EXPLOITING ARTIFICIAL INTELLIGENCE FOR PERFORMANCE-OPTIMIZED RAW DATA QUANTIZATION IN INSAR SYSTEMS

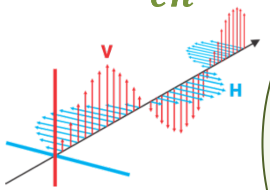
Michele Martone, Nicola Gollin, Paola Rizzoli, Gerhard Krieger

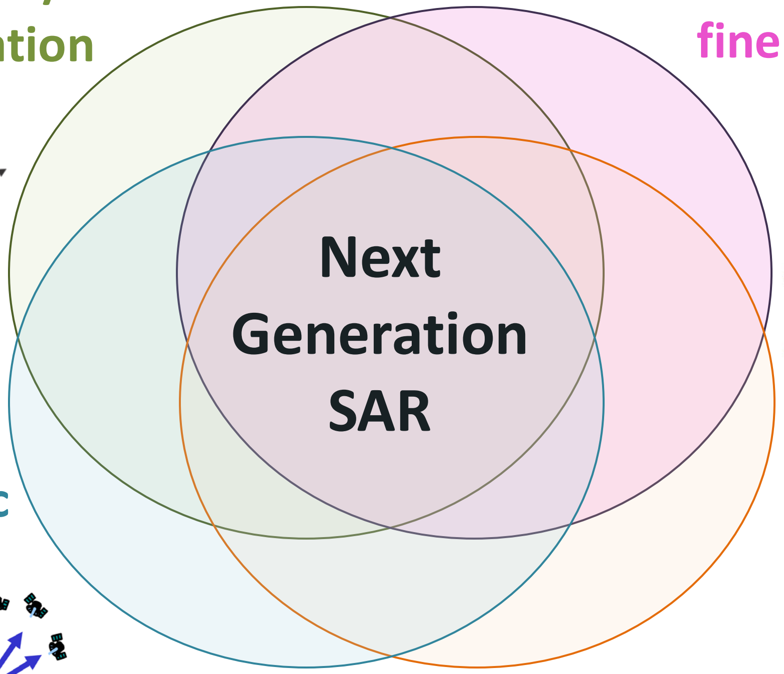
Microwaves and Radar Institute, German Aerospace Center (DLR)

FRINGE 2023 – University of Leeds

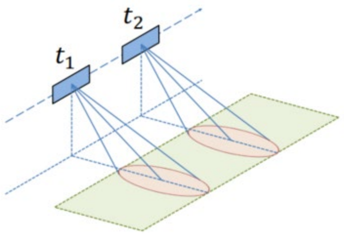
Spaceborne SAR Missions and Data Volume Challenges

Multi-channel / multi-polarization
N_{ch}

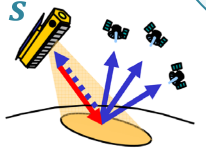




finer resolution
δa



multi-static
N_s



wider swath
W_g

Data rate $\propto N_s \cdot N_{ch} \cdot \dfrac{W_g}{\delta a}$

	Current Systems	Next Generation
Swath width W_g	30 km	100 km
Resolution δa	3 m	1 m

- Next-generation spaceborne SAR missions
  - **Large data rates required**
  - Harder requirements for: **Onboard memory**
    Downlink capacity

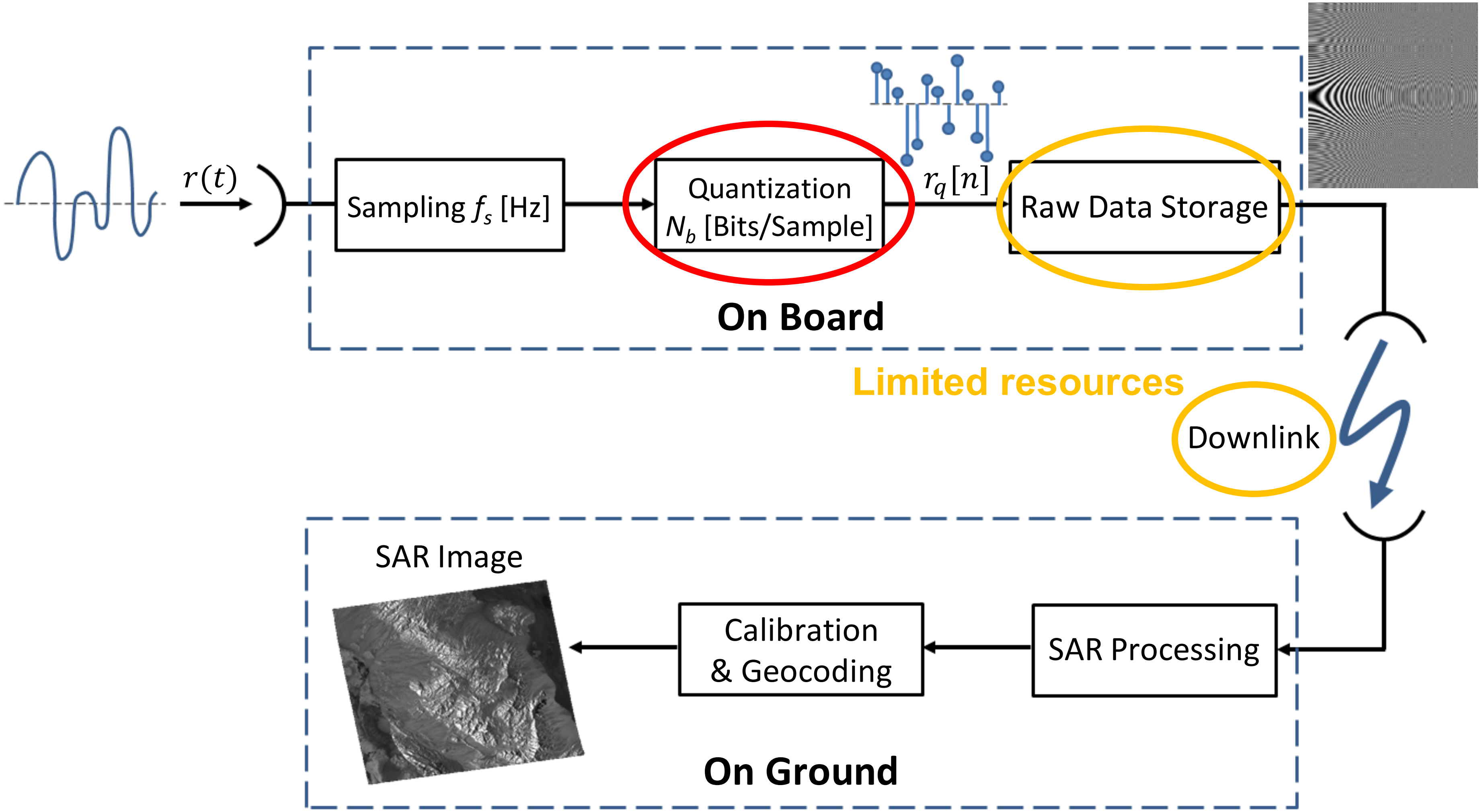
- **Quantization** of SAR raw data affects
  - **Amount of data** to be handled
  - **Quality** of the SAR products

Need for efficient resource allocation:

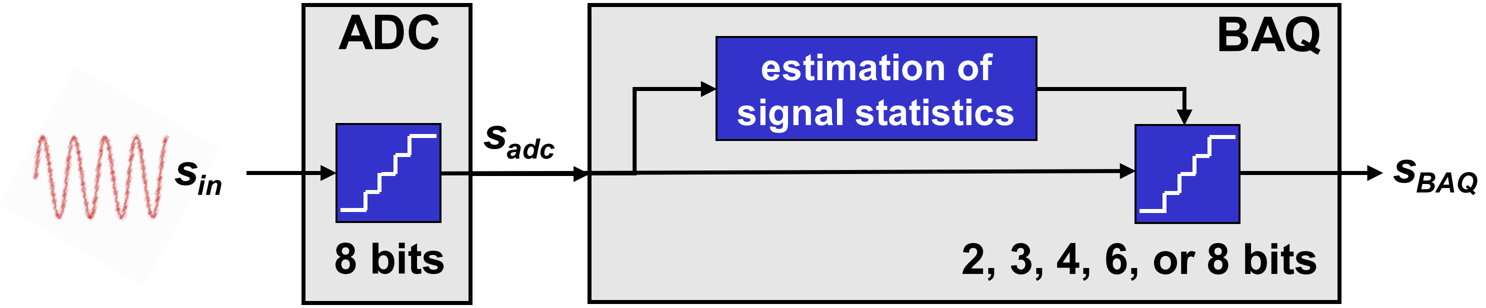
- **Performance aligned with requirements**
- **Design feasibility**

