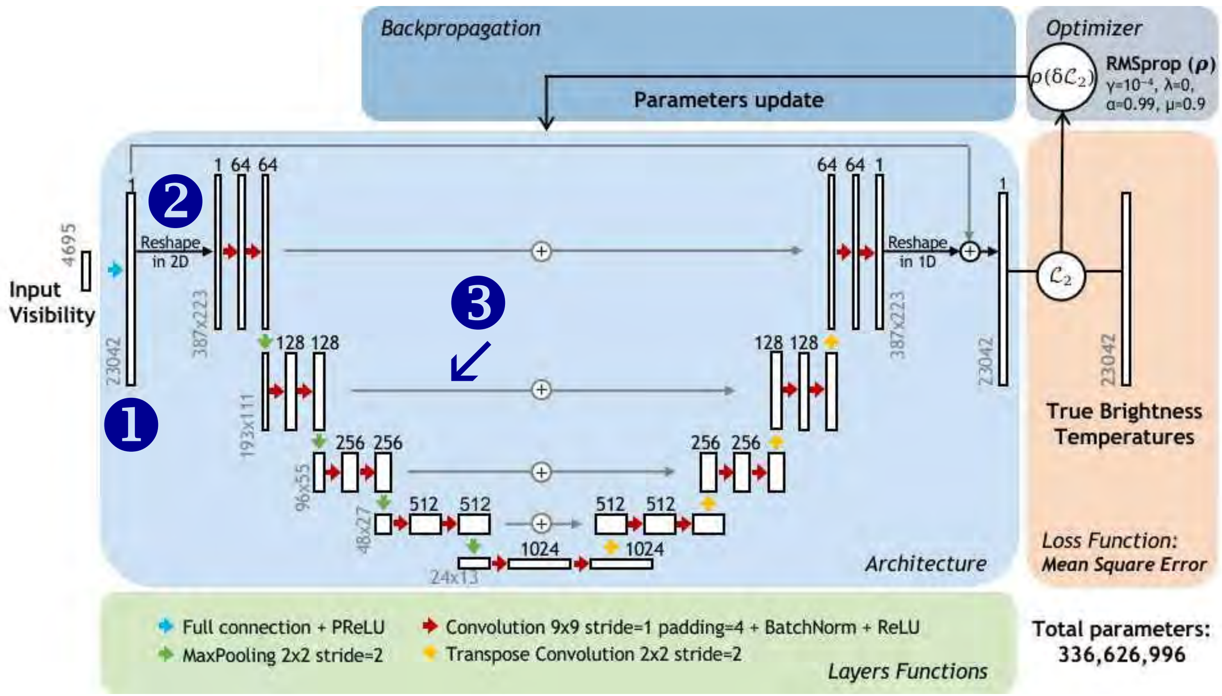
❶ fully connected layer: raw inversion of visibilities
❷ reshaped into a 2D sparse regular grid 387x223



A deep-learning approach

➢ *DNN architecture*

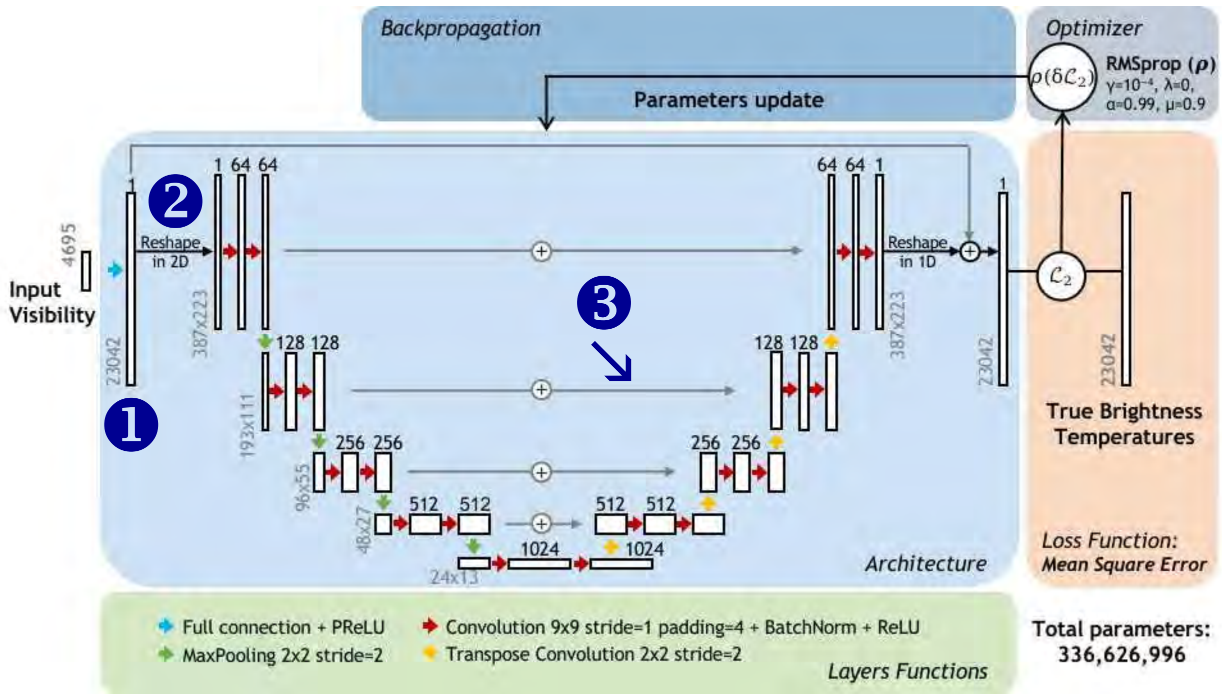
❶ fully connected layer: raw inversion of visibilities
❷ reshaped into a 2D sparse regular grid 387x223
❸ contracting path: sampling ÷2, feature maps ×2



A deep-learning approach

➢ *DNN architecture*

❶ fully connected layer: raw inversion of visibilities
❷ reshaped into a 2D sparse regular grid 387x223
❸ expansive path: sampling ×2, feature maps ÷2



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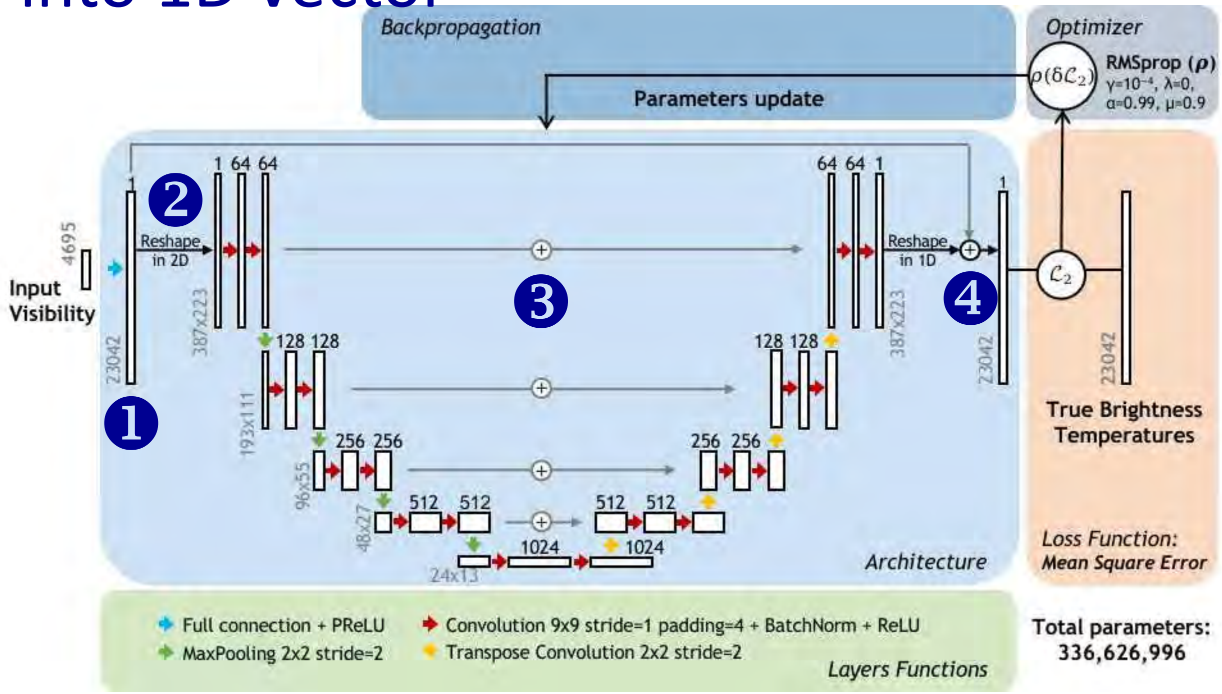
A deep-learning approach

