MACHINE LEARNING IN MODEL-BASED FOREST HEIGHT INVERSION

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Background: Forest Height inversion from InSAR Data

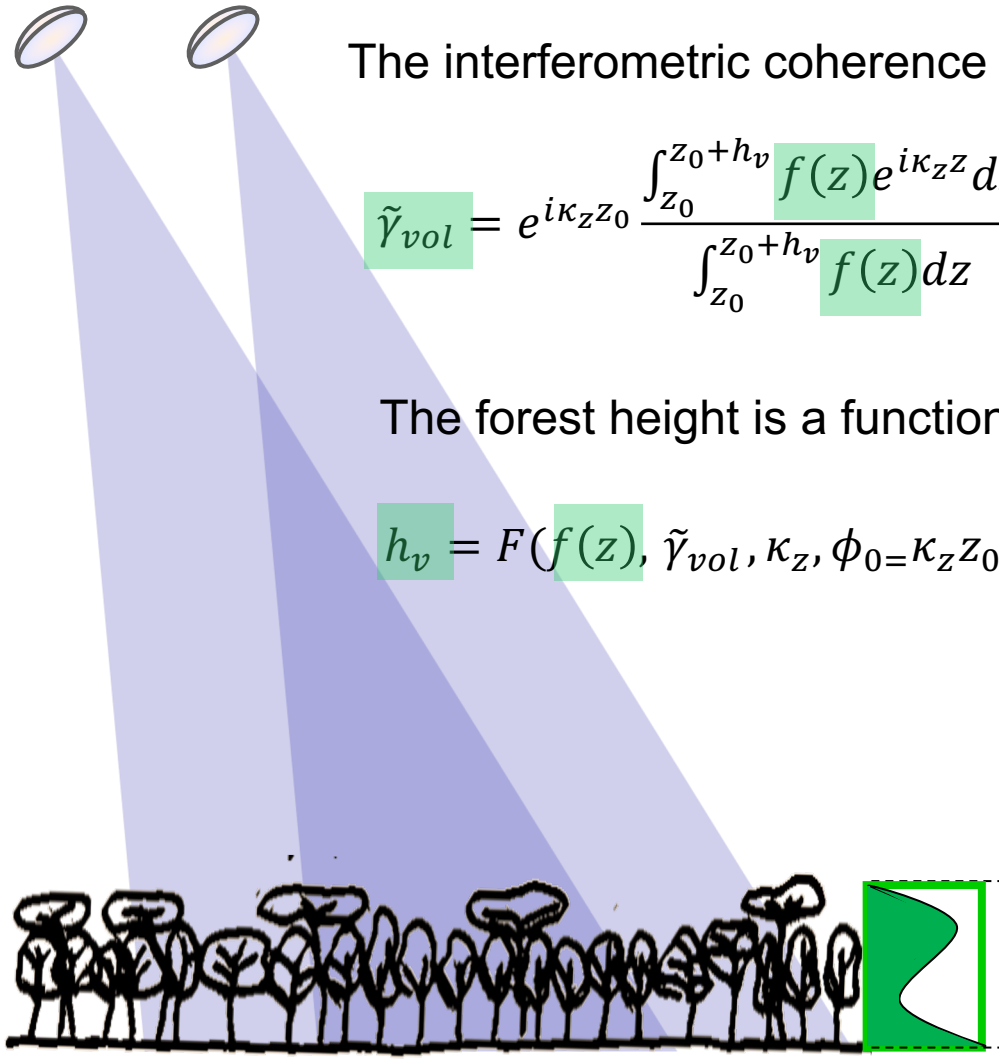
The interferometric coherence model:

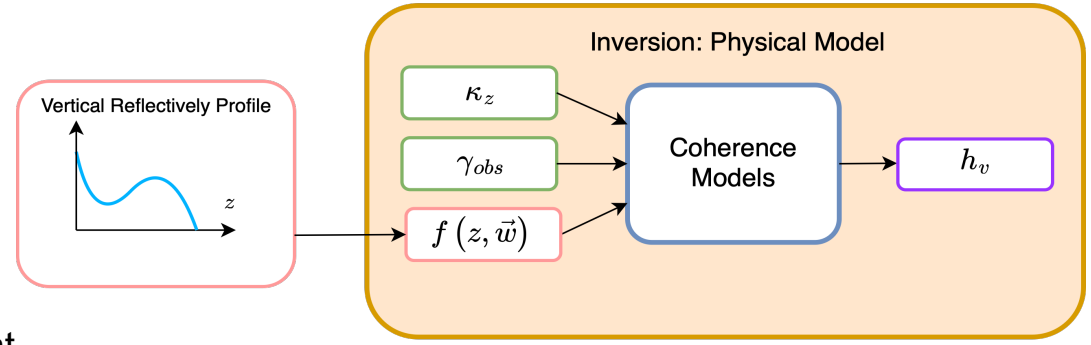
$$\tilde{\gamma}_{vol} = e^{i\kappa_z z_0} \frac{\int_{z_0}^{z_0+h_v} f(z) e^{i\kappa_z z} dz}{\int_{z_0}^{z_0+h_v} f(z) dz}$$

$f(z)$ ... vertical reflectivity function κ_z ... vertical wavenumber

The forest height is a function of:

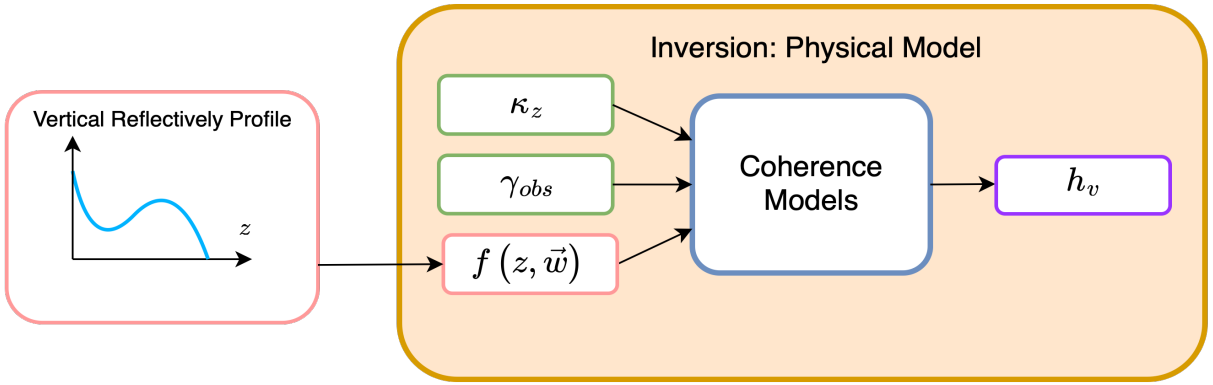
$h_v = F(f(z), \tilde{\gamma}_{vol}, \kappa_z, \phi_{0=}\kappa_z z_0)$ The description of $f(z)$ is one of the key challenges in FH inversion





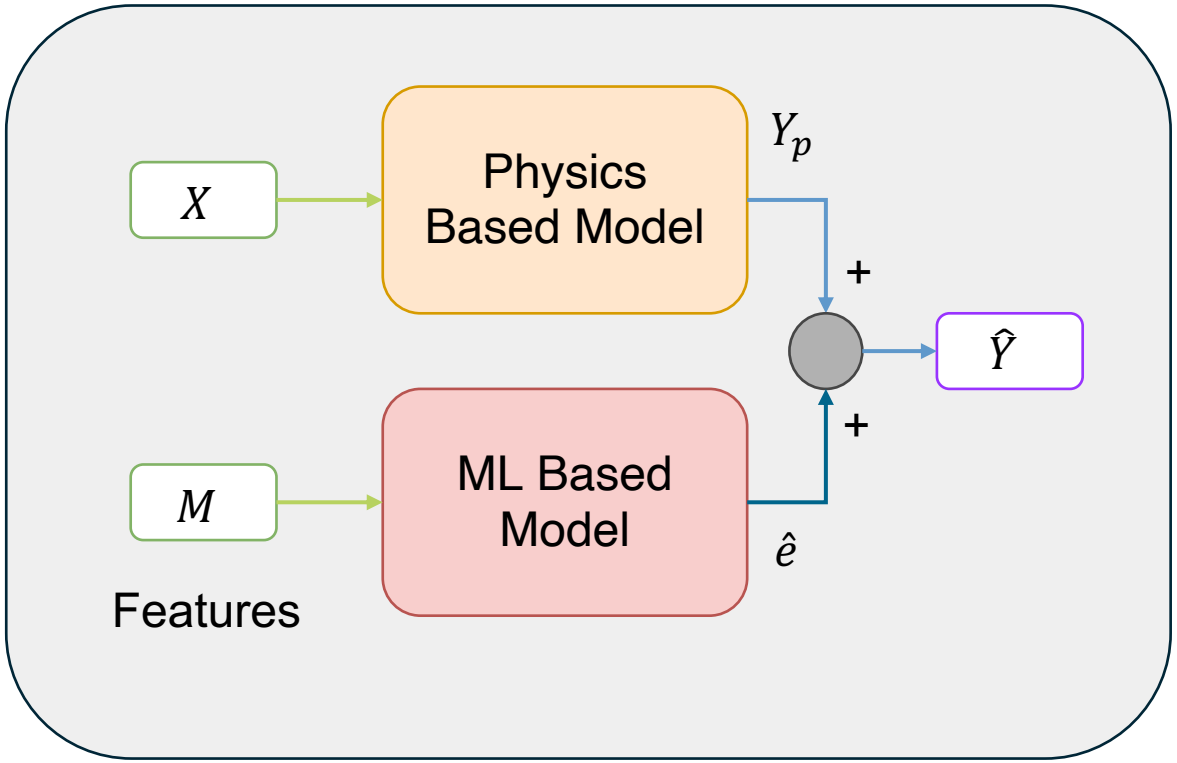
Background: Model-based Inversion and its Limitations