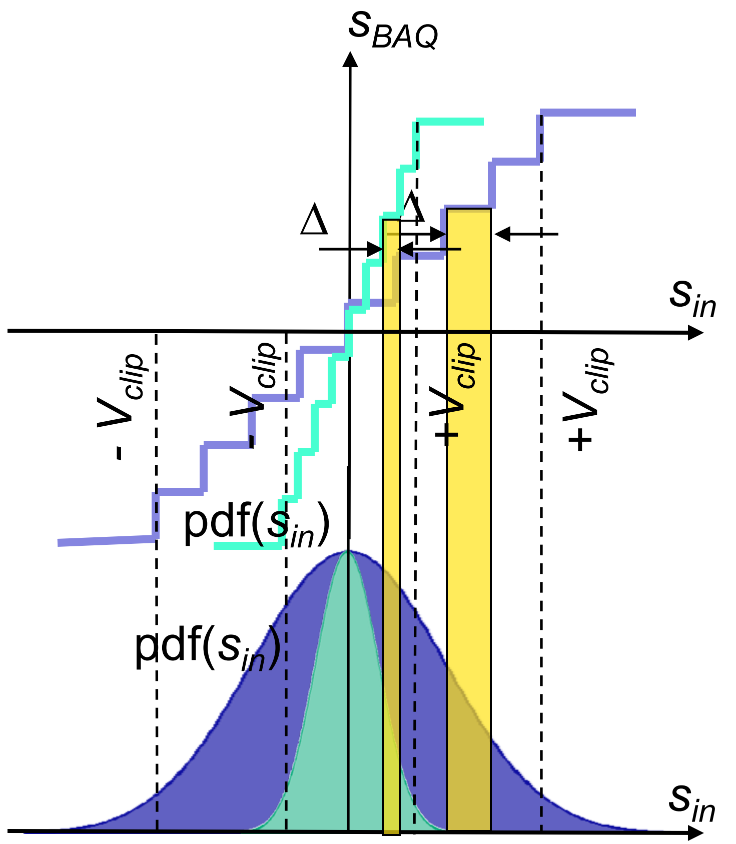
Example: TanDEM-X 1 year / global InSAR acquisition

From Raw Data Acquisition to SAR Products



SAR Raw Data Compression – State of the Art

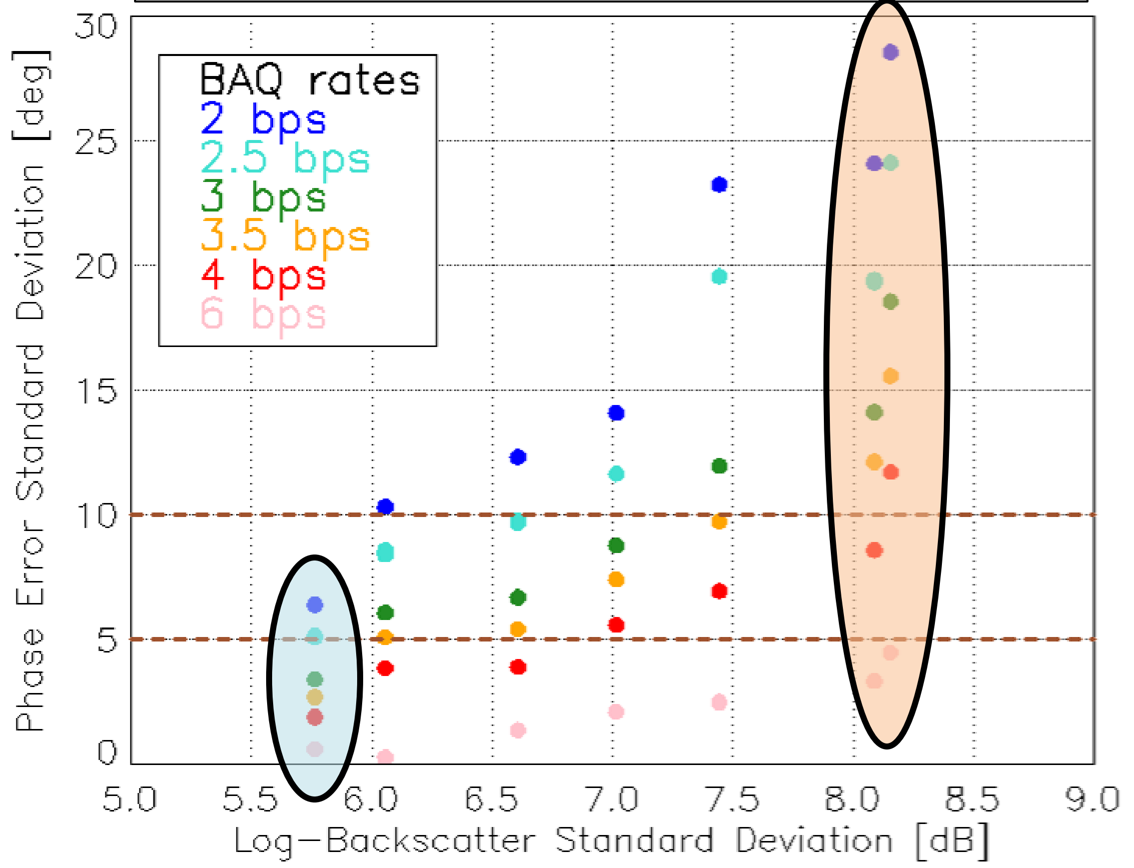




- **Block-Adaptive Quantization**: local statistics of raw data blocks to set the decision levels Δ
  → adapts to space-varying dynamic range of SAR data
- For SAR applications, typical BAQ rates between 2 and 6 bits/sample
- **Flexible Dynamic FD-BAQ** for Sentinel-1: on-board bitrate selection based on raw data statistics (large bitrates for high power blocks and vice-versa)
- Quantization as AWGN source holds <u>for homogeneous targets</u>

Impact of Raw Data Quantization on InSAR Performance

TanDEM-X data – BAQ – 12 m x 12 m posting



Test Site	σ_{σ^0}	**bps for $\sigma_{\Delta\varphi}$ = 5°**	**bps for $\sigma_{\Delta\varphi}$ = 10°**
Greenland - snow & ice, flat	Homogeneous		
Iowa (USA) - agricultural, flat	**6.1 dB**	**3.5 bps**	**2.1 bps**
Rondonia (Brazil) - rainforest, flat	**6.6 dB**	**3.6 bps**	**2.5 bps**
Death Valley (USA) - soil & rock, mountainous	**7.0 dB**	**4.4 bps**	**2.8 bps**
Las Vegas - urban, flat	**7.4 dB**	**5.1 bps**	**3.5 bps**
Mexico City - urban, mountainous	**8.1 dB**	**5.6 bps**	**3.8 bps**
Malaysia - tropical forest, mountainous	Heterogeneous		

Strong impact of local backscatter characteristics on quantization performance

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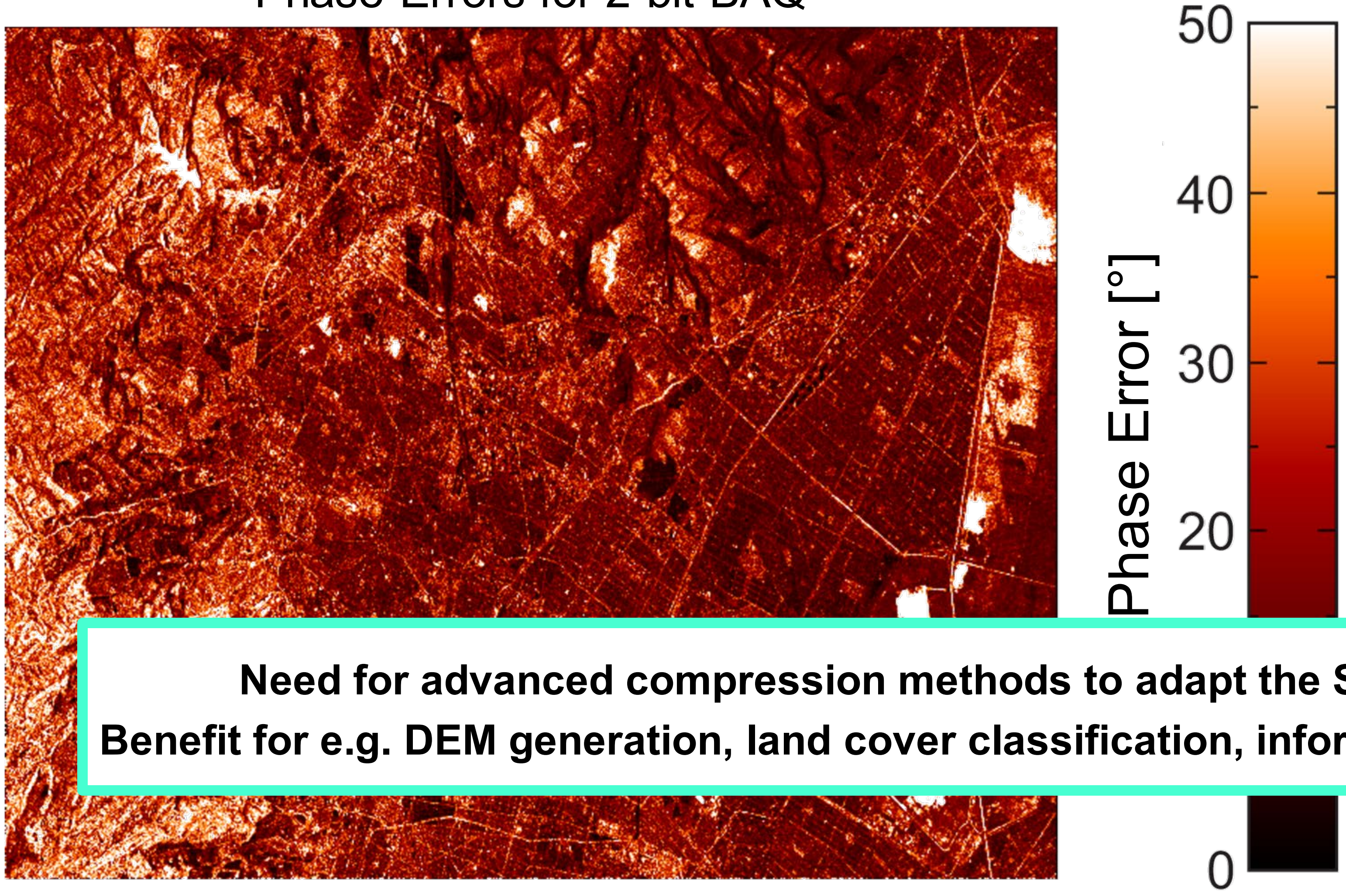
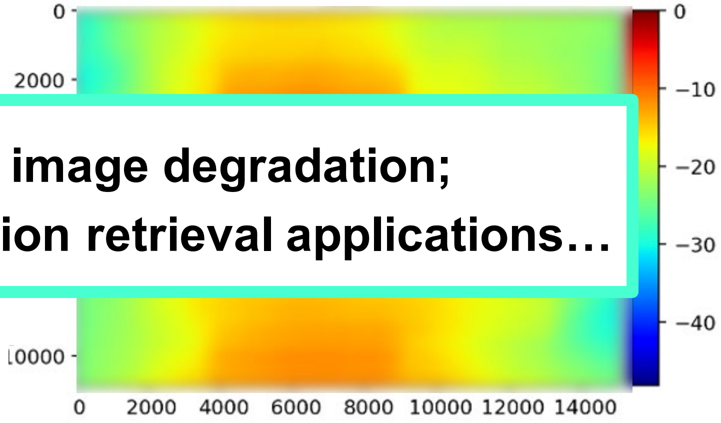
Impact of Raw Data Quantization on InSAR Performance