➢ DNN architecture

❶ fully connected layer: raw inversion of visibilities
❷ reshaped into a 2D sparse regular grid
❸ contracting/expansive path
❹ reshape into 1D vector



A deep-learning approach

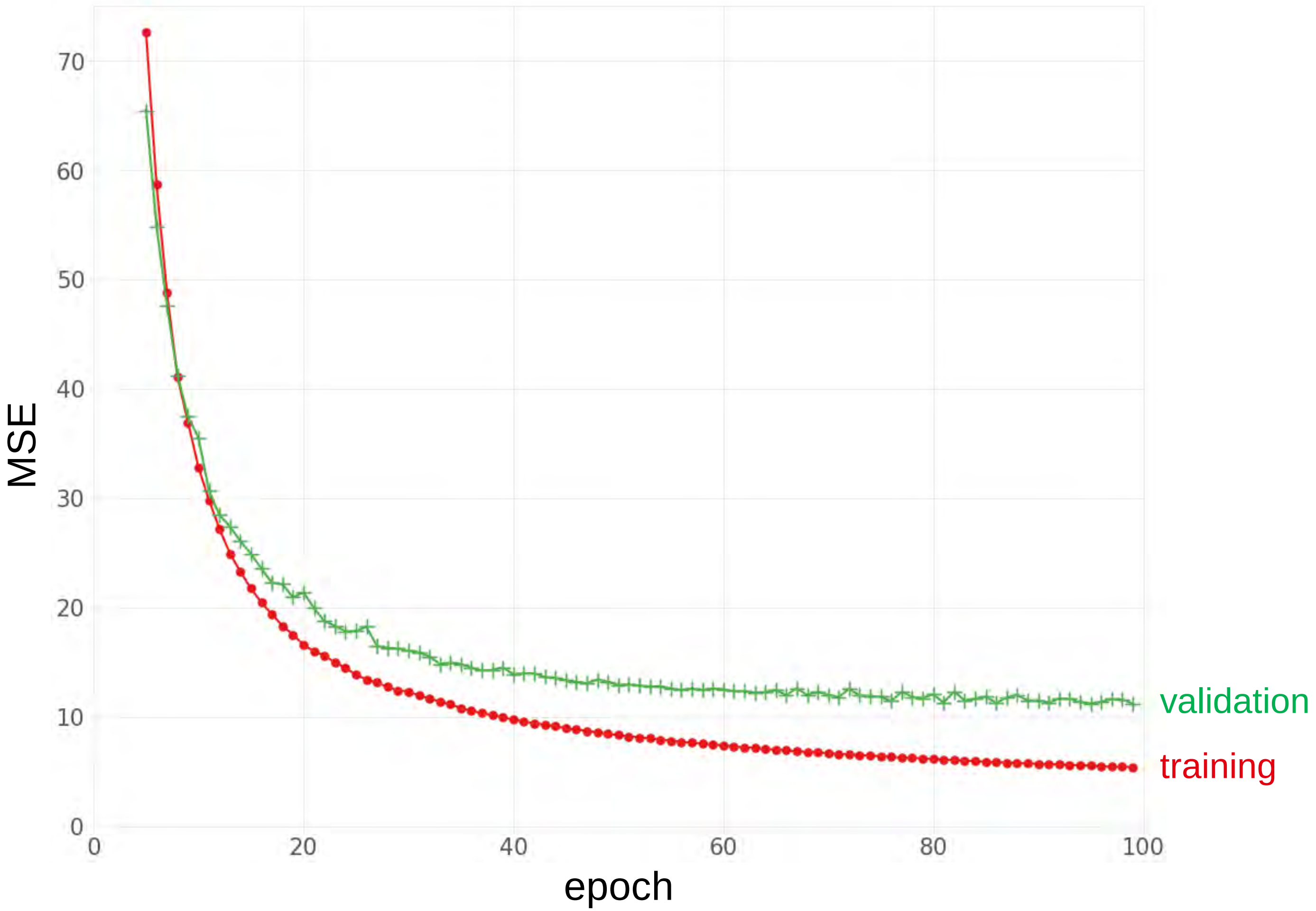
➢ *Training+Validating*

Model trained over 100 epochs
with mini-batch sizes set to 32
implemented in Python using PyTorch V1.8.

Training 99774 {T,V} + Validating 33257 {T,V} = 182 h
on two TESLA V100 SXM2 32 Gbytes GPUs.