- **Limitations:** These models struggle with the high spatial variability of forest and terrain conditions, which reduces estimation accuracy and introduces biases.
- **Need for Improvement:** To tackle these limitations, there's a need for a model that can handle the spatial variability of the vertical reflectivity function without reducing estimation accuracy.



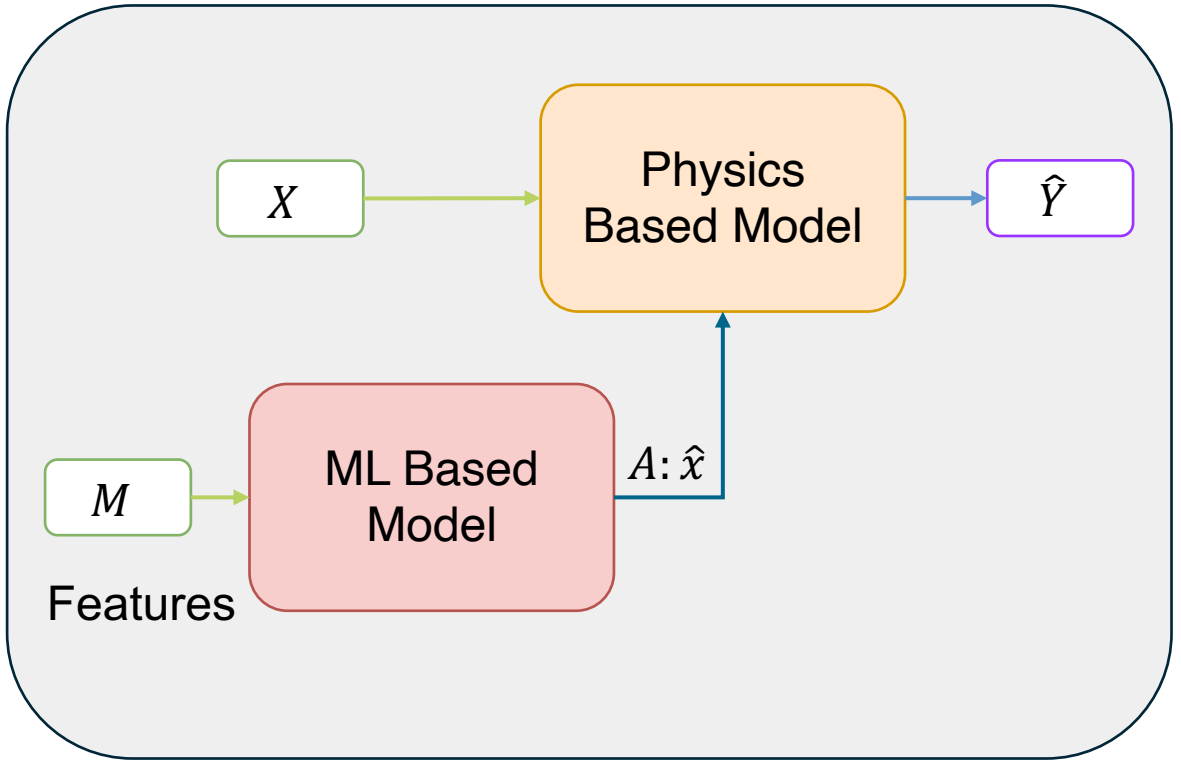
The Hybrid Approach: Integrating Machine Learning and Physical Modeling (Architecture)

Parallel Hybrid Model



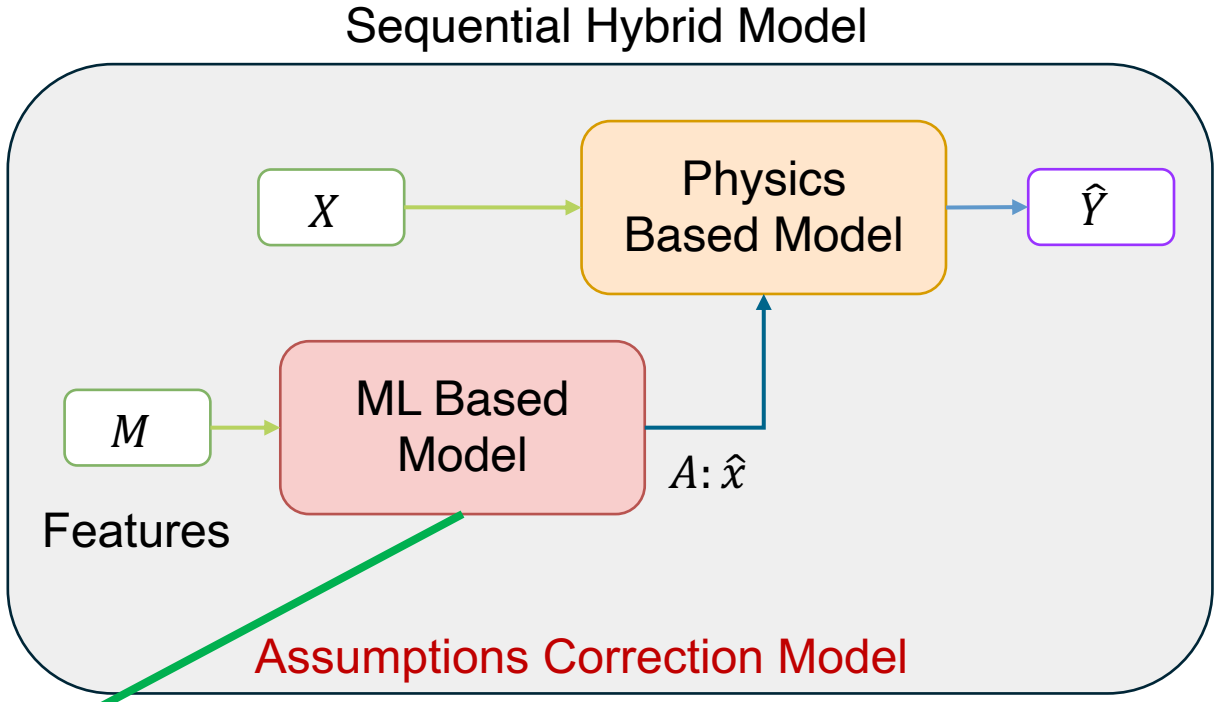
Error-Correction Model

Sequential Hybrid Model

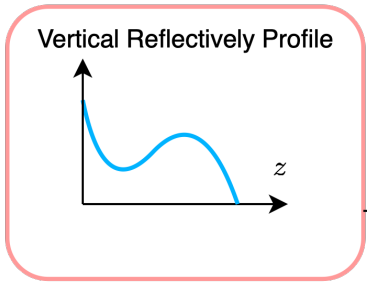


Assumptions Correction Model

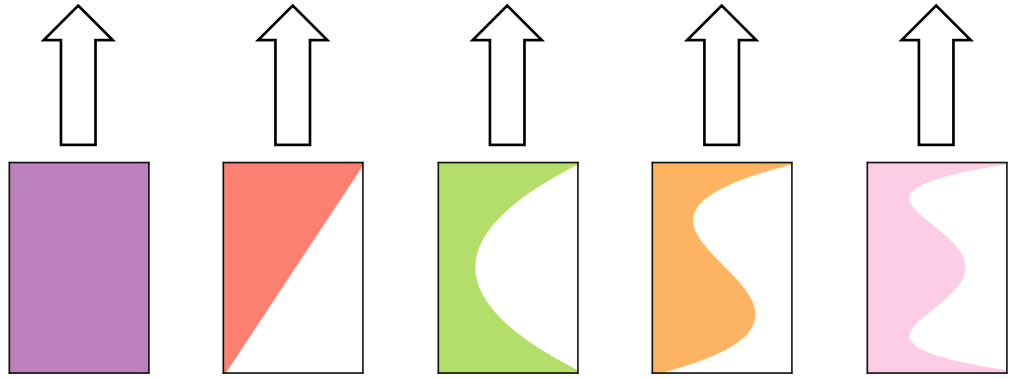
Integration of Machine Learning and Physical Models