Phase Errors for 2-bit BAQ



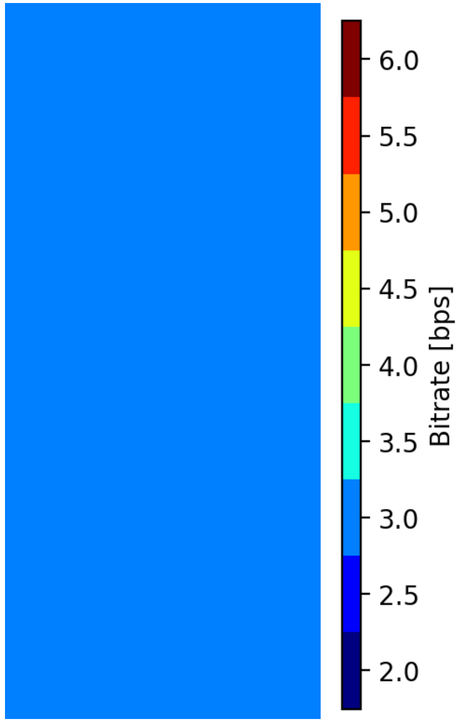
Raw Data



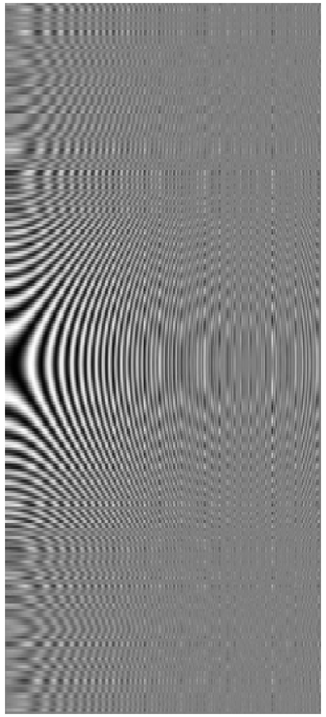
Need for advanced compression methods to adapt the SAR image degradation;
Benefit for e.g. DEM generation, land cover classification, information retrieval applications…

From Constant BAQ Rate…

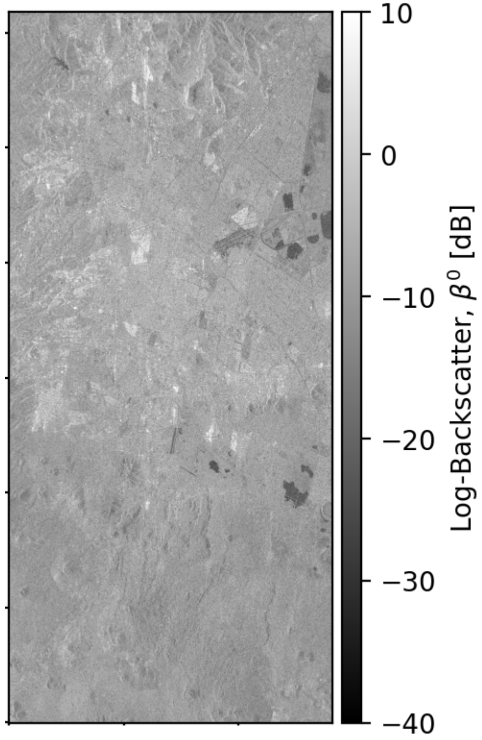
3-bit BAQ



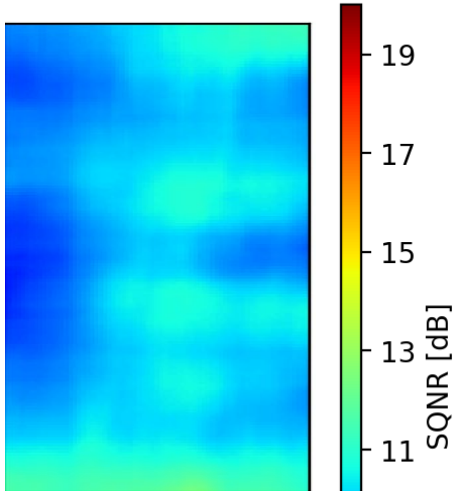
Raw Data

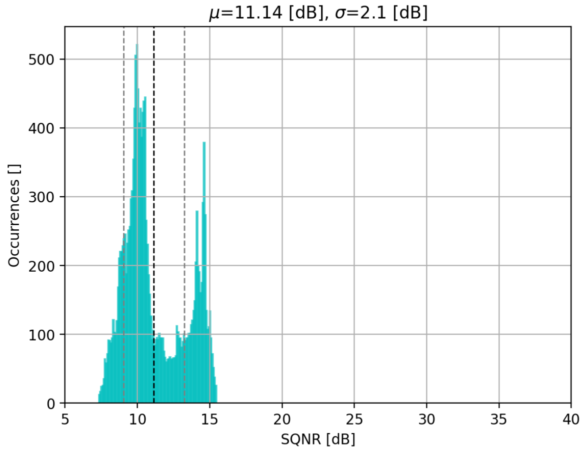


SAR Image



Signal-to-Quantization Noise Ratio (SQNR)

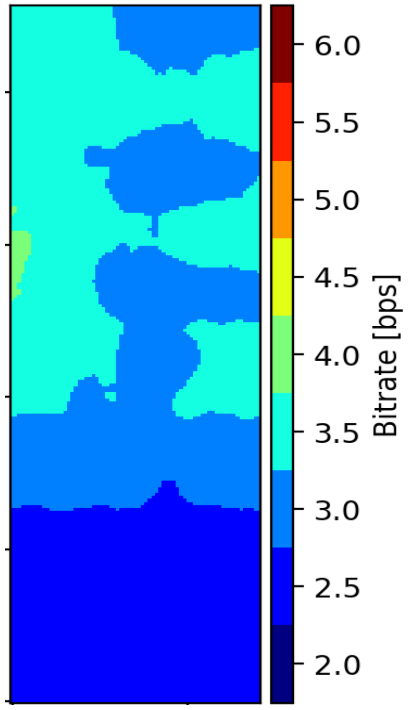




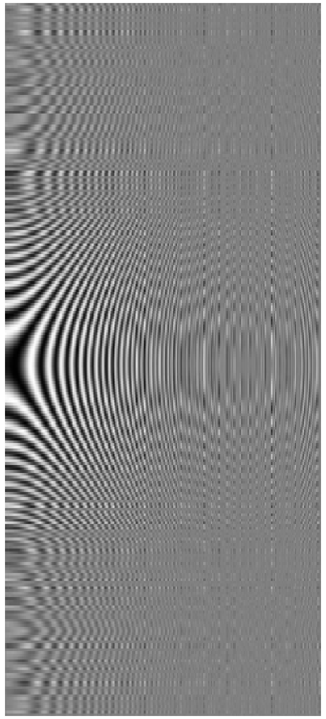
$$\mathrm{SQNR} = \frac{\sigma_x^2}{\sigma_q^2} \qquad q = x - \hat{x}$$

…to Performance-Optimized (PO)-BAQ[1]