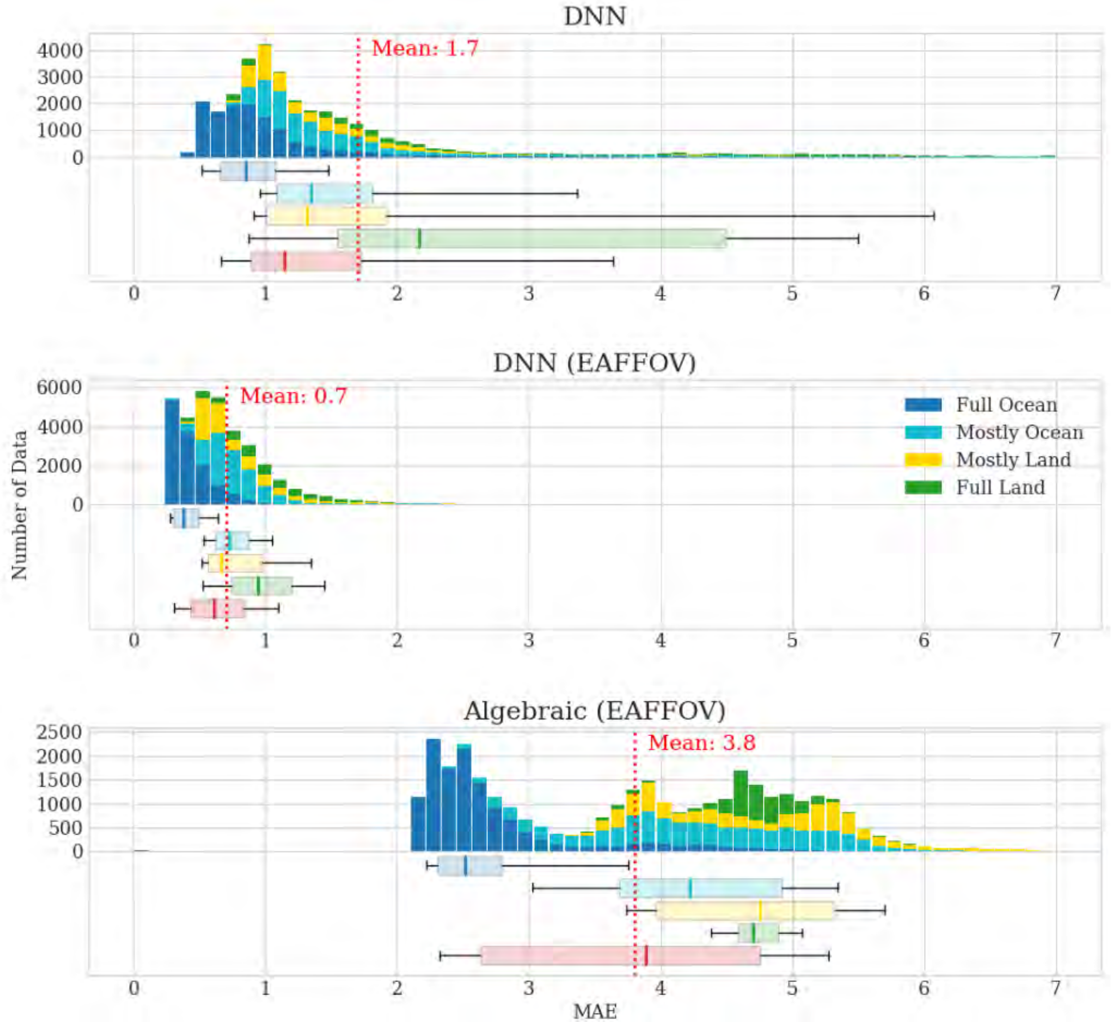
A deep-learning approach

➢ *Training+Validating: convergence*



A deep-learning approach

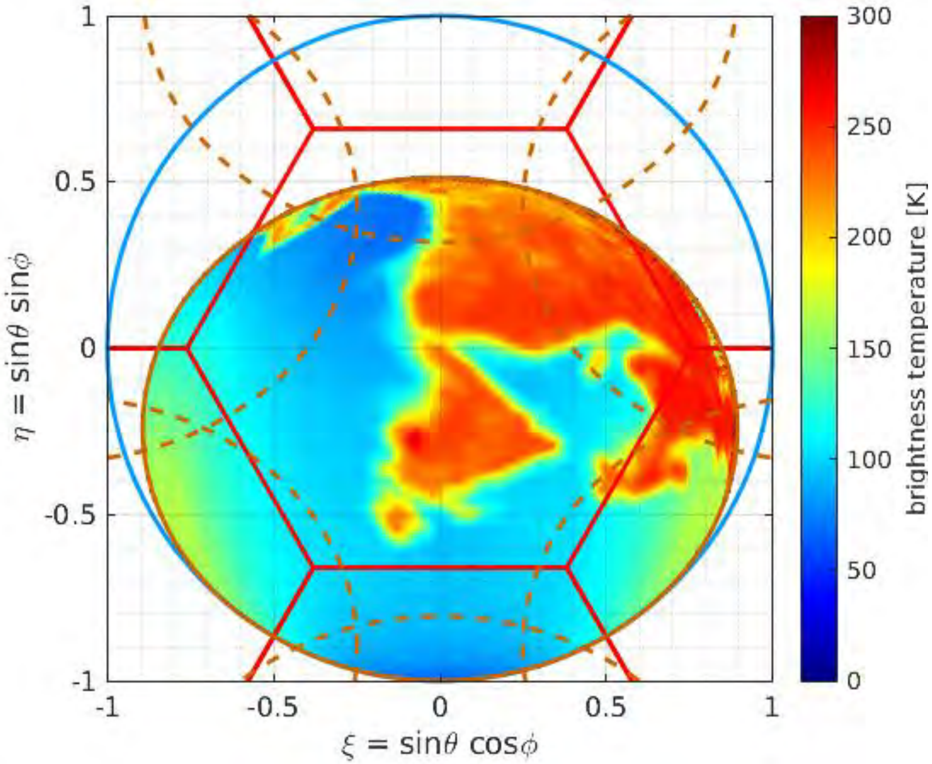
➢ *Testing: reconstructions performances (K-means split)*



A deep-learning approach

➢ *Testing: representative example*

ground truth



average errors
(entire testing subset)

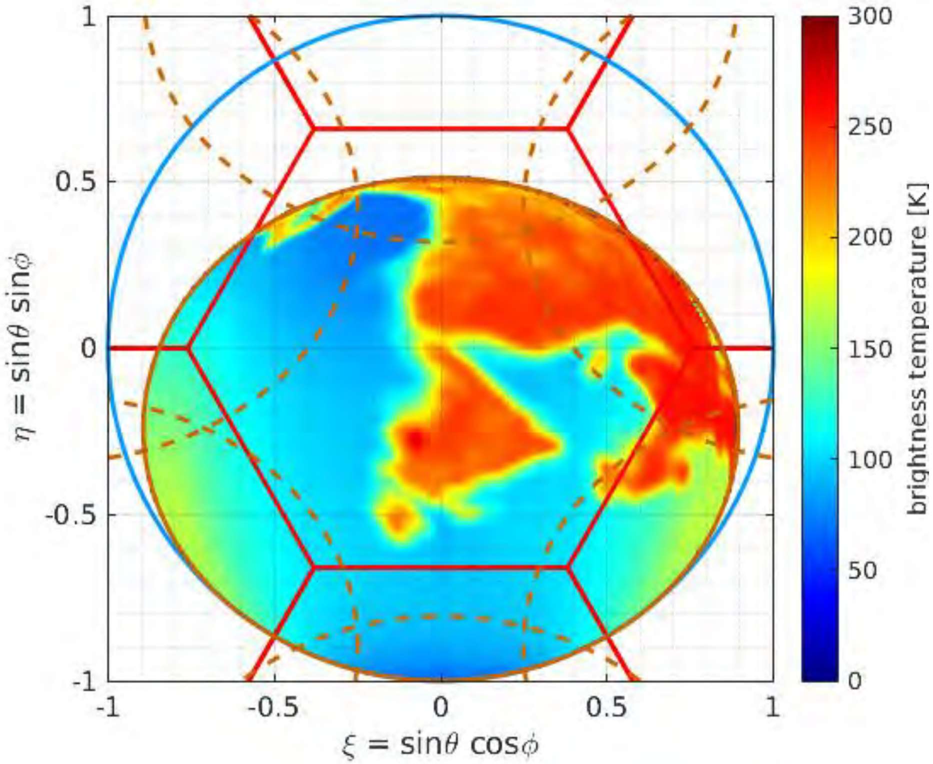
	MAE	RMSE
DNN (fullFOV)	1.53 K	2.90 K
DNN (EAFFOV)	0.70 K	0.98 K
ALG (EAFFOV)	3.75 K	7.78 K

This example representative of DNN average MAE over fullFOV

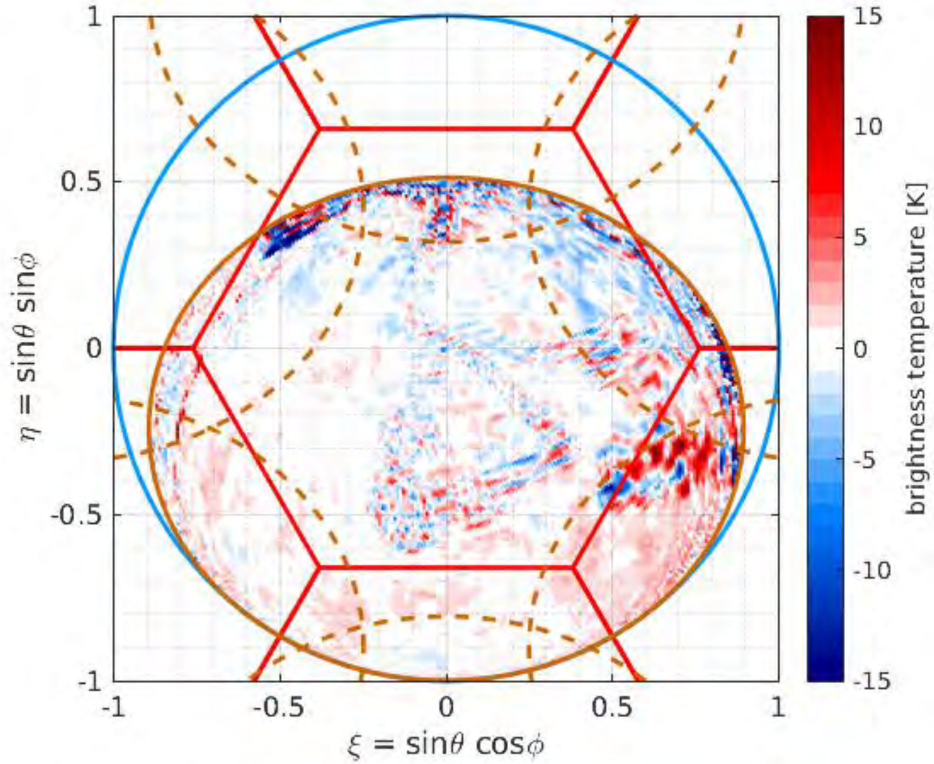
A deep-learning approach

➢ *Testing: representative example*

DNN reconstruction



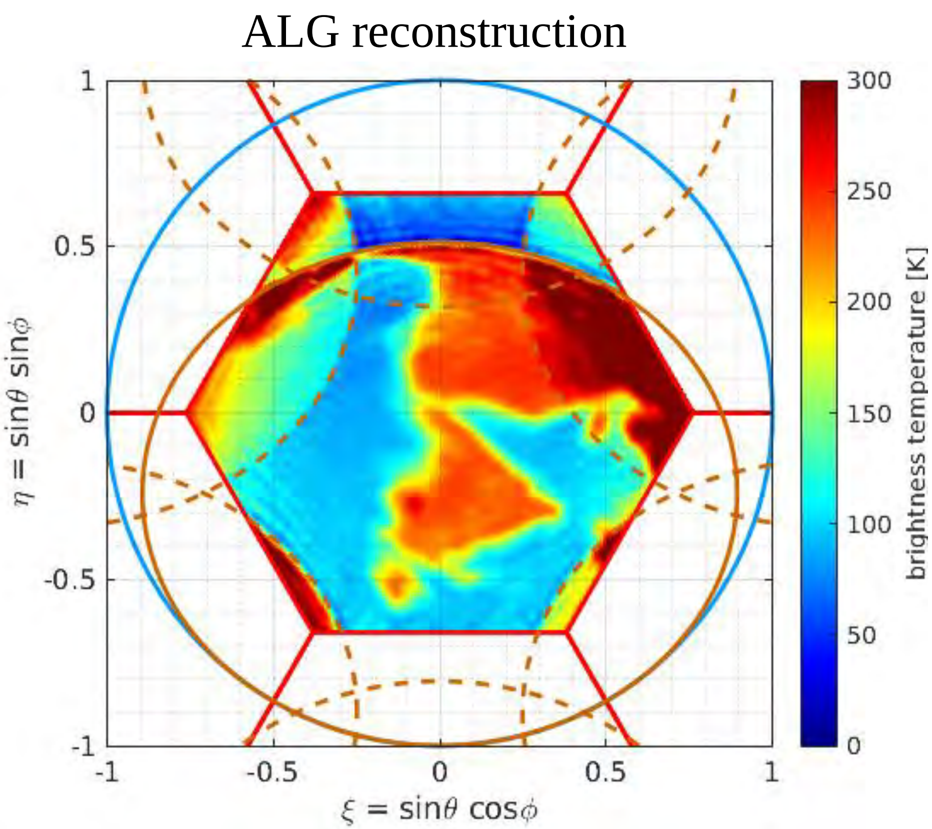
MAE = 1.5 K (fullFOV)
MAE = 1.0 K (EAFFOV only)