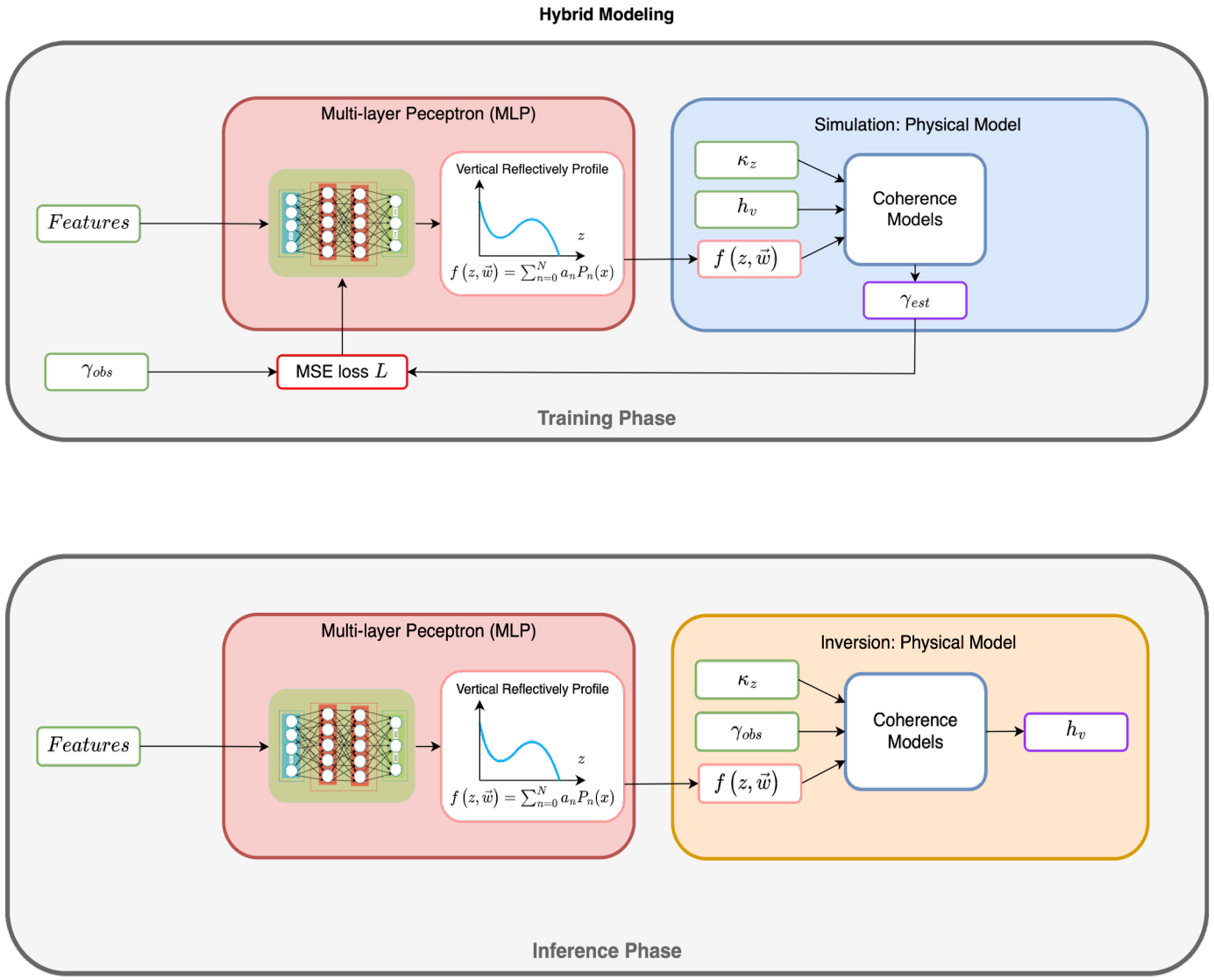
How many Legendre coefficients are required to approximate the function?



$$f(z,\vec{w}) = \sum_{n=0}^{N} a_n P_n(z) \simeq a_0 P_0(z) + a_1 P_1(z) + a_2 P_2(z) + a_3 P_3(z) + a_4 P_4(z) + \cdots$$