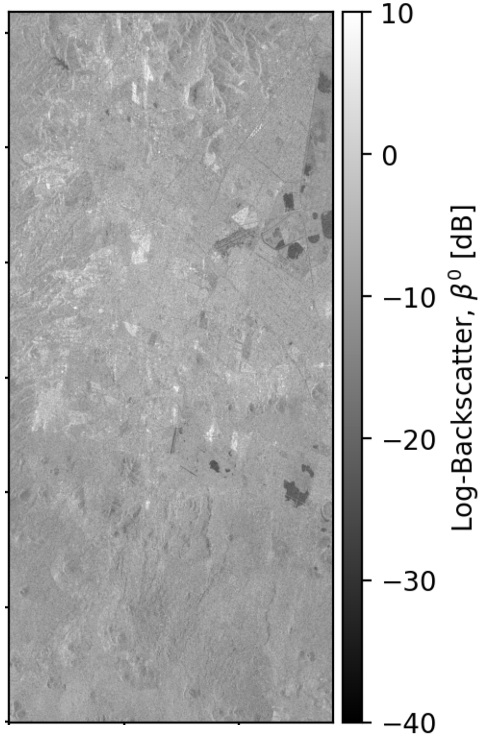
Bit Rate Map (BRM)
Variable BAQ



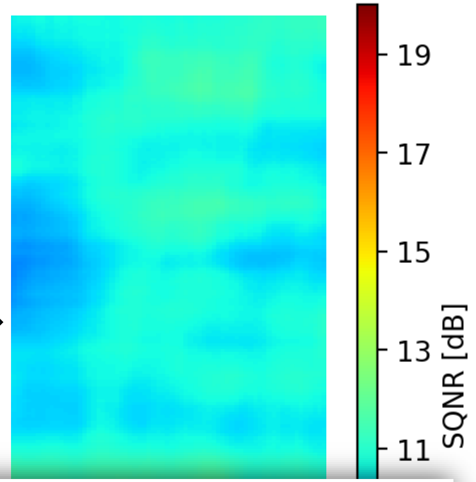
Raw Data

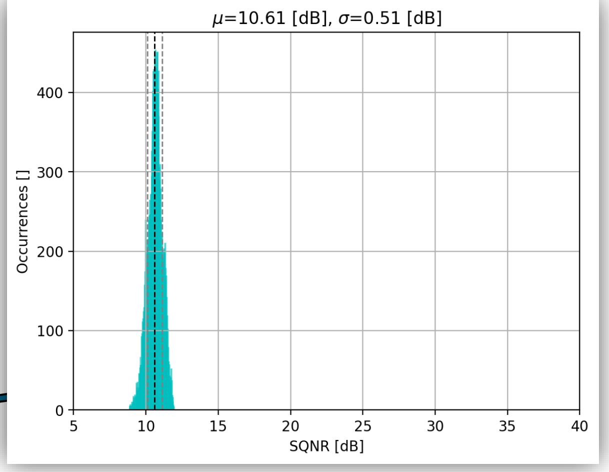


SAR Image



Signal-to-Quantization Noise Ratio (SQNR), Target 10 dB

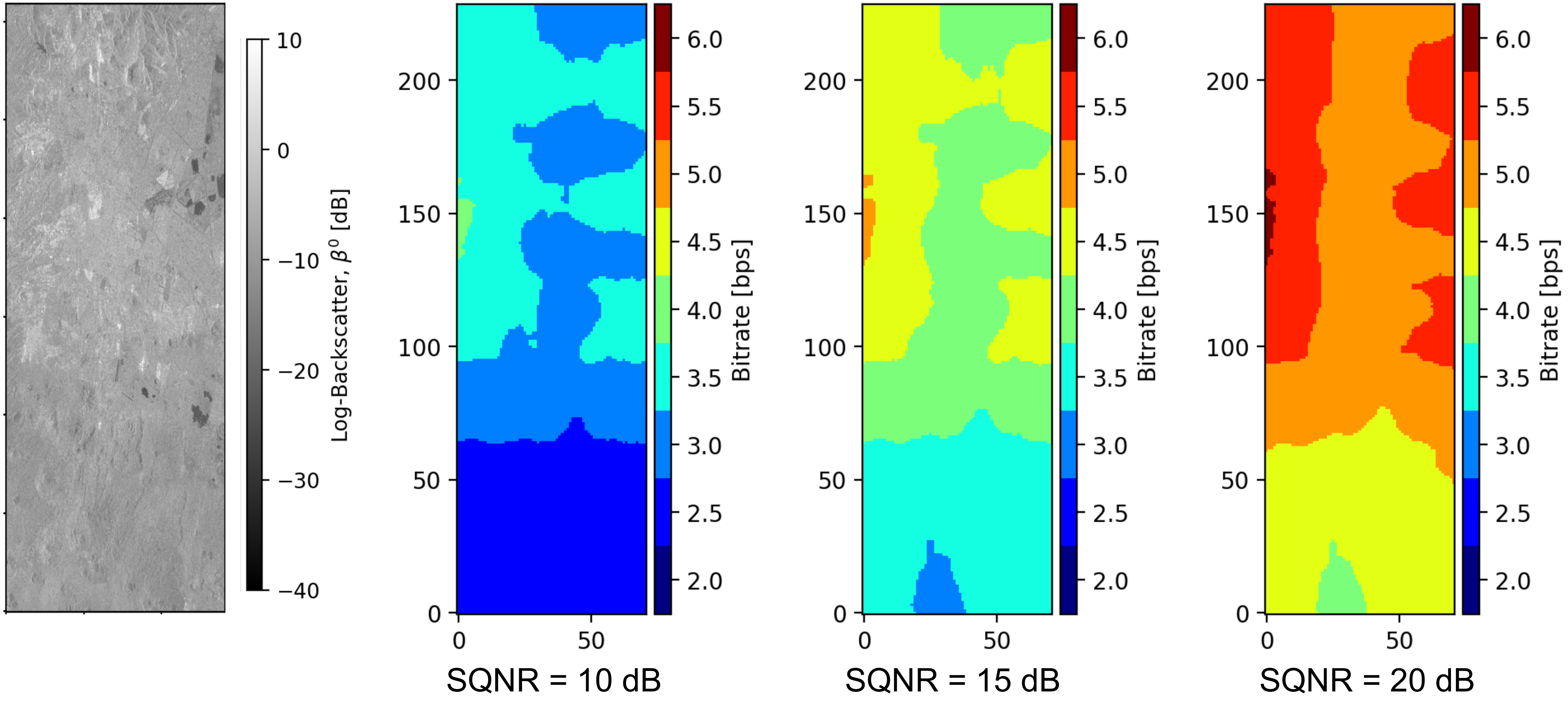




Bit rate adapted to the target performance

[1] Martone et al. *Performance-optimized quantization for SAR and InSAR applications,* TGRS 2022.

BRM Examples – Mexico City



SQNR and SAR Performance

uncompressed

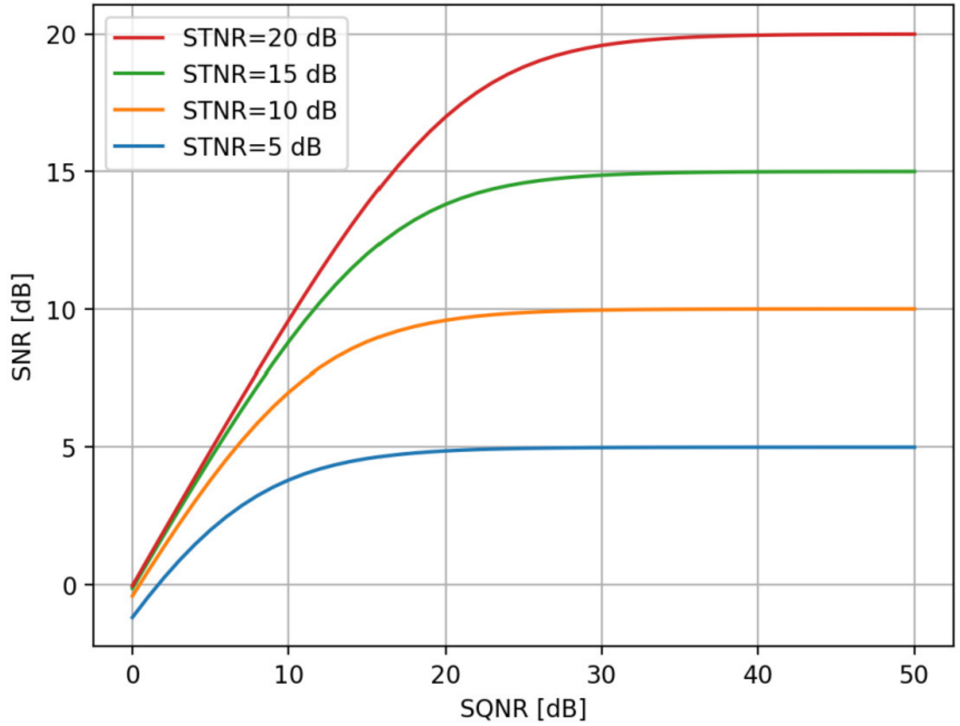
$$\mathrm{SQNR} = \frac{\sigma_x^2}{\sigma_{n_q}^2} \qquad n_q = x - \hat{x}$$

compressed

- Impact on (total) SNR:

$$\mathrm{SNR} = \frac{\sigma_x^2}{\sigma_n^2} = \frac{\sigma_x^2}{\sigma_{n_t}^2 + \sigma_{n_q}^2} \rightarrow \mathrm{SNR}^{-1} = \mathrm{STNR}^{-1} + \mathrm{SQNR}^{-1}$$