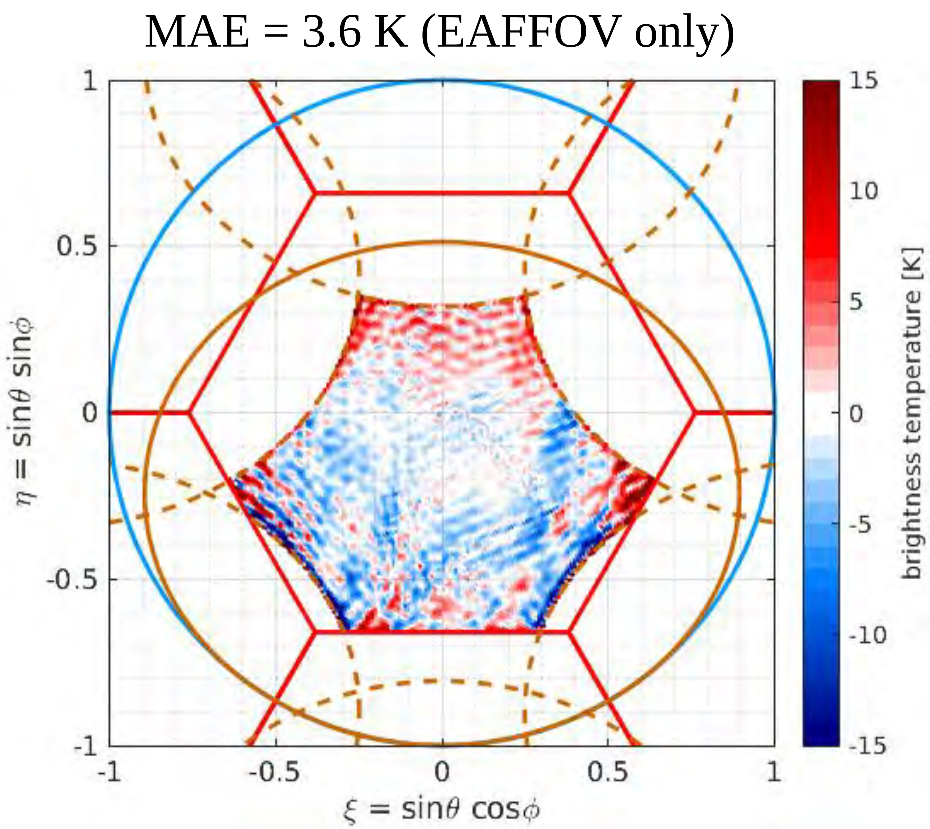


This example representative of DNN average MAE over fullFOV

A deep-learning approach

➢ *Testing: representative example*

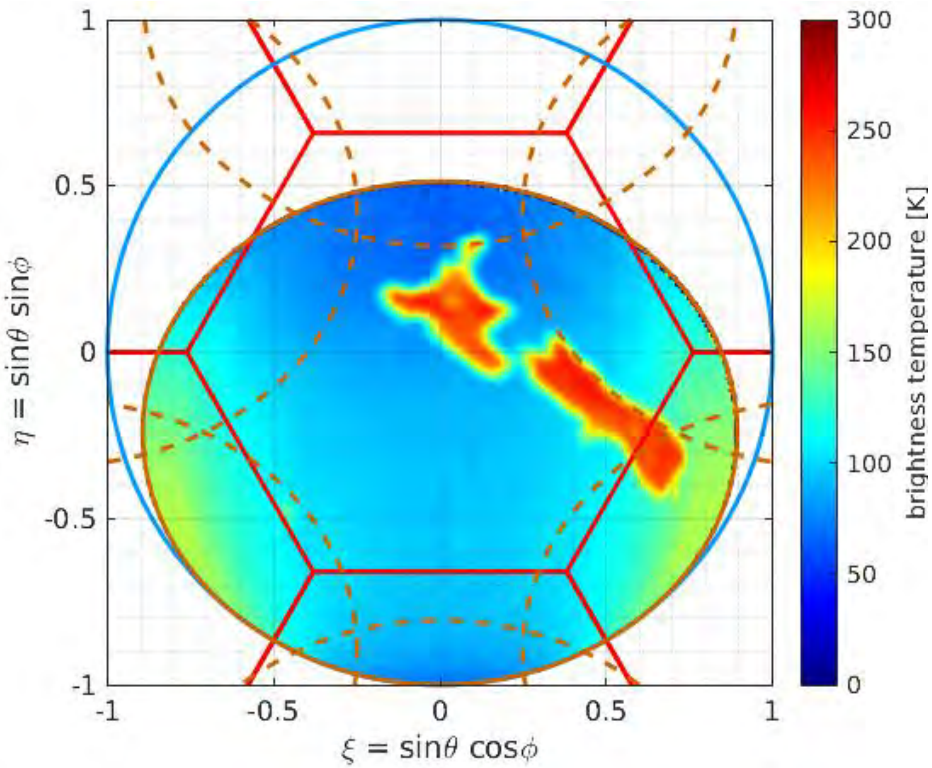




A deep-learning approach

➢ Testing: representative example

ground truth



average errors
(entire testing subset)

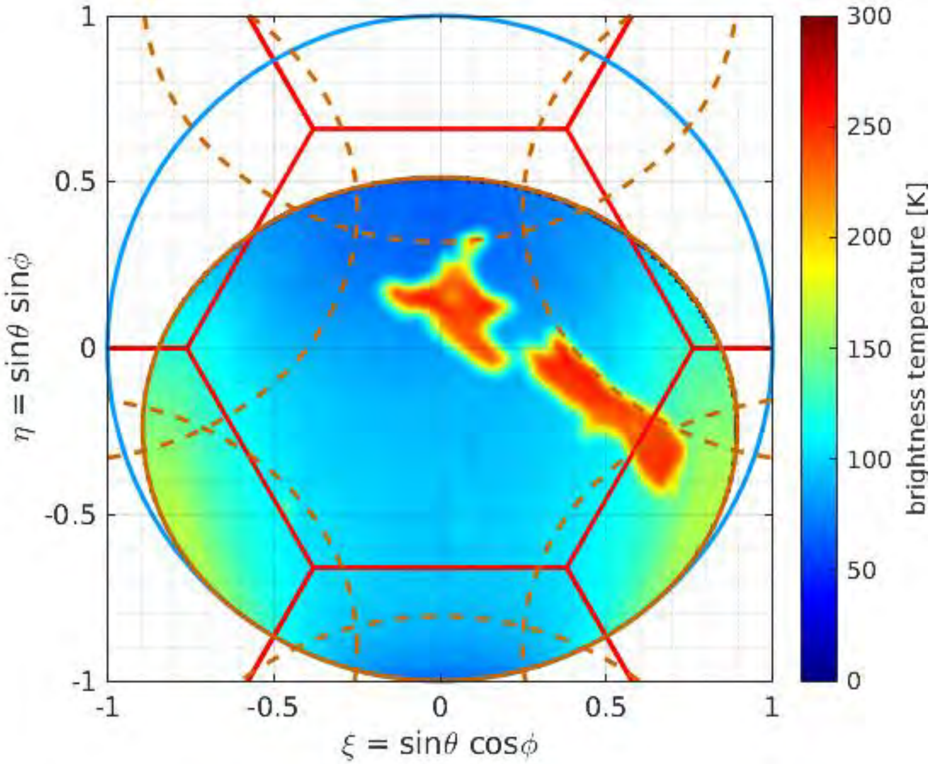
	MAE	RMSE
DNN (fullFOV)	1.53 K	2.90 K
DNN (EAFFOV)	0.70 K	0.98 K
ALG (EAFFOV)	3.75 K	7.78 K