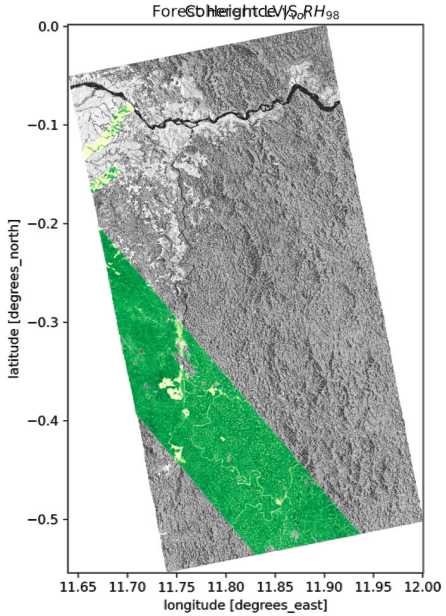


where $P_n(z)$: Legendre Polynomials

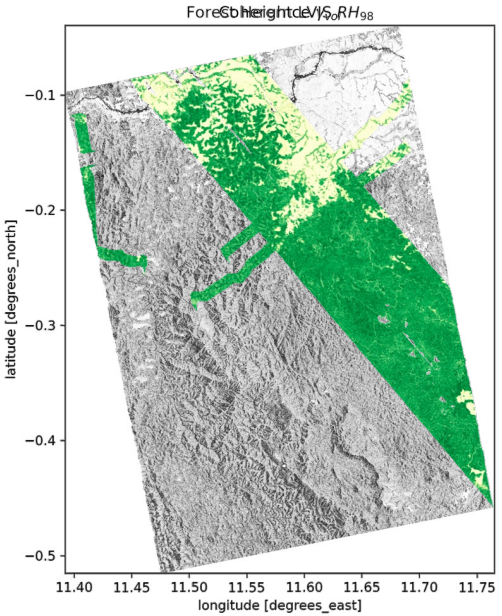


Integration of Machine Learning and Physical Models

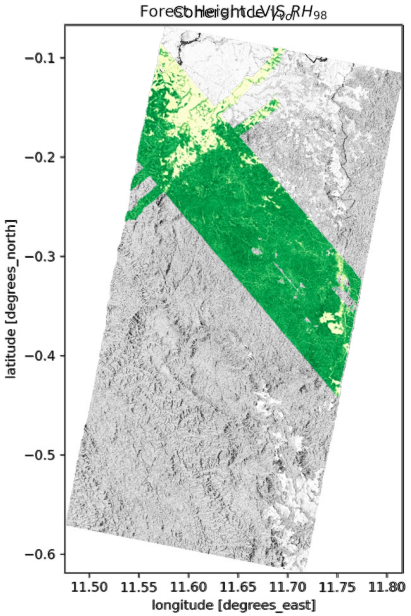
HoA: 52.45

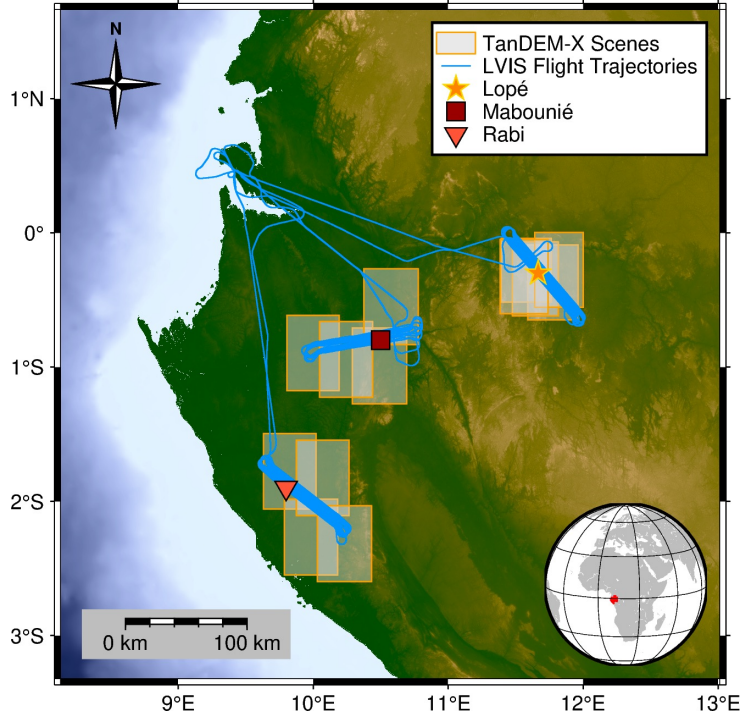


HoA: -65.22

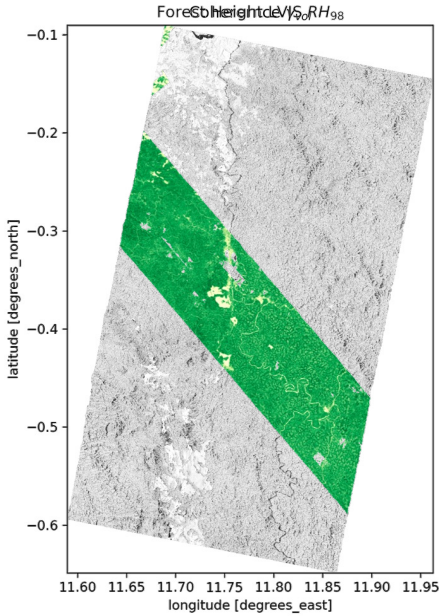


HoA: 86.34

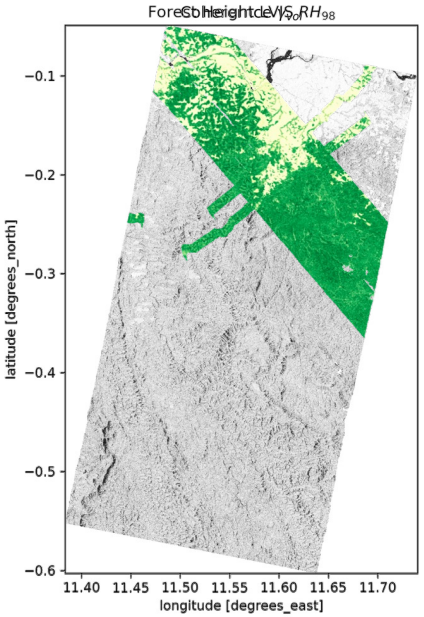


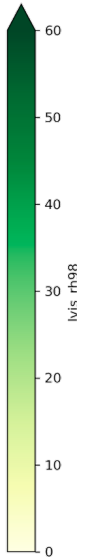


HoA: 94.89



HoA: 95.41

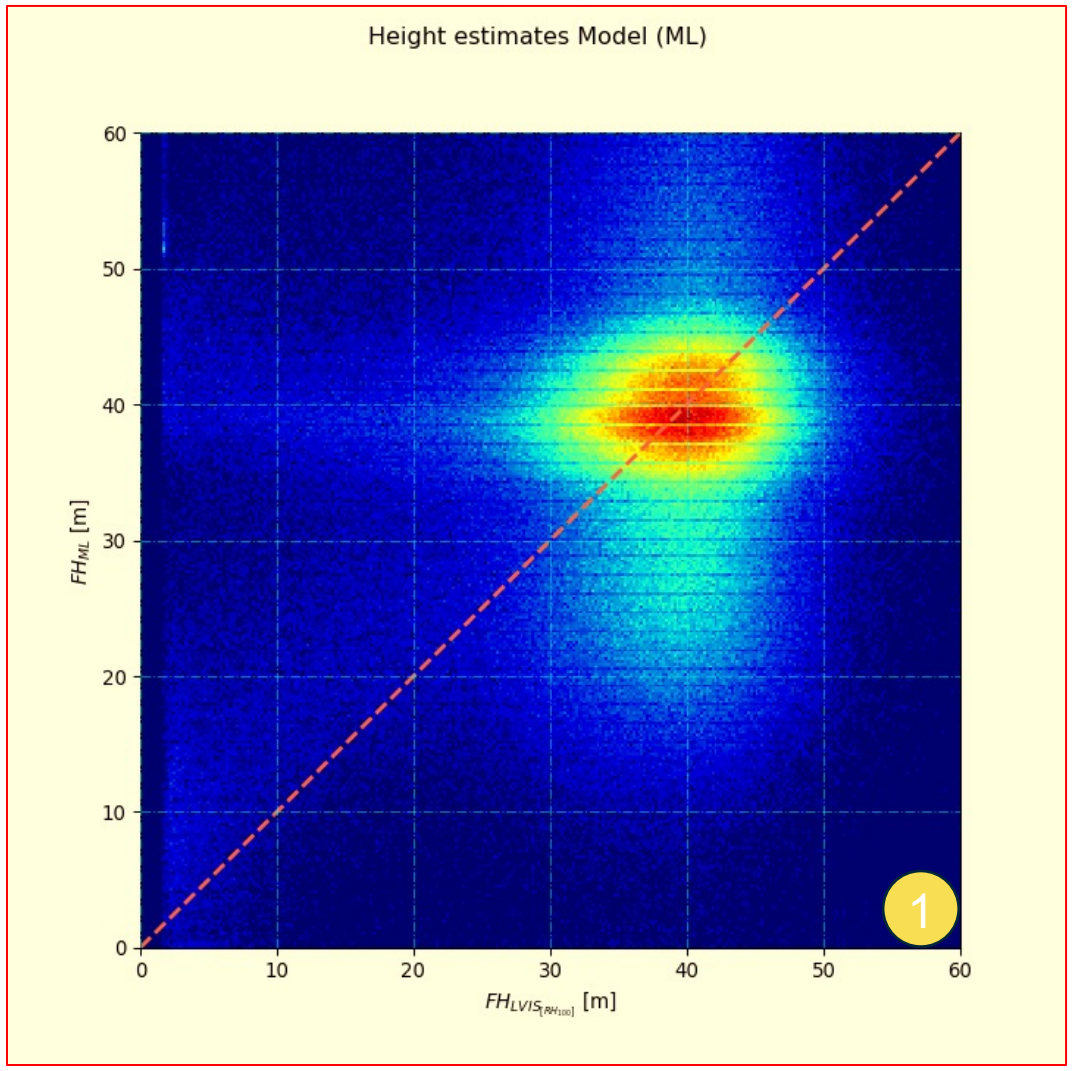


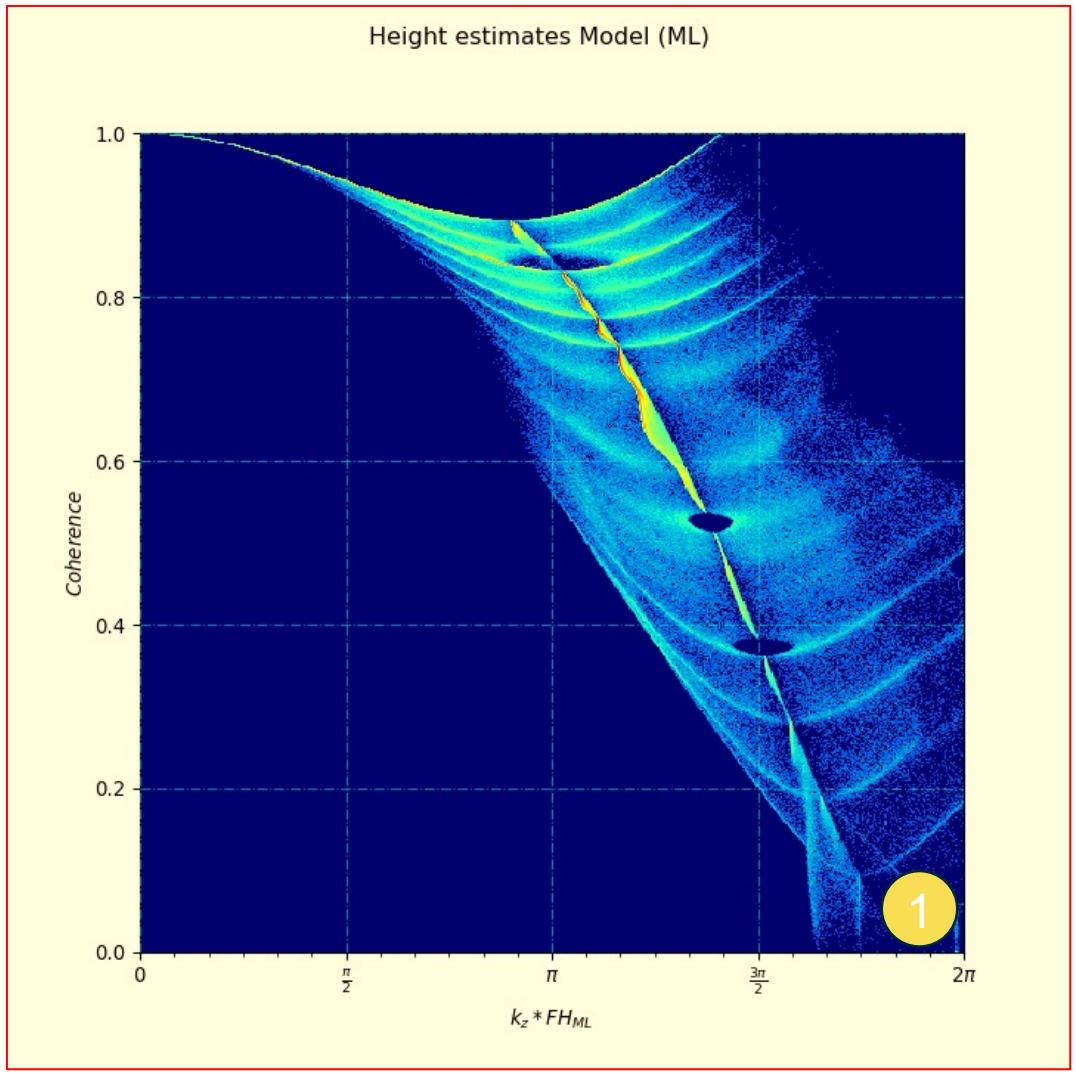