$\sigma_{n_t}^2$: thermal noise
$\sigma_{n_q}^2$: quantization noise

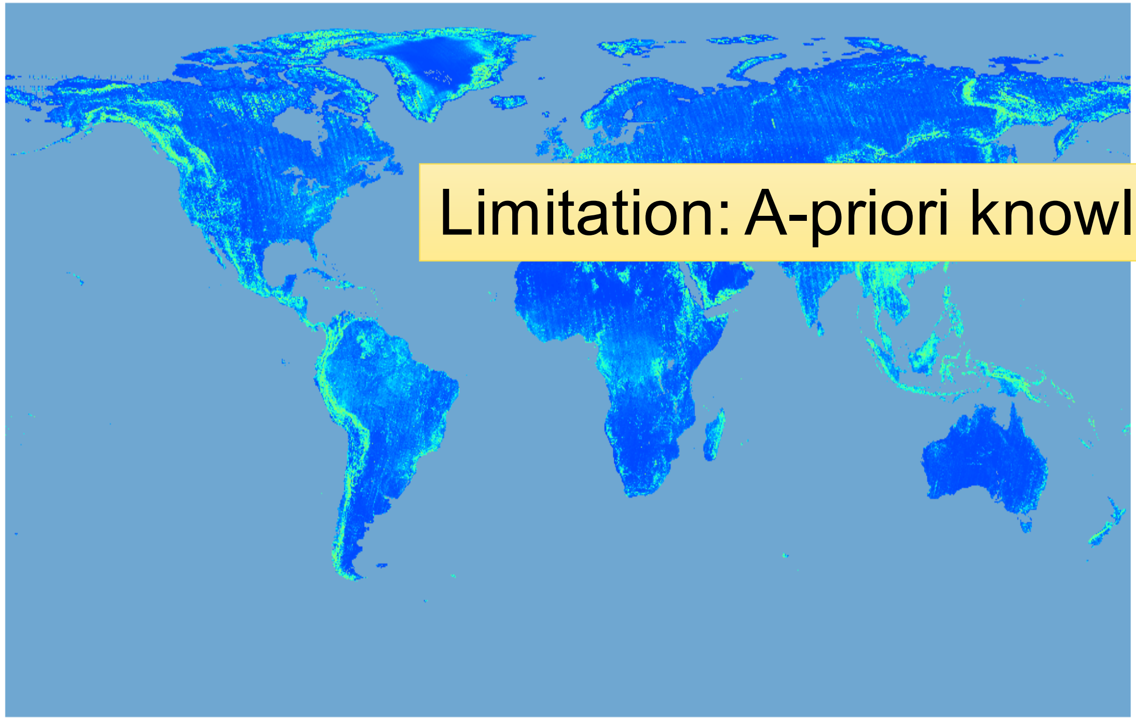


- Relation with coherence loss:

$$\gamma_q = \frac{1}{1 + \mathrm{SQNR}^{-1}}$$

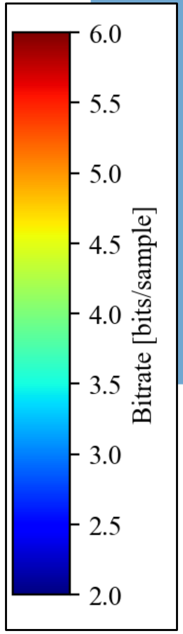
PO-BAQ – Example for Global Bitrate Allocation

Global bitrate map (TerraSAR-X backscatter map as input)



Limitation: A-priori knowledge of the scene is required!

SQNR = 15 dB



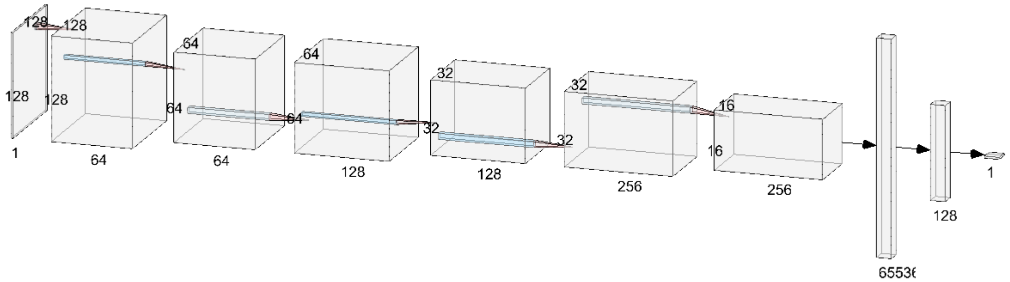
SQNR = 20 dB

Artificial Intelligence for SAR Data Compression – ARTISTE

- Research funded by the European Space Agency (ESA/ESTEC) project "Adaptive SAR Signal Compression Through Artificial Intelligence" Contract Nr. ESA AO/1-11419/22/NL/GLC/my

- Objective: exploit Deep Learning for deriving the **required bitrate** for on-board **raw data** compression in order to control the **performance** in the resulting **SAR/InSAR products**

- CNN-based architecture for self-supervised regression:
  - 128x128 pixel patch
  - 3 Convolutional Layers (3x3)
  - Max-Pool (2x2)



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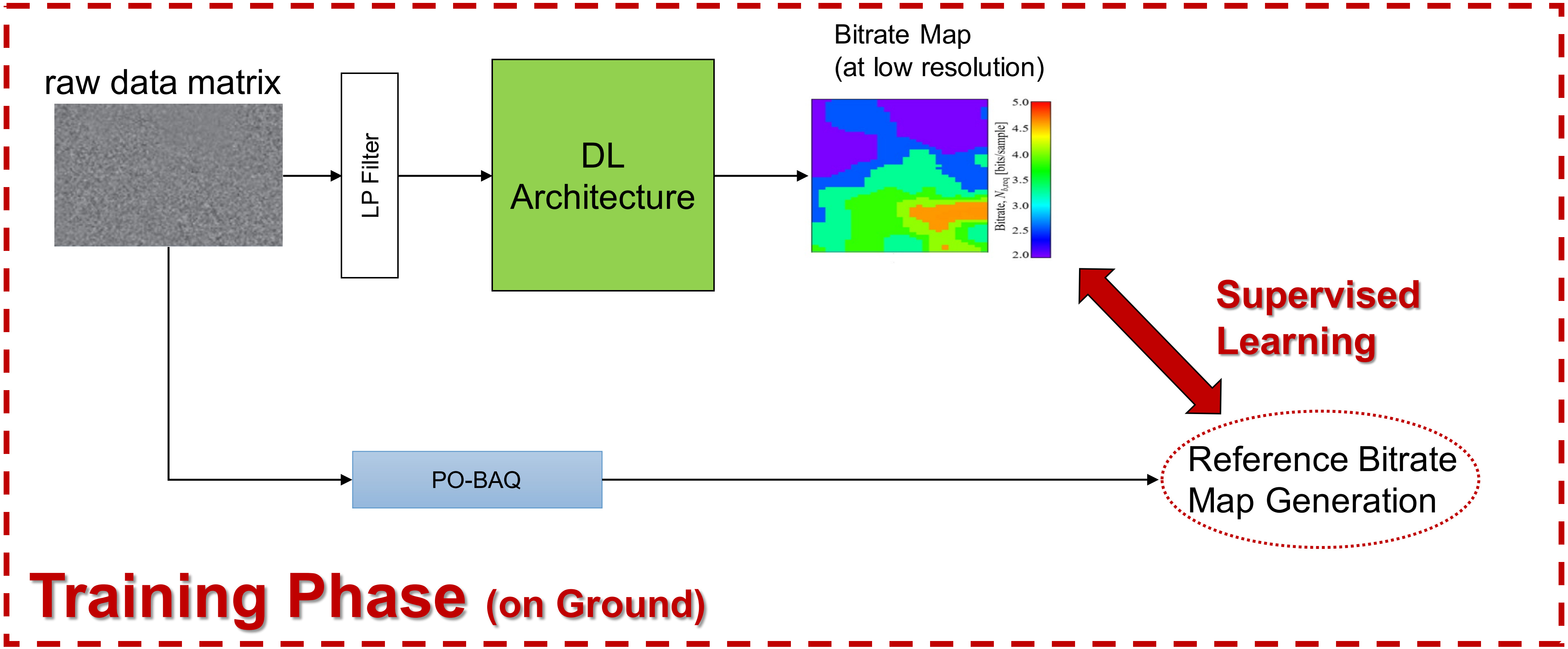
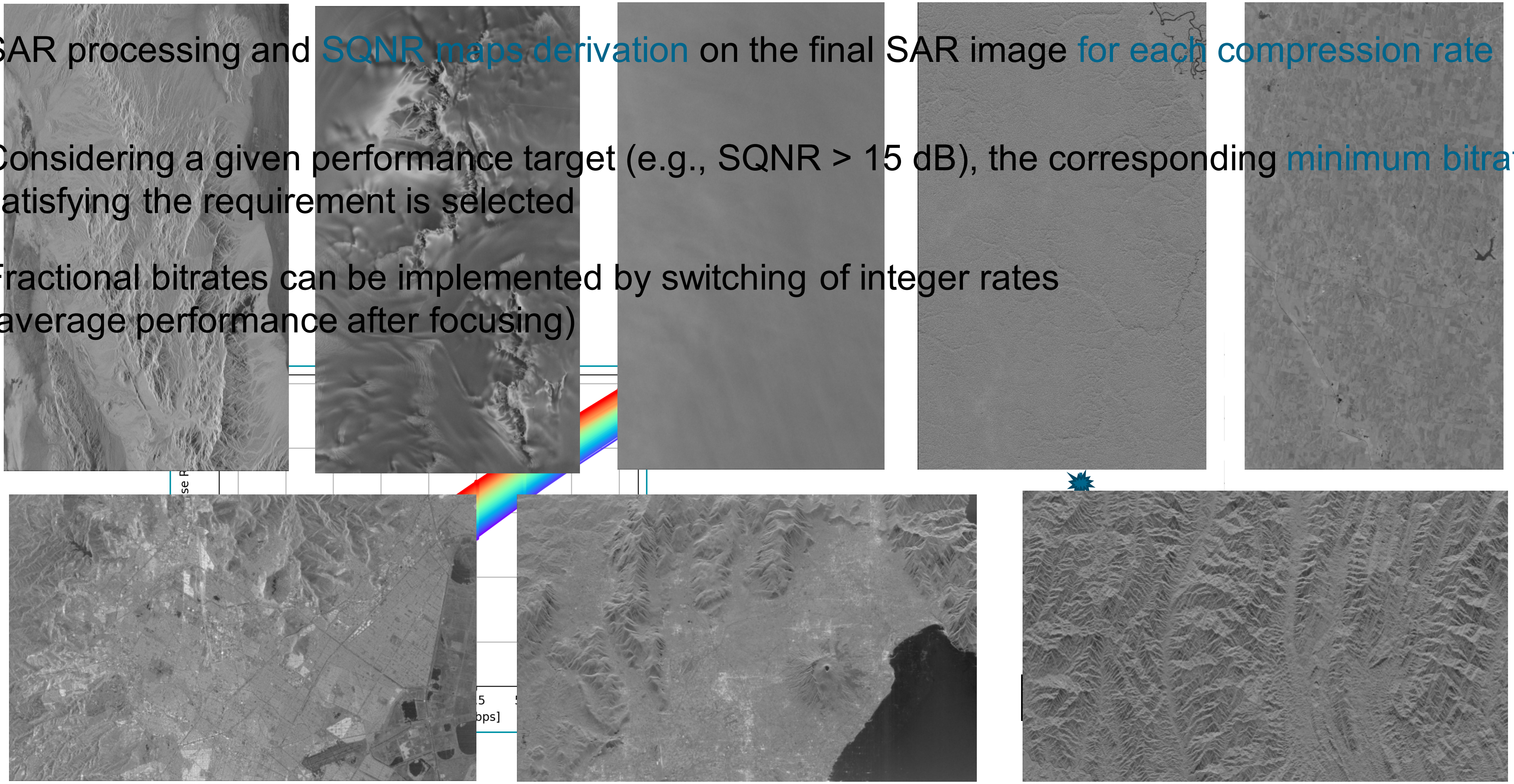
Bitrate Allocation: a Deep Learning-Based Approach