This example representative of DNN average MAE over EAFFOV

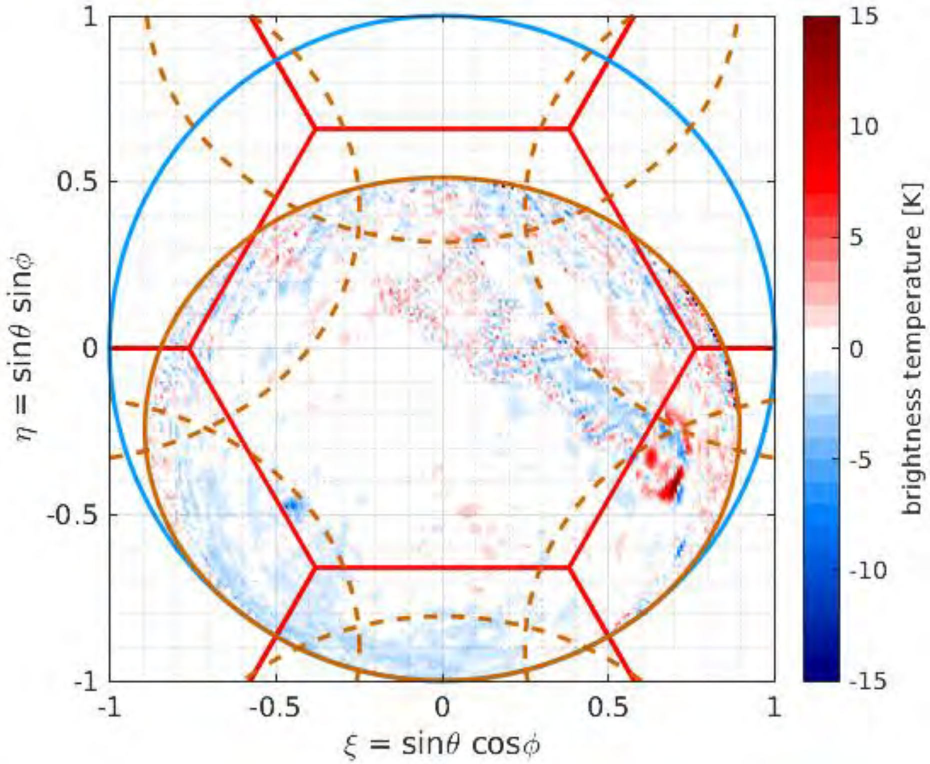
A deep-learning approach

➢ *Testing: representative example*

DNN reconstruction



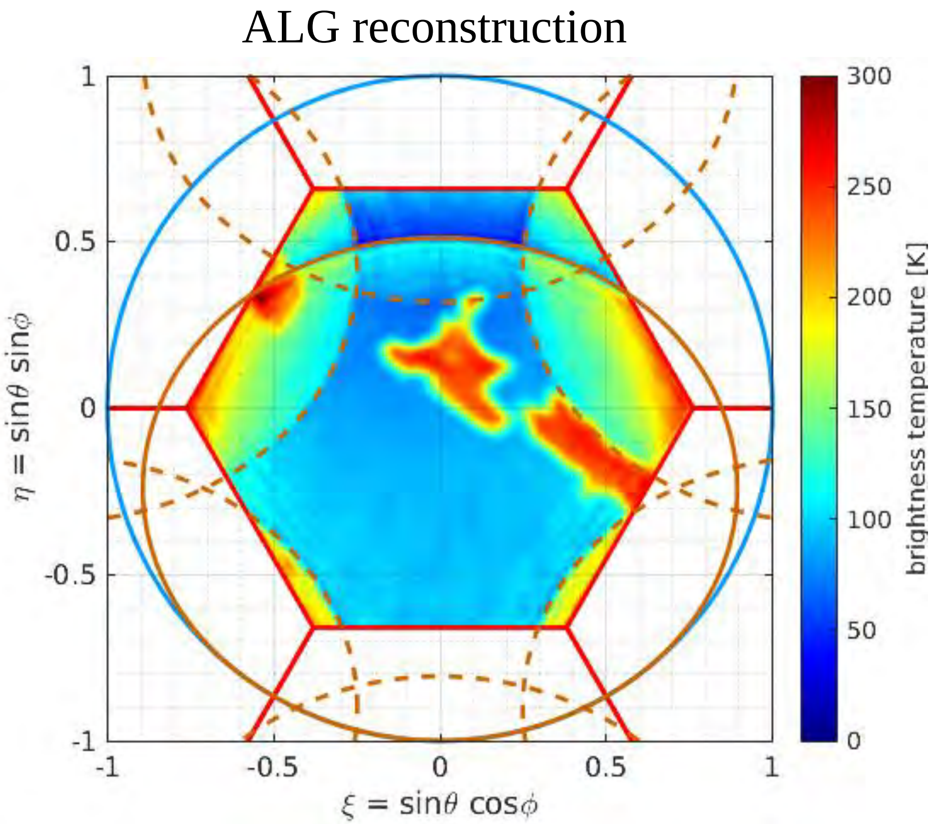
MAE = 0.9 K (fullFOV)
MAE = 0.7 K (EAFFOV only)