Dataset and Site Overview

- We focused our test over Lope with TanDEM-X Acquisitions with varying Height of Ambiguity (HoA) to test the models according to the following criteria, **Generalizability, Robustness, Large-Scale Estimation Capability.**

Results Explanation





HoA: 52.45

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1

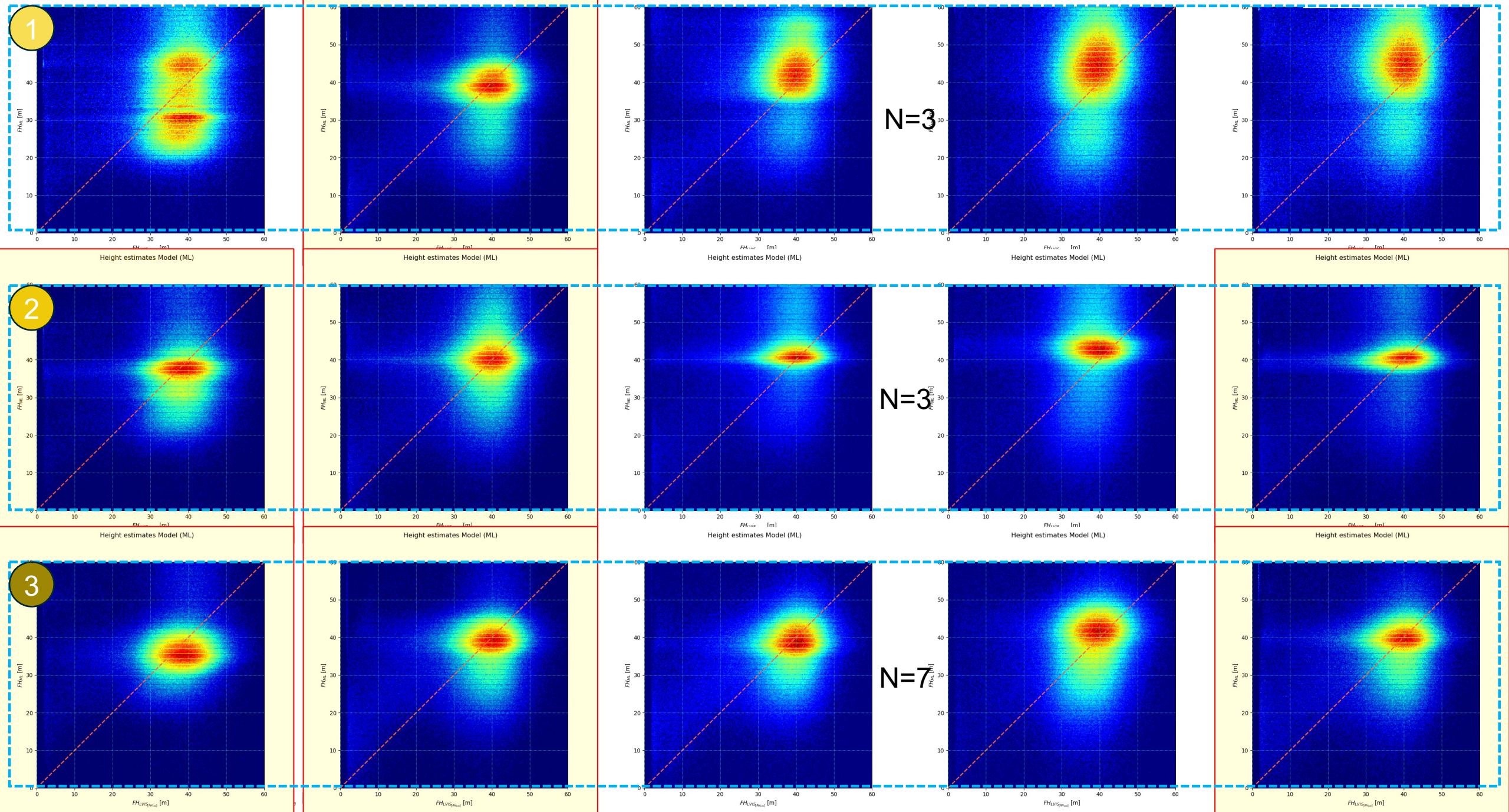
N=3

2

N=3

3

N=7



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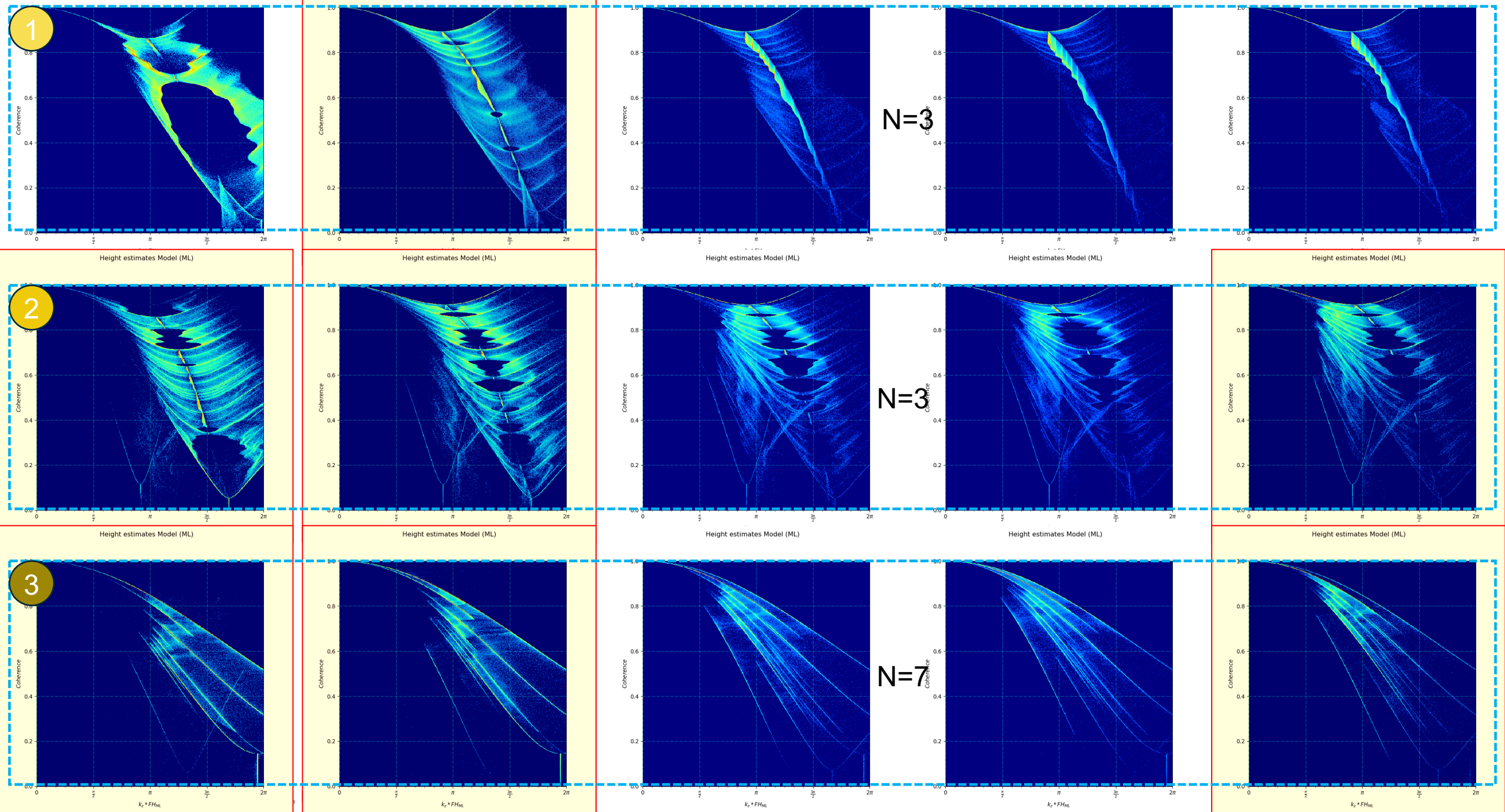