Goal: definition of a DL-architecture to derive the required bitrate <u>without</u> a-priori scene knowledge



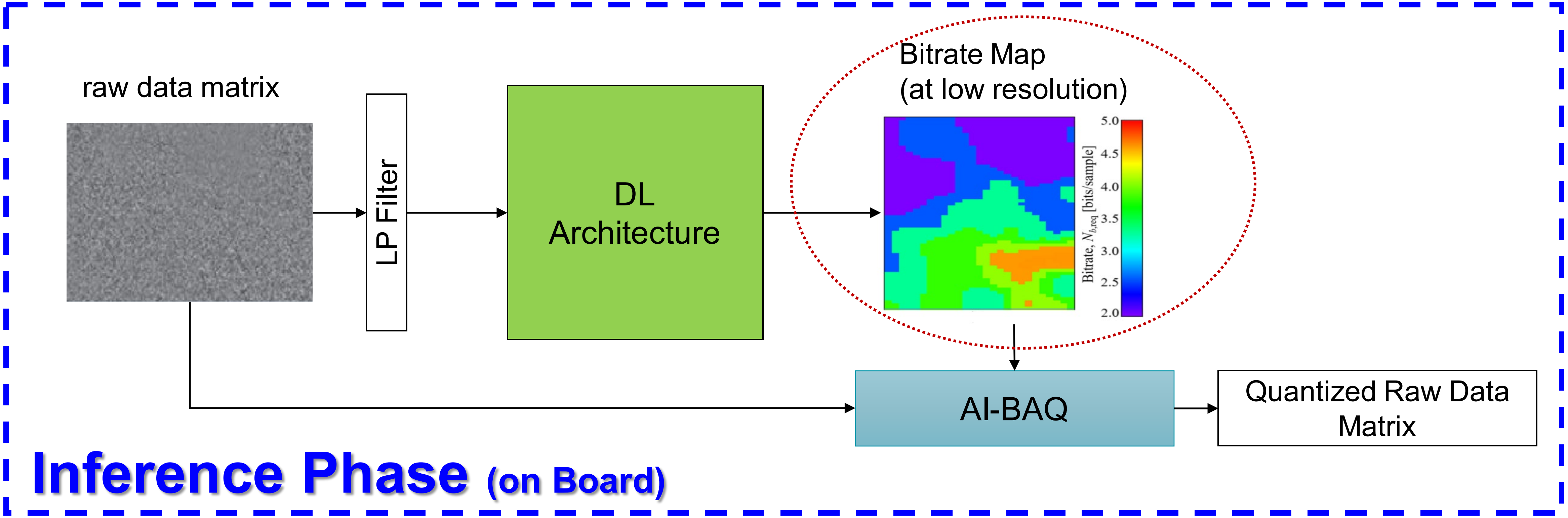
Reference Bitrate Maps Generation

- Set of 20 TerraSAR-X and TandDEM-X uncompressed (BAQ 8 bps) SAR acquisitions used for training (16) & testing (4)
- SAR processing and SQNR maps derivation on the final SAR image for each compression rate
- Considering a given performance target (e.g., SQNR > 15 dB), the corresponding minimum bitrate satisfying the requirement is selected
- Fractional bitrates can be implemented by switching of integer rates (average performance after focusing)



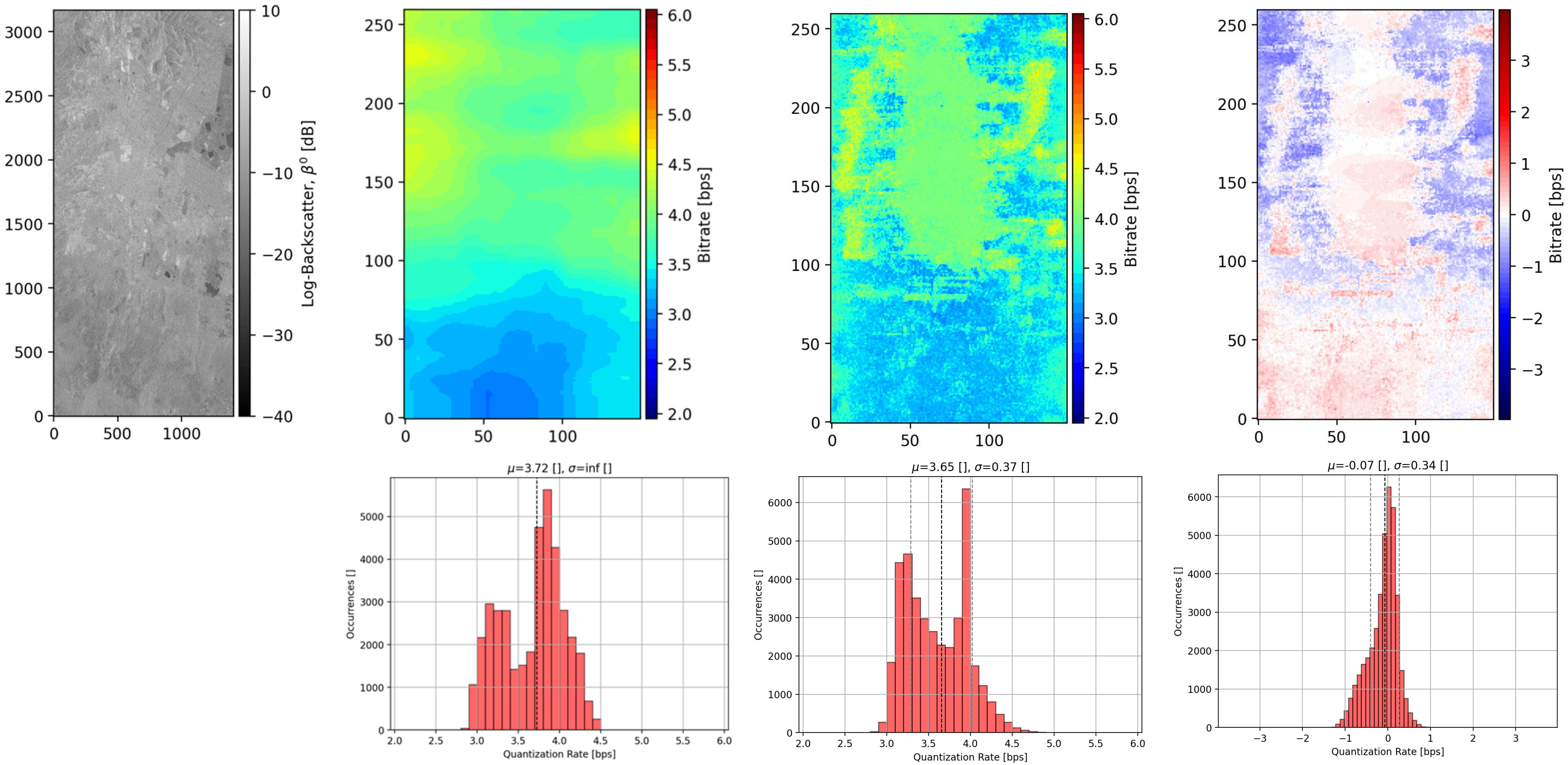
Deep Learning Approach: Inference and Results Evaluation

- At Inference the estimated BRM is generated and used for on-board compression
- For each raw data block standard BAQ is used



AI-BAQ – Inference (1/2)