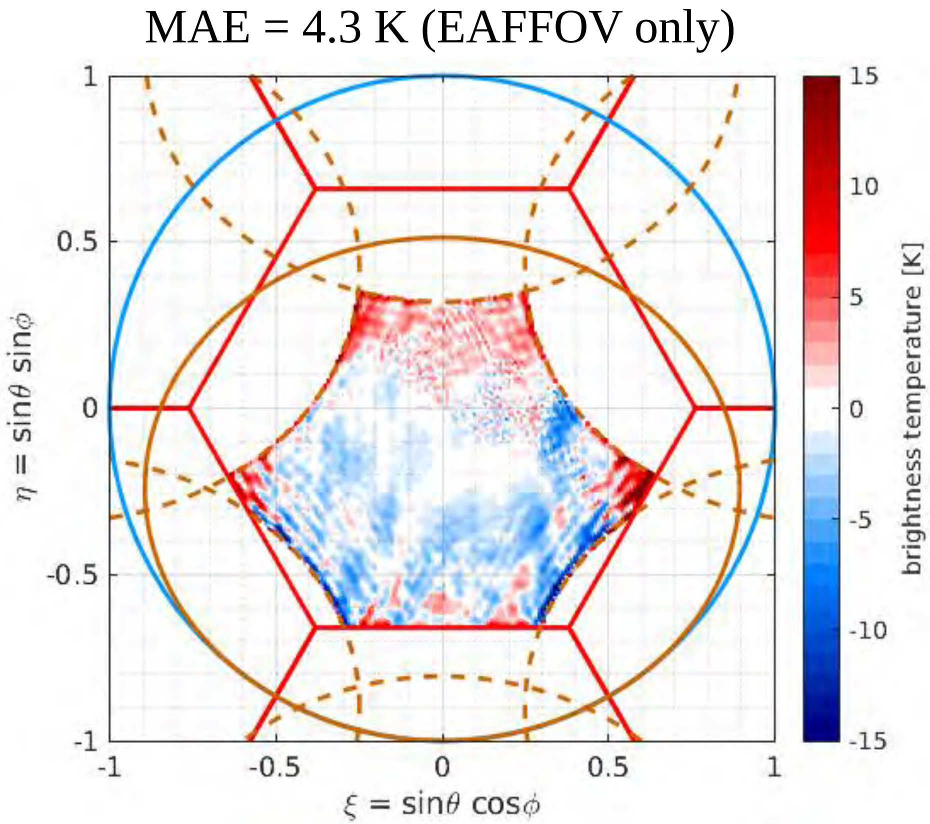


This example representative of DNN average MAE over EAFFOV

A deep-learning approach

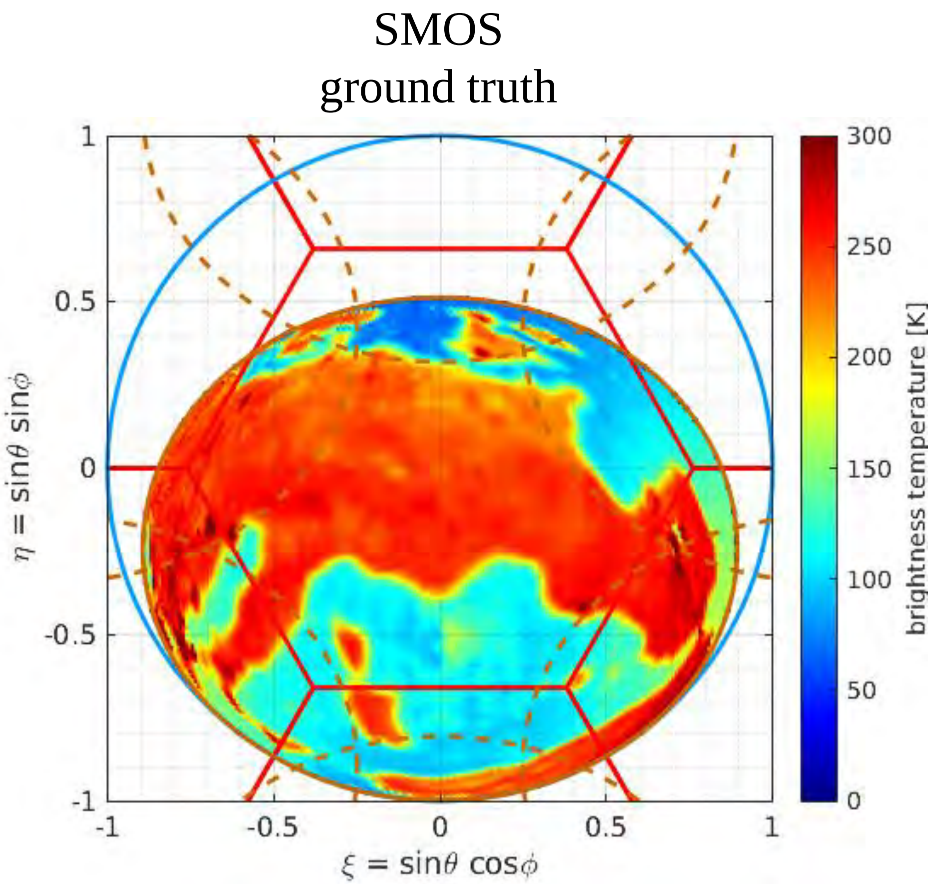
➢ *Testing: representative example*

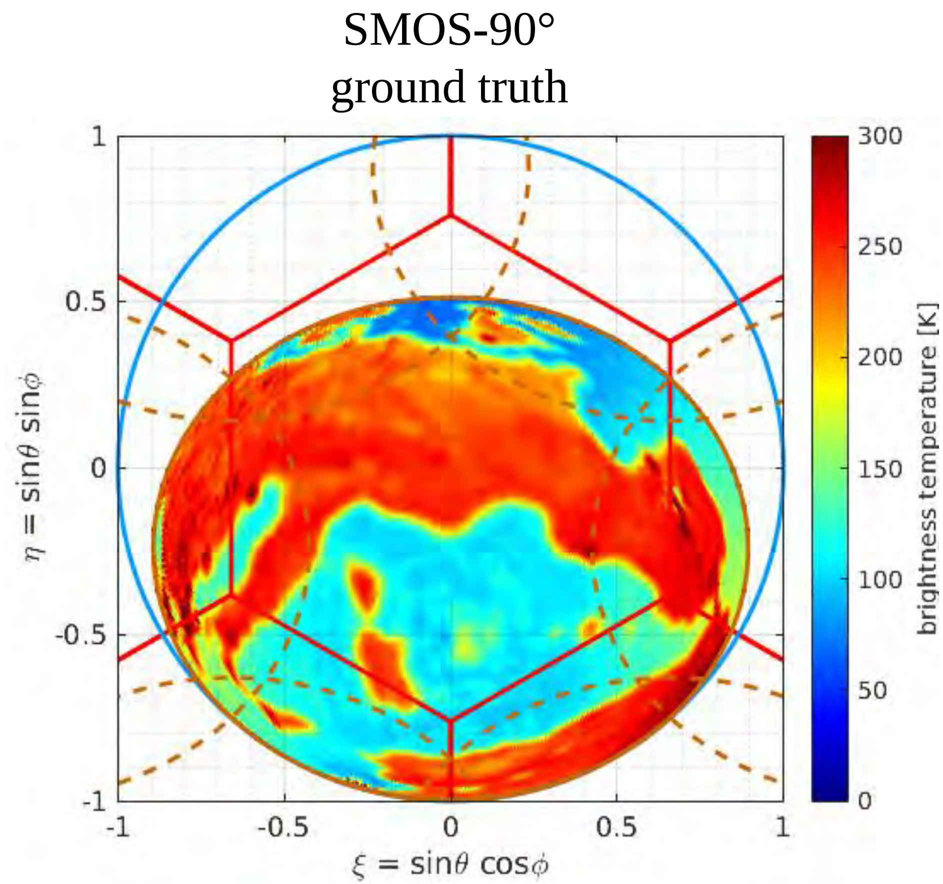




A deep-learning approach

➢ *Aliases investigations*

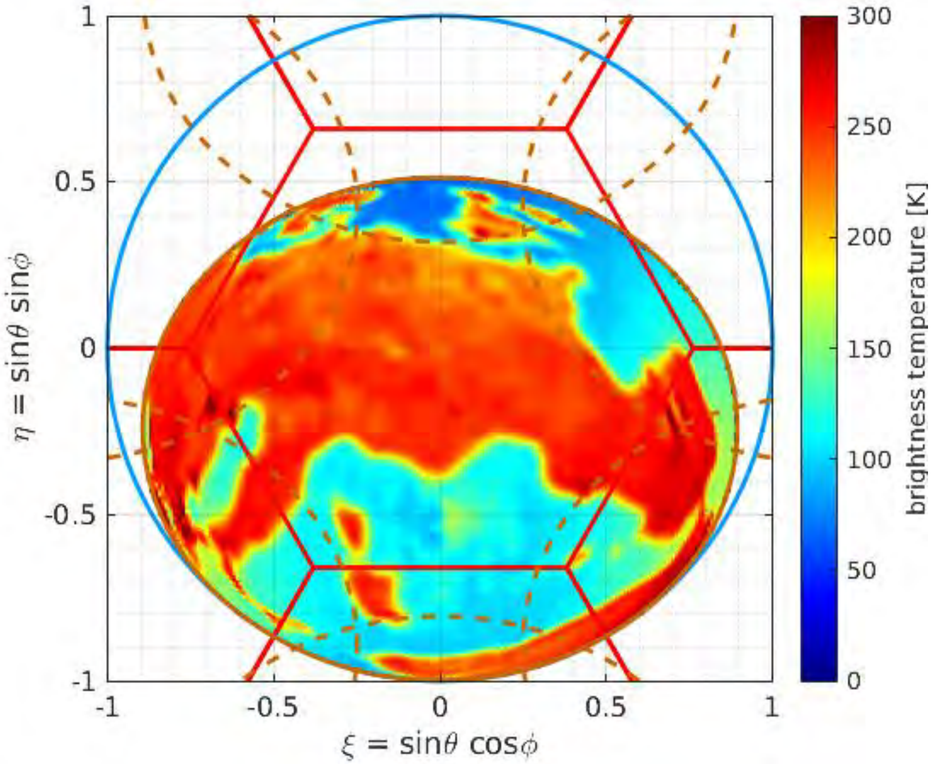




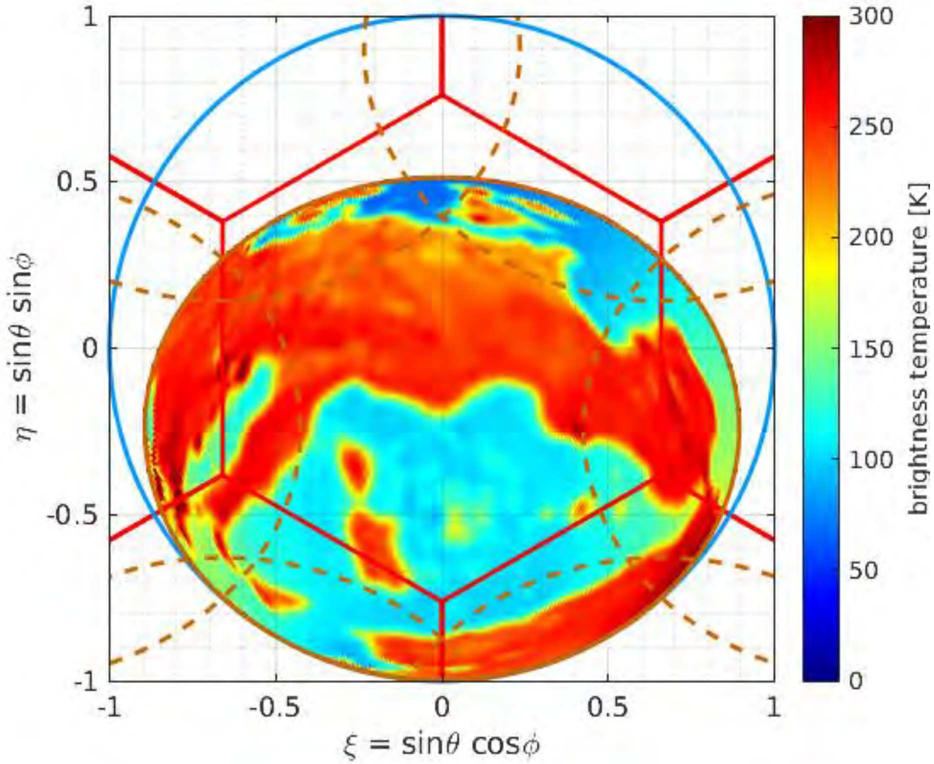
A deep-learning approach

➢ *Aliases investigations*

SMOS
DNN reconstruction



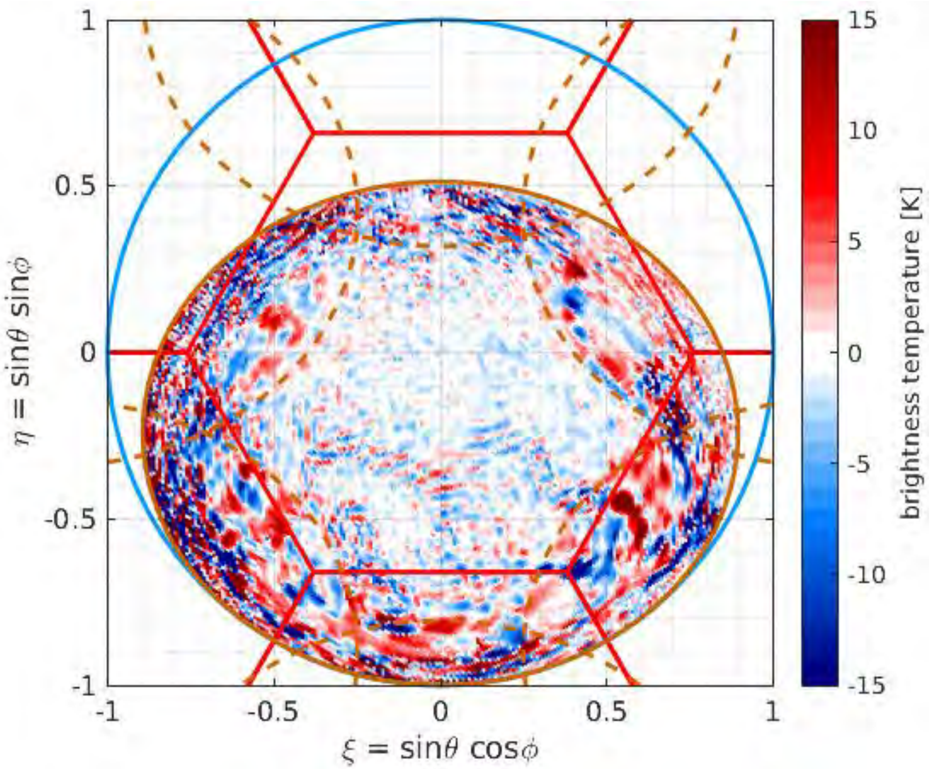
SMOS-90°
DNN reconstruction



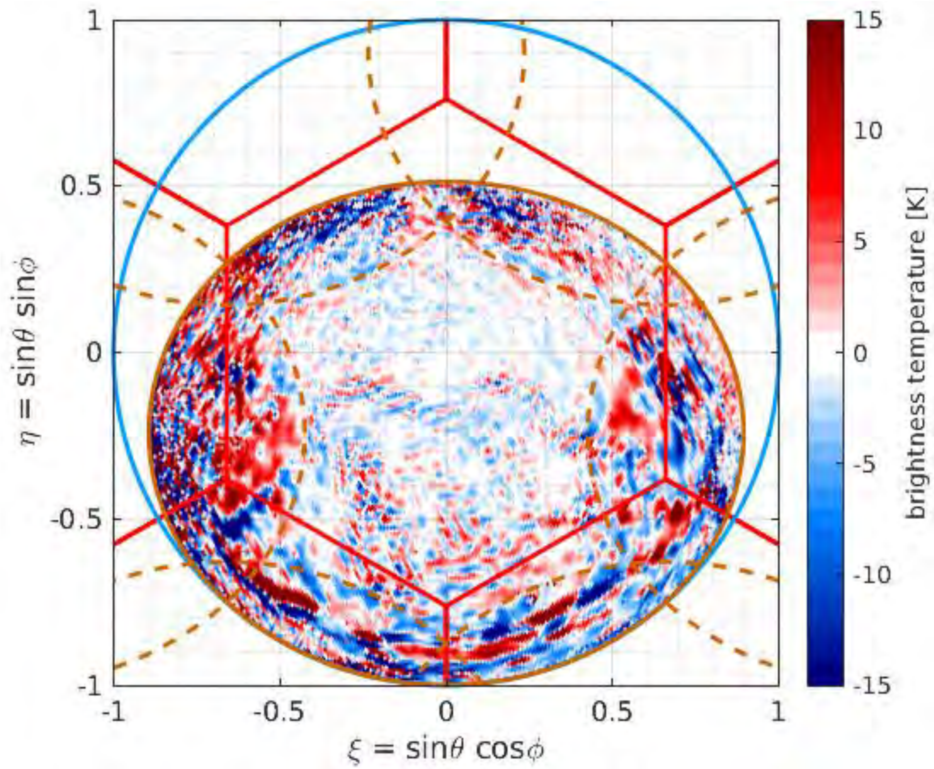