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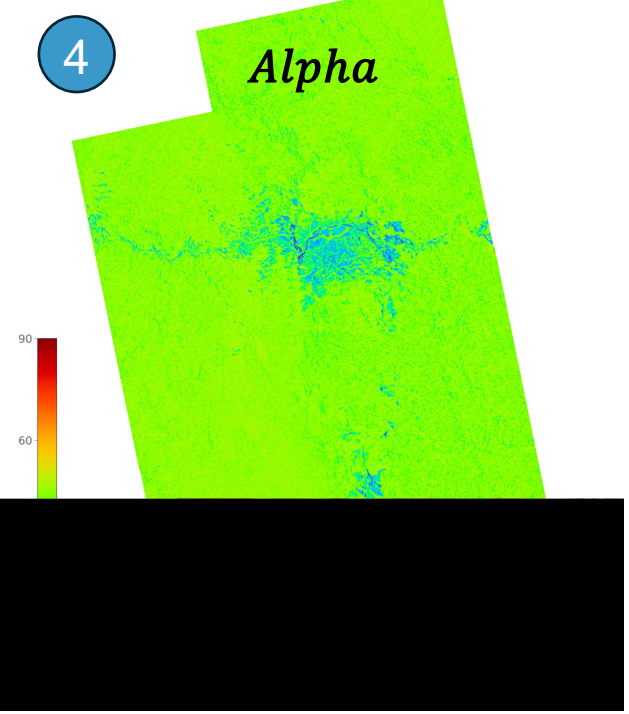