Mexico City | True | Estimation | Error



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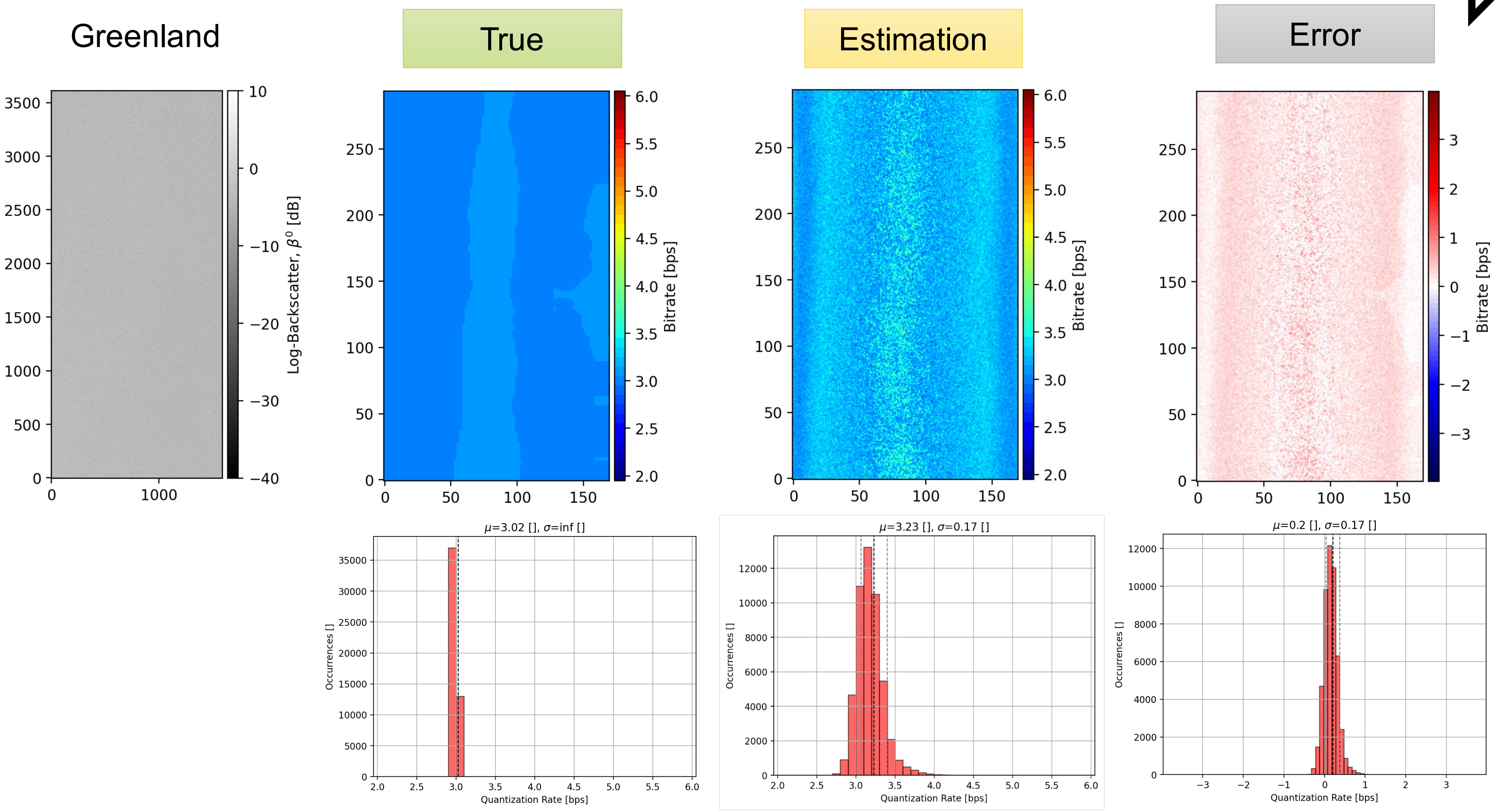
AI-BAQ – Inference (2/2)



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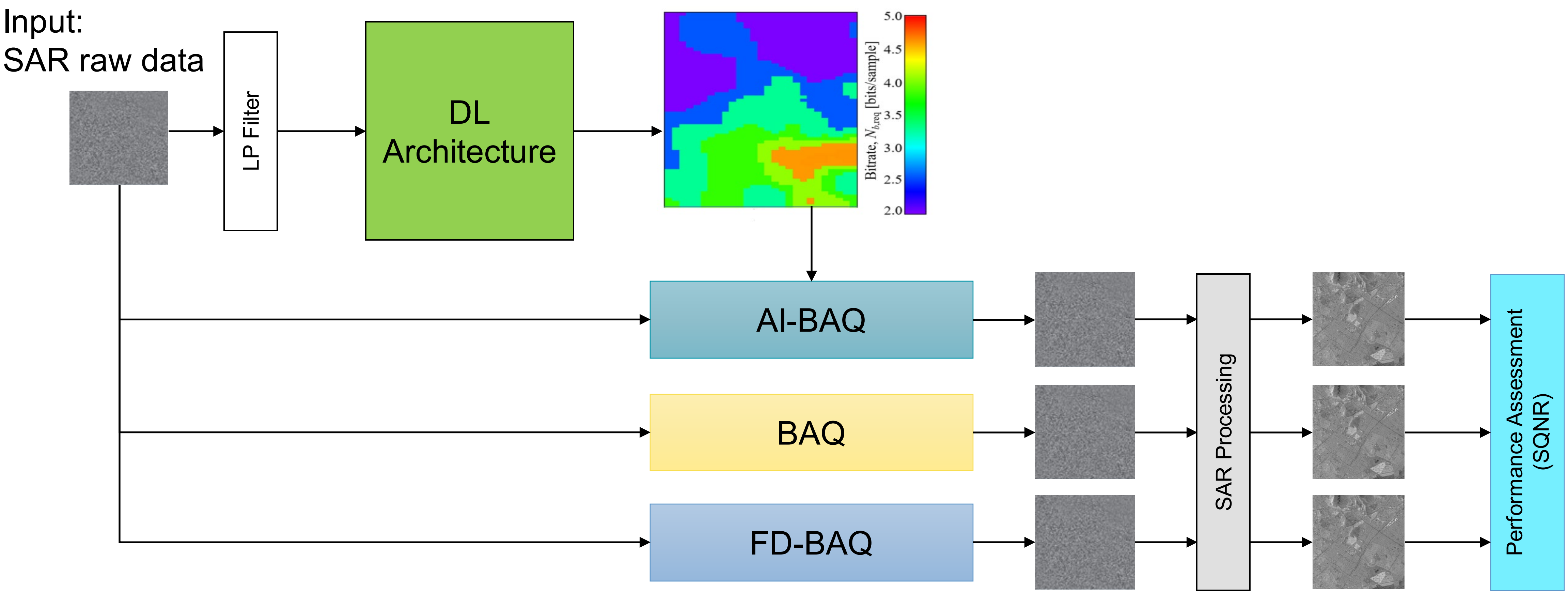
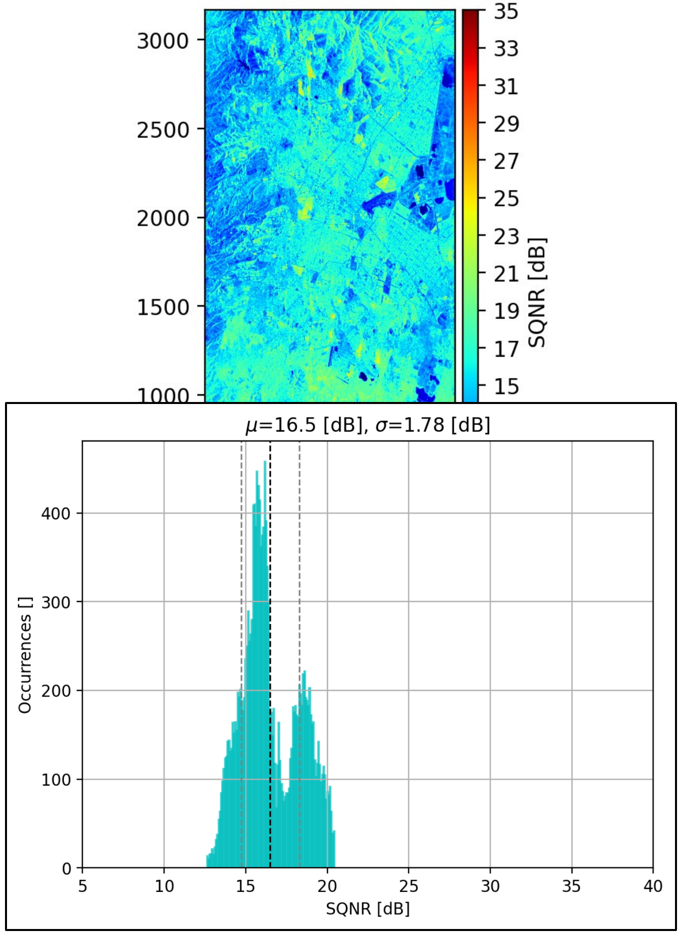
SAR Performance Assessment