A deep-learning approach

➢ *Aliases investigations*

SMOS
DNN reconstruction

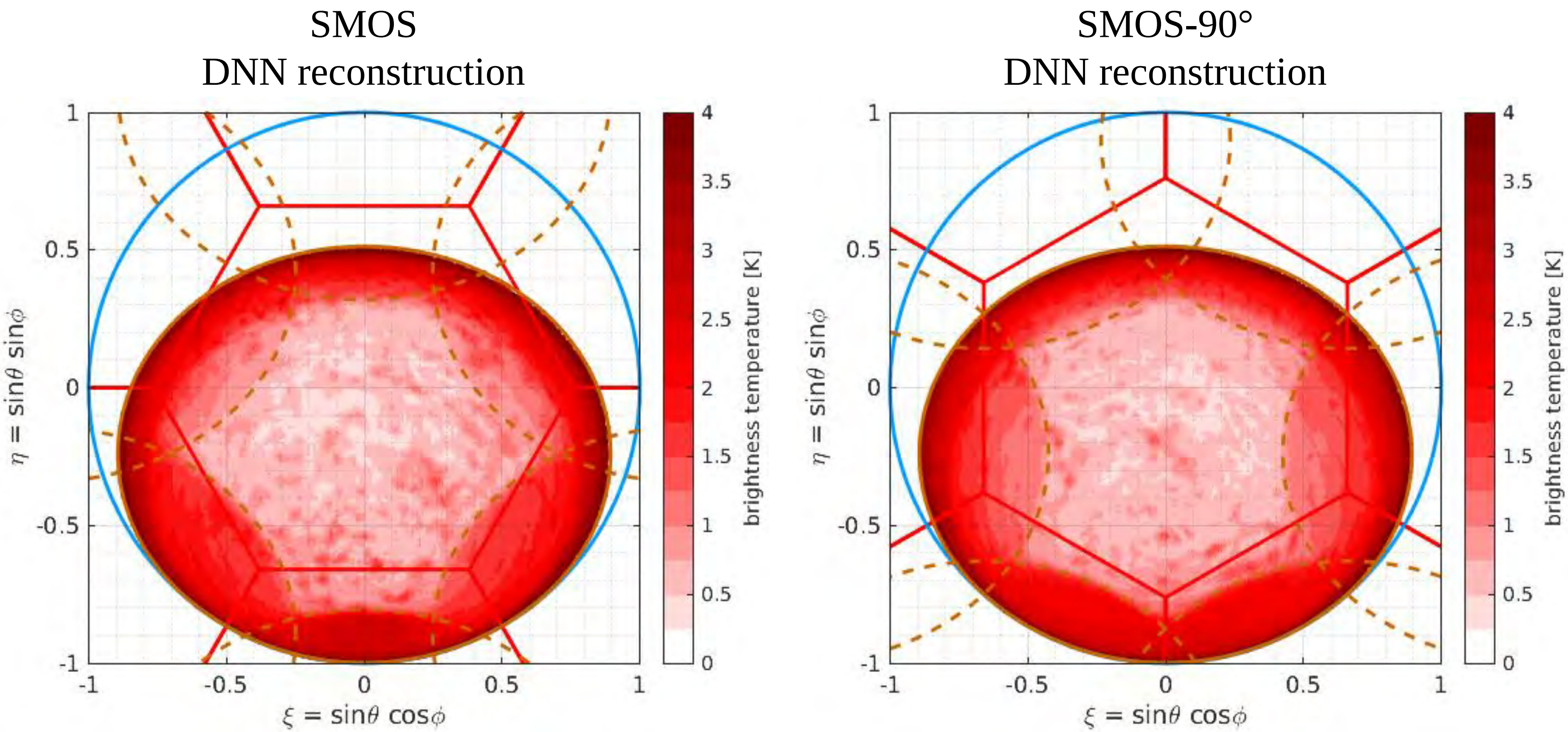


SMOS-90°
DNN reconstruction



A deep-learning approach

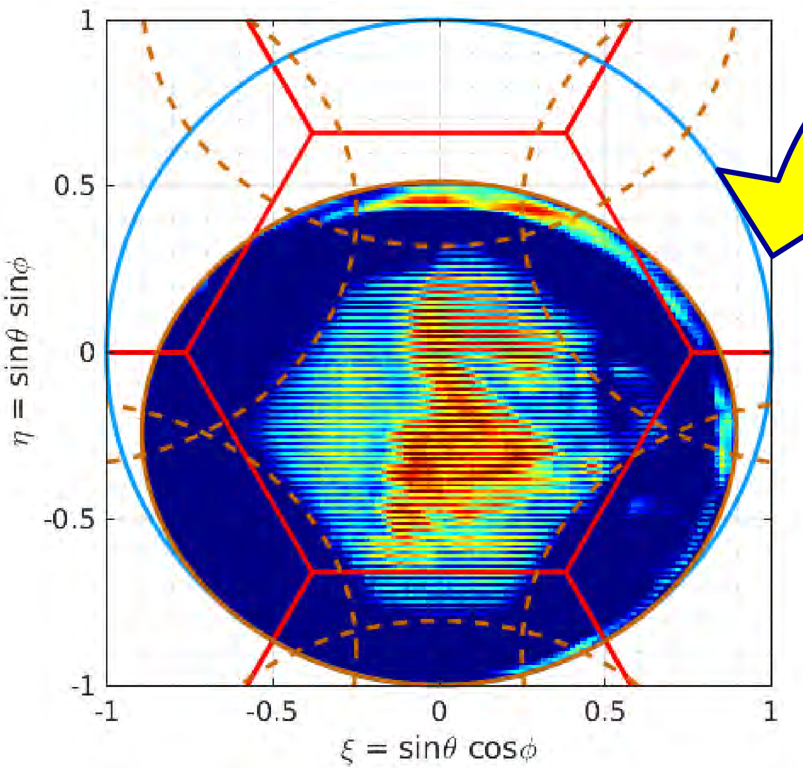
➢ *Aliases investigations*

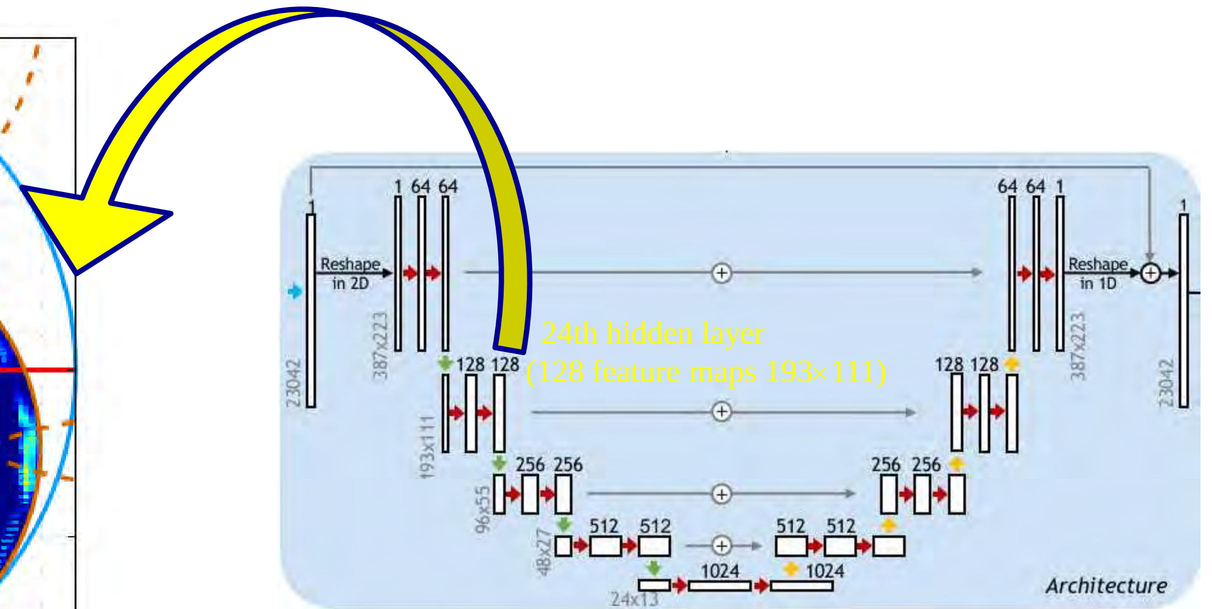


A deep-learning approach

➤ *Hidden layers investigations*

neurones activate
inside EAFFOV





RESEARCH PROGRAM

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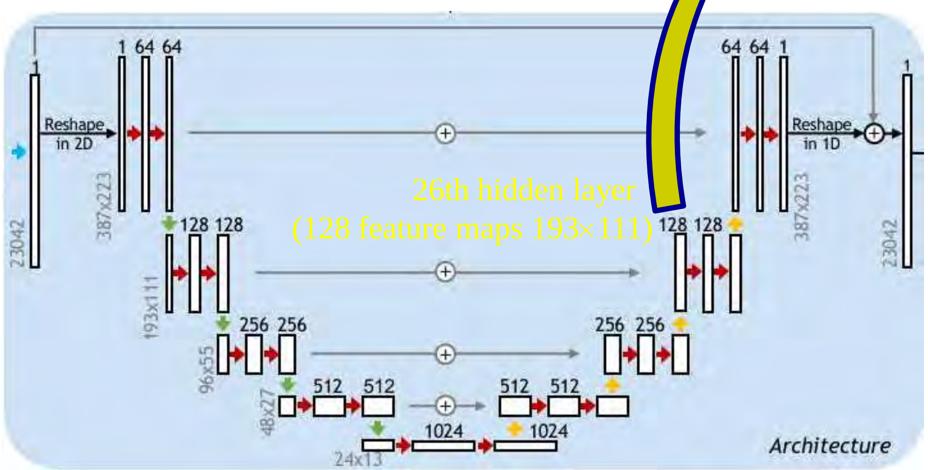
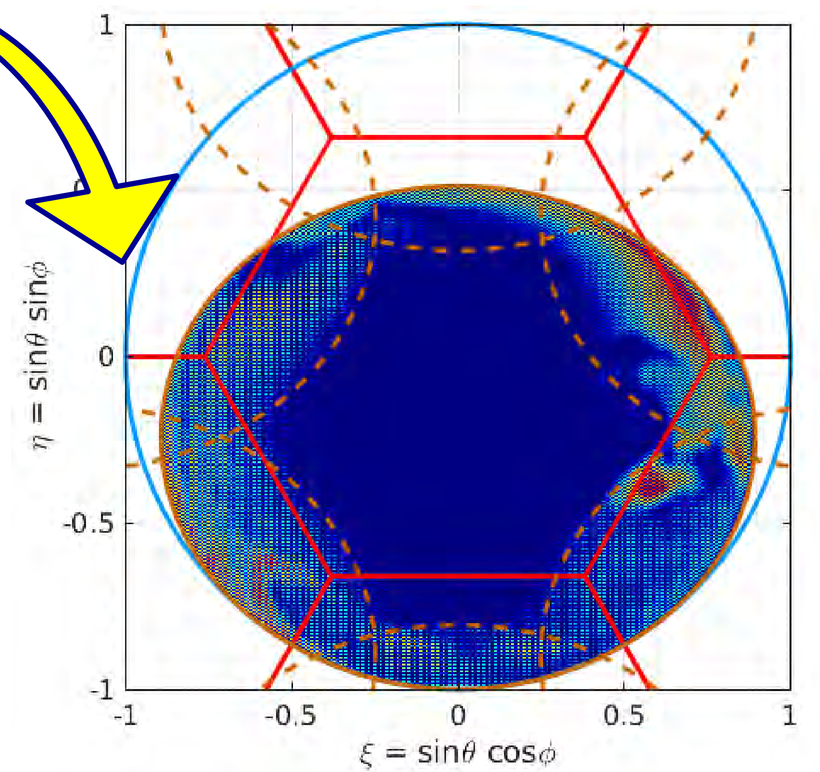
A deep-learning approach

➢ *Hidden layers investigations*



neurones activate outside EAFFOV



Conclusion

➢ *The inversion of interferometric data in imaging radiometry has been realized with a Deep Learning approach.*

➢ *This first experiment has been realized at simulation level: next step is to process SMOS data (on going).*

☺ *The main lesson learnt from this first experiment is amazing and very promising for the design of future aperture synthesis radiometers (reduced field aliasing!)*

☹ *A long road from idea to (operational) implementation!*

☹ *The key role played by training dataset!*

☹ *The time/memory necessary for training dataset…*