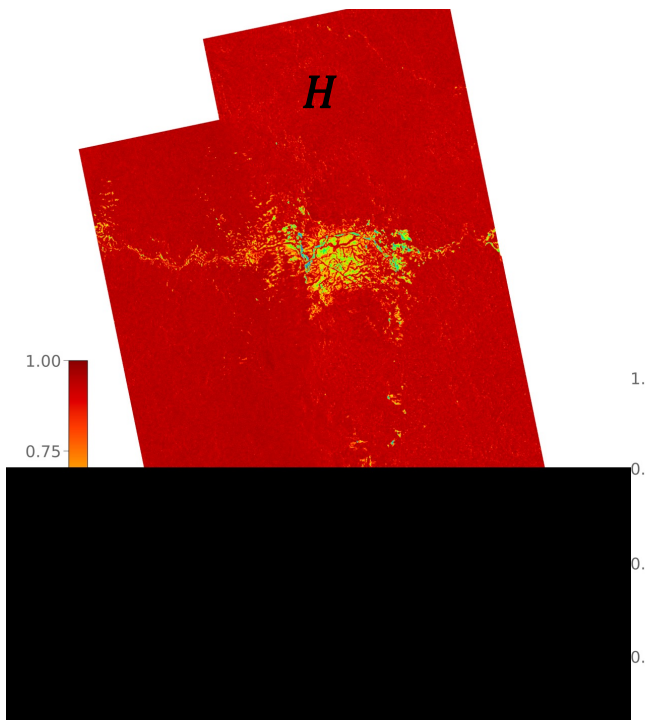

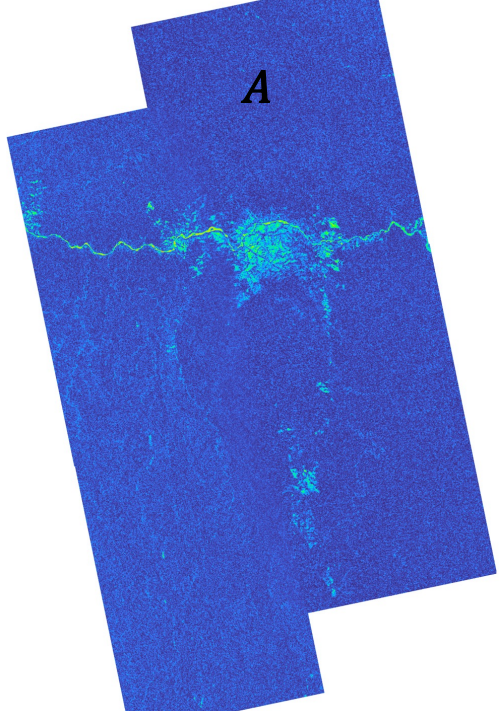

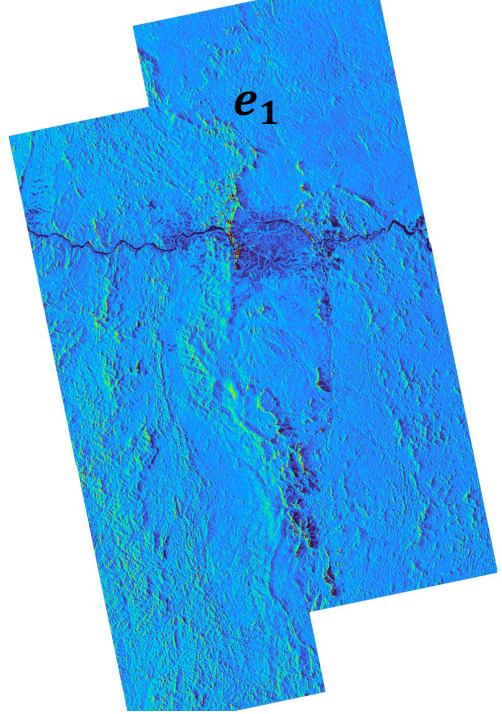

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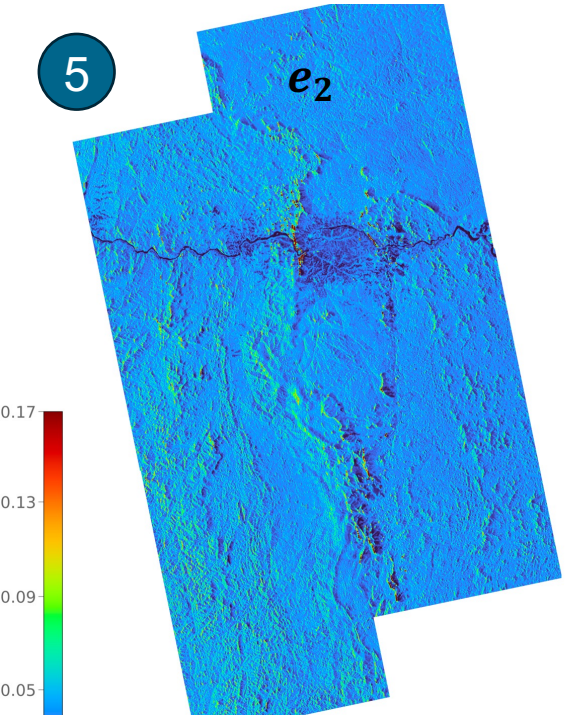
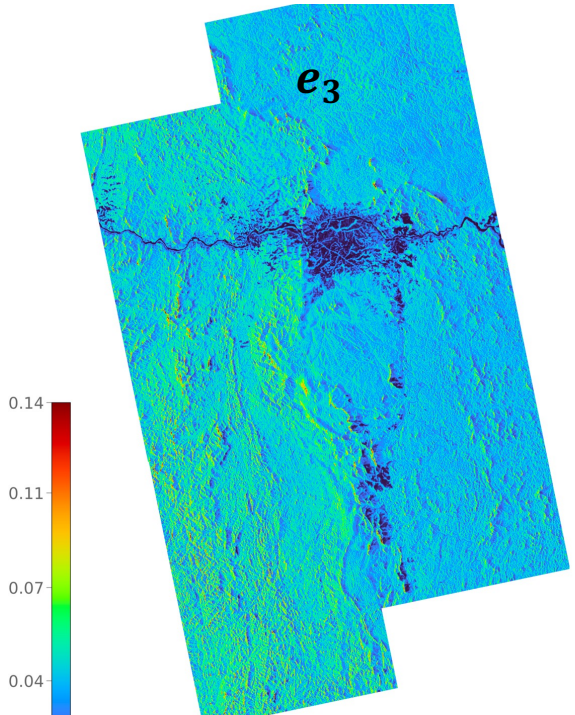
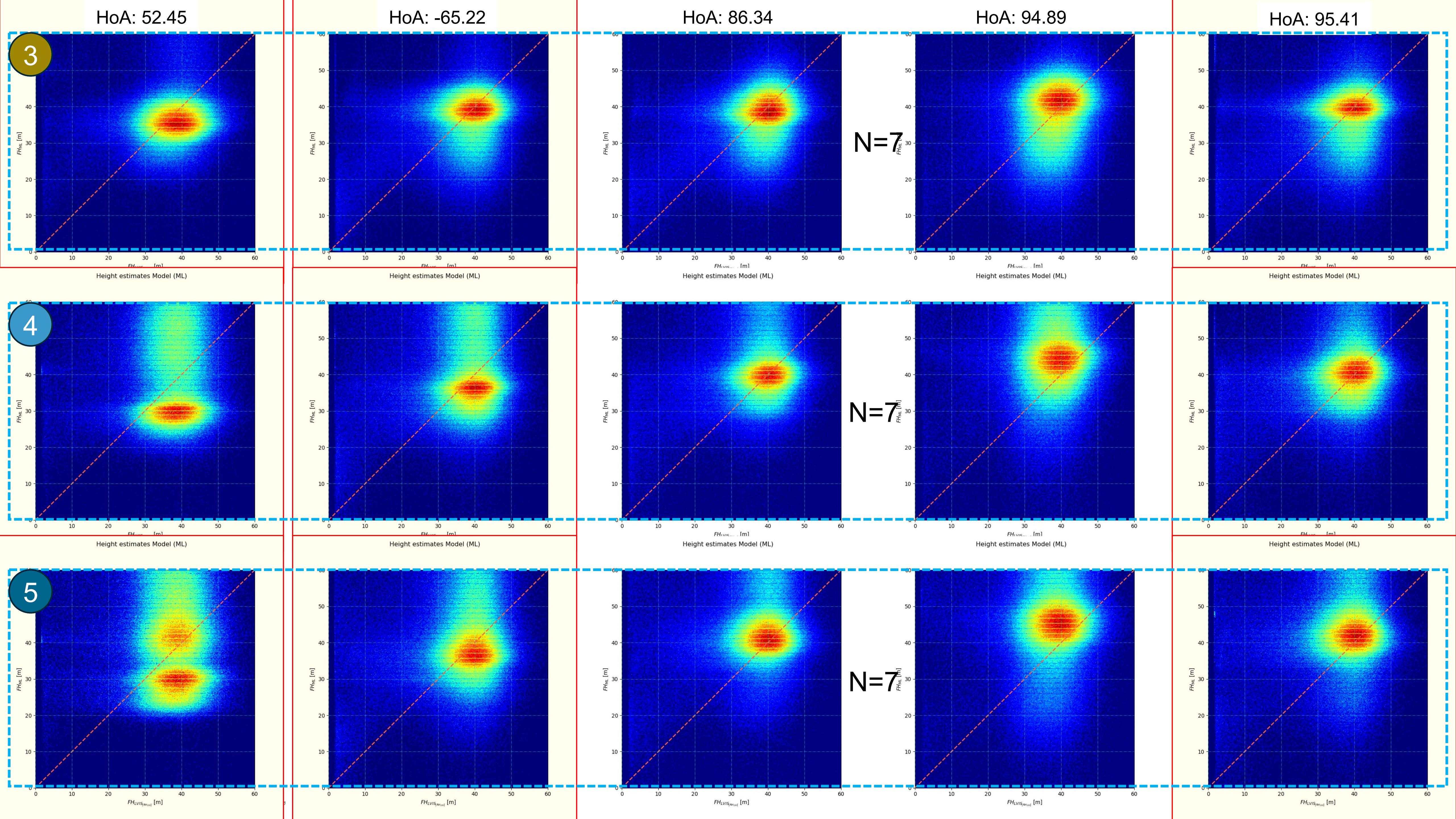




DATA INTEGRATION

- Use of ALOS2 Data
  - $H, A, Alpha$
  - $H, A, Alpha, e_1, e_2, e_3$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3
4
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N=7
N=7
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Height estimates Model (ML)

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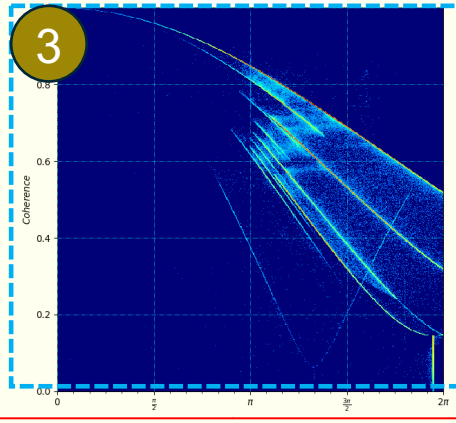

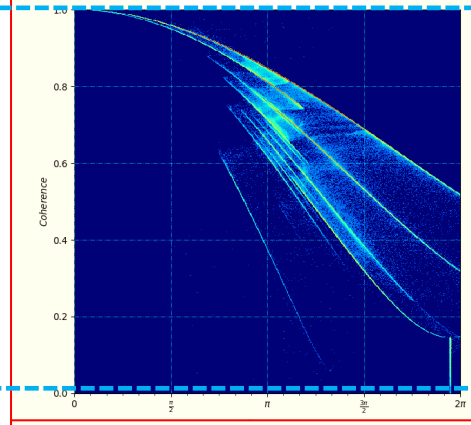

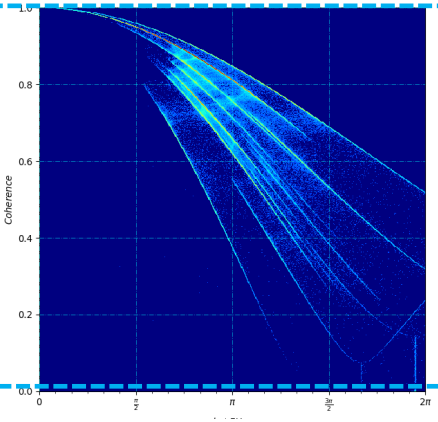

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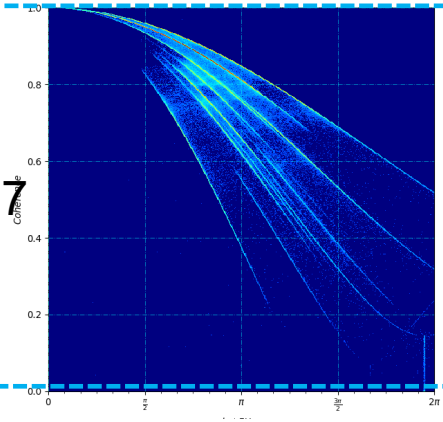

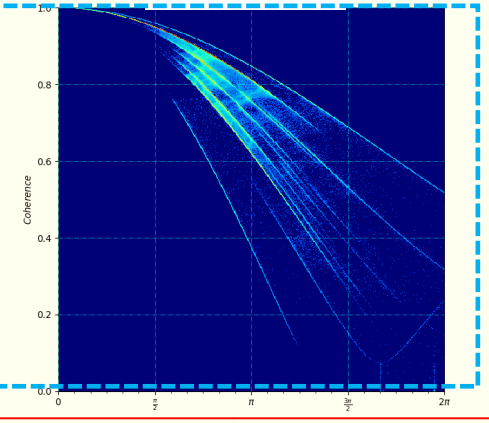

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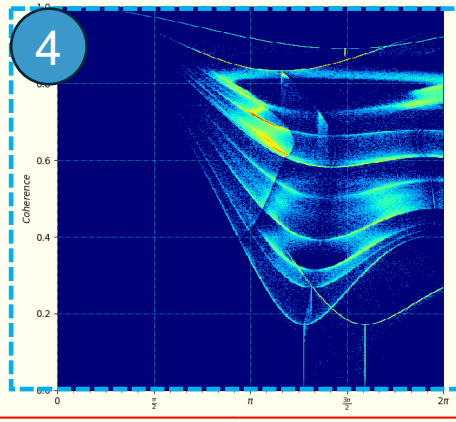

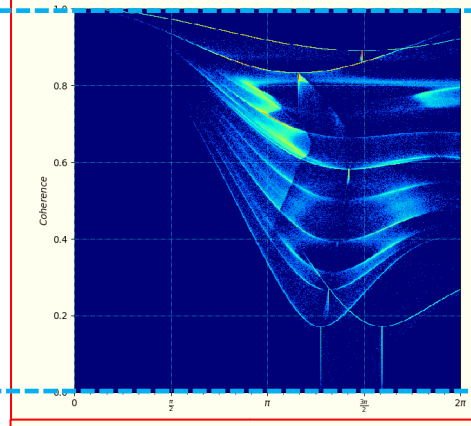

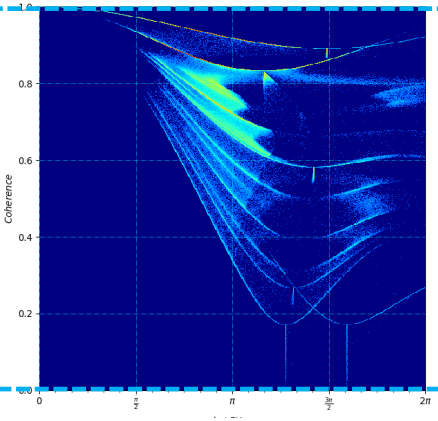

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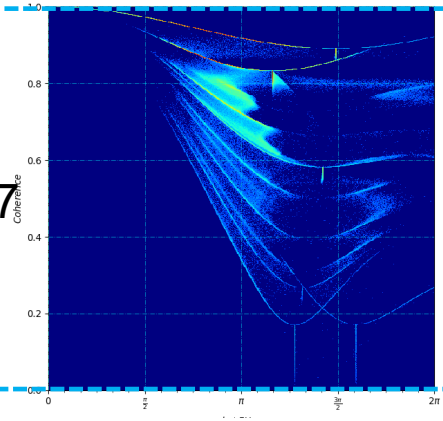

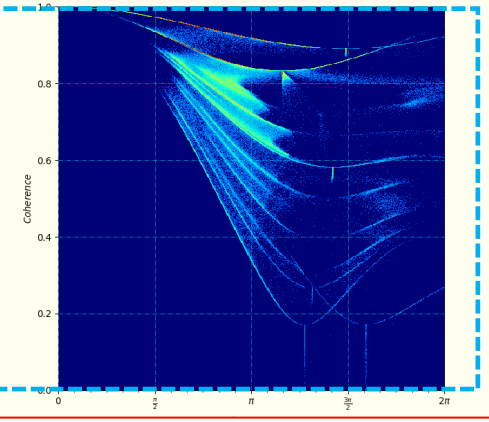

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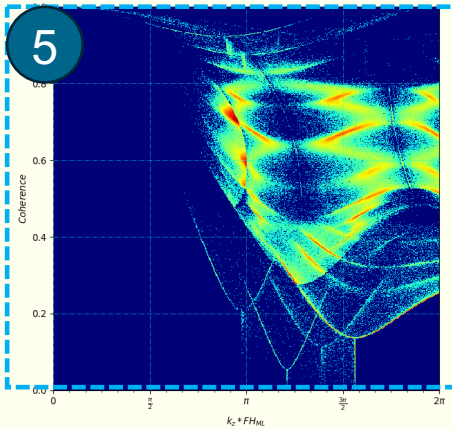

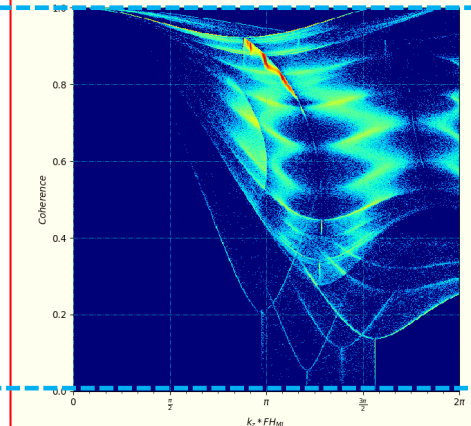

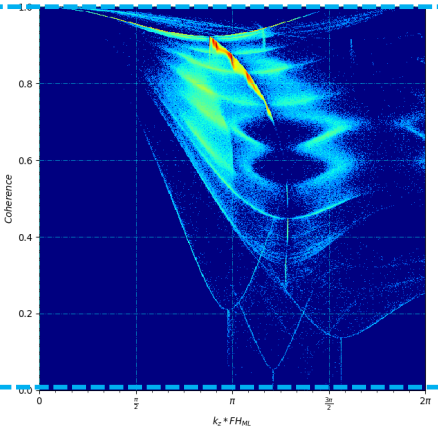

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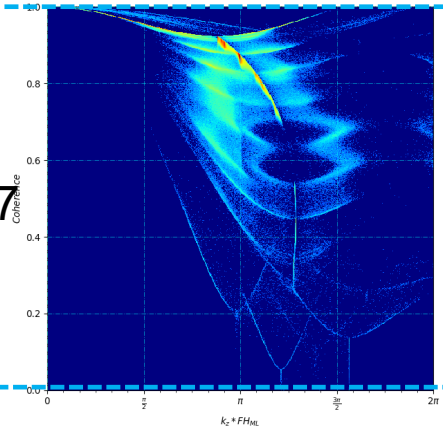

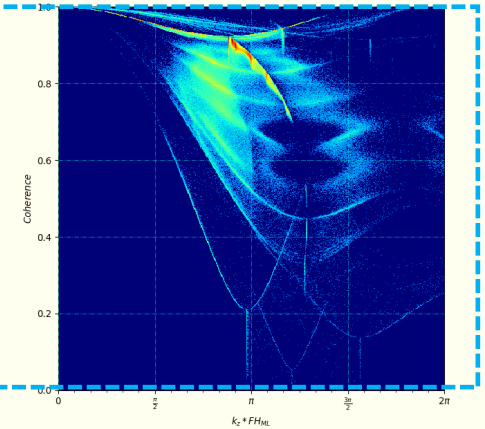

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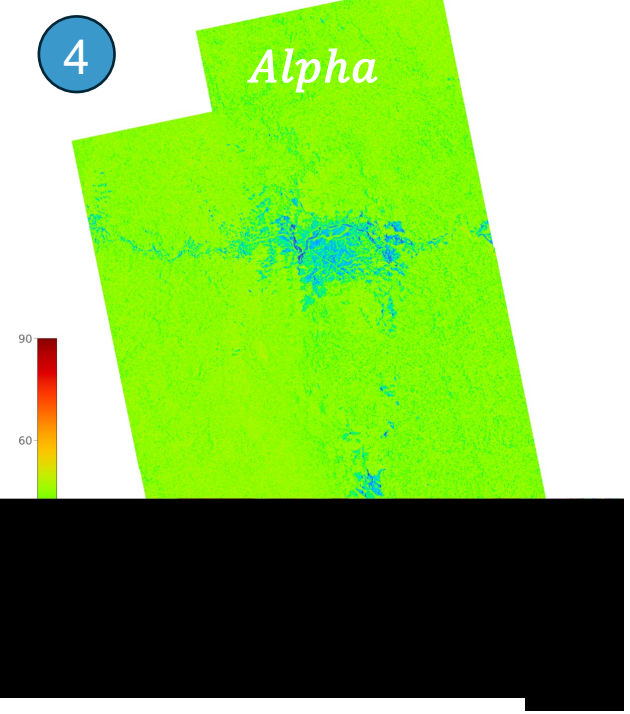