SAR Performance Results – Mexico City

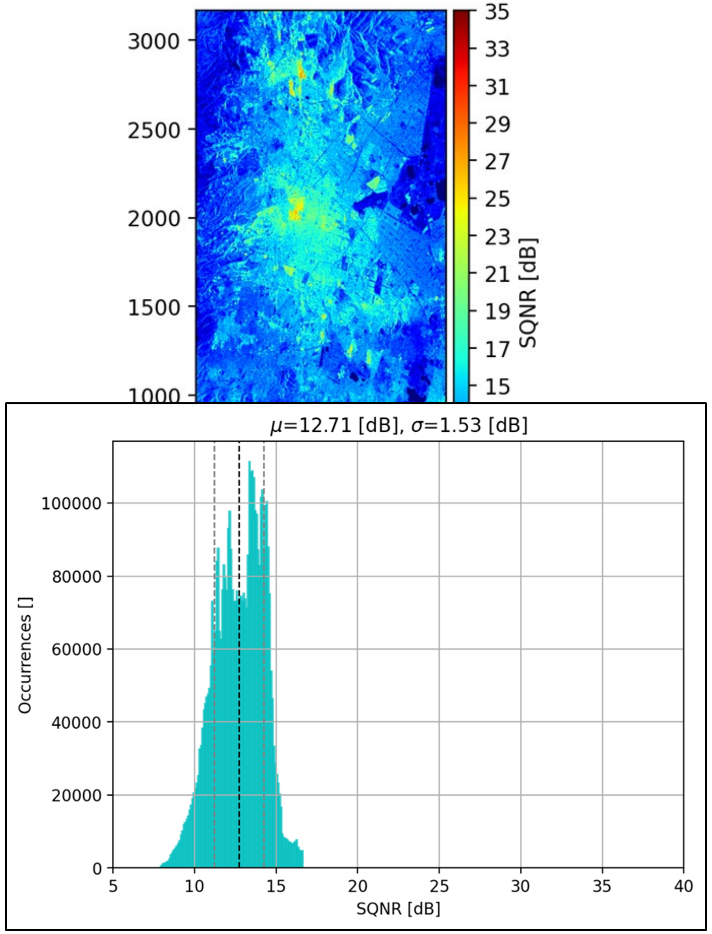
BAQ

4.0 bps



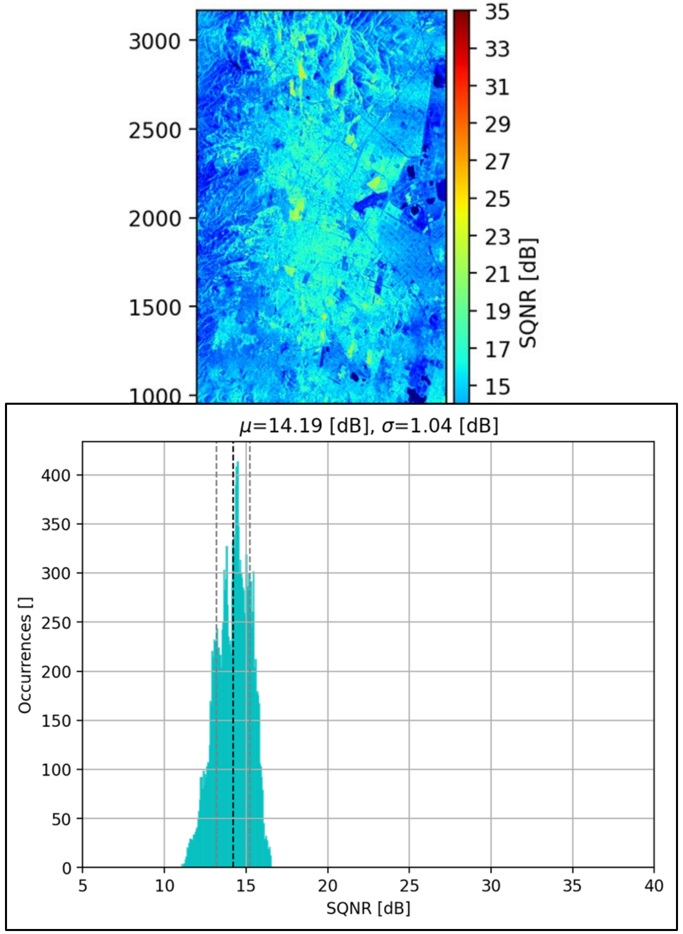
FDBAQ

3.3 bps



AI-BAQ – SQNR @15 dB

3.7 bps



Performance Comparison & Data Volume Reduction

SQNR = 10 dB (μ ± σ) / mean bitrate	2-bit BAQ	FDBAQ		AI-BAQ	
Greenland (Snow/Ice)	9.7 dB ± 0.2 dB	14.8 dB ± 0.1 dB	3.1 bps	11.9 dB ± 0.4 dB	2.4 bps
Uyuni (Soil & rock)	9.5 dB ± 0.2 dB	15.1 dB ± 0.3 dB	3.2 bps	10.5 dB ± 0.7 dB	2.2 bps
Las Vegas (Urban)	7.7 dB ± 1.3 dB	12.6 dB ± 1.7 dB	3.1 bps	9.8 dB ± 1.1 dB	2.4 bps
Mexico City (Urban + Topography)	6.6 dB ± 1.4 dB	12.7 dB ± 1.5 dB	3.3 bps	9.6 dB ± 0.9 dB	2.7 bps

SQNR = 15 dB (μ ± σ) / mean bitrate	3-bit BAQ	FDBAQ		AI-BAQ	
Greenland (Snow/Ice)	15.1 dB ± 0.1 dB	14.8 dB ± 0.1 dB	3.1 bps	15.6 dB ± 0.1 dB	3.3 bps
Uyuni (Soil & rock)	15.0 dB ± 0.4 dB	15.1 dB ± 0.3 dB	3.2 bps	15.4 dB ± 0.7 dB	3.2 bps
Las Vegas (Urban)	12.9 dB ± 1.6 dB	12.6 dB ± 1.7 dB	3.1 bps	14.3 dB ± 1.2 dB	3.4 bps
Mexico City (Urban + Topography)	11.6 dB ± 1.8 dB	12.7 dB ± 1.5 dB	3.3 bps	14.2 dB ± 1.0 dB	3.7 bps

Performance Comparison & Data Volume Reduction

SQNR = 10 dB ($\mu \pm \sigma$) / mean bitrate	2-bit BAQ	FDBAQ		AI-BAQ	
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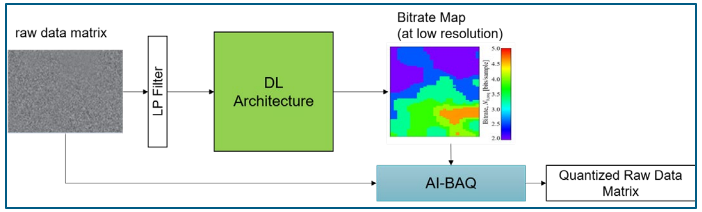
Mexico City (Urban + Topography)	6.6 dB ± 1.4 dB	12.7 dB ± 1.5 dB	3.3 bps	9.6 dB ± 0.9 dB	2.7 bps

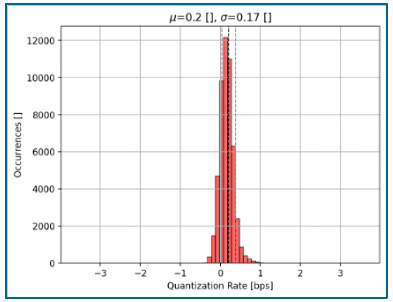
- AI-BAQ achieves **more targeted performance** w.r.t. BAQ and FDBAQ for all cases
- Assuming a requirement SQNR = 10 dB: About 1 bps less w.r.t. FDBAQ
  → **data volume reduction of up to ~30%**

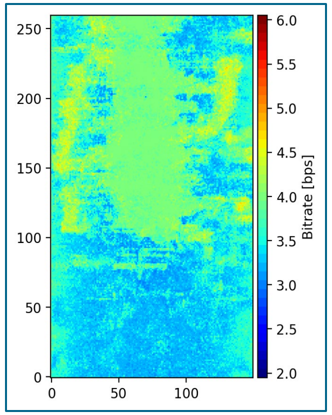
AI-BAQ – Conclusions and Outlook

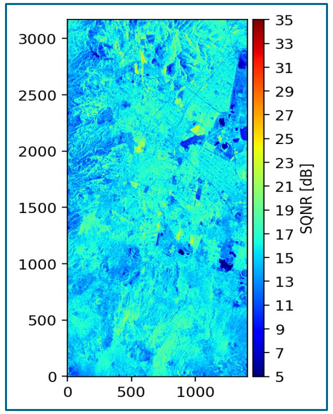
- Novel AI-based SAR data compression method for joint optimization of **datarate** and **SAR image performance**
- **No a-priori knowledge** of the backscatter/scene required
- **Combined** use of AI-BAQ with other **data volume reduction** approaches (e.g. transform/predictive coding) possible
- Promising results w.r.t. state-of-the-art compression methods; potential **improvements** (e.g. CNN architecture) and **HW implementation** currently investigated
- Method to be tested on other **performance parameters** (e.g. radiometry & phase errors)

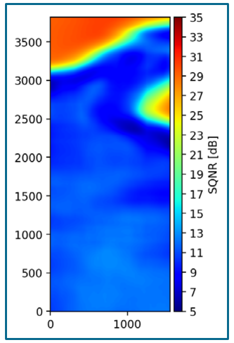
Patent pending



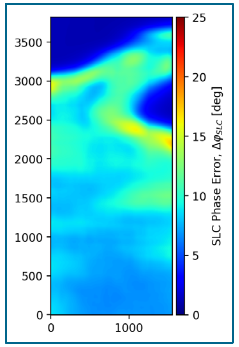




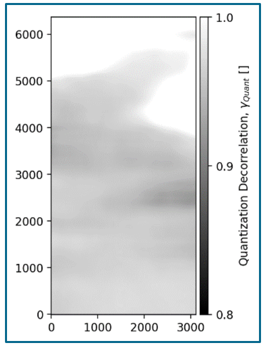




SQNR



$\Delta\varphi_{error}^{SLC}$



γ_{Quant}

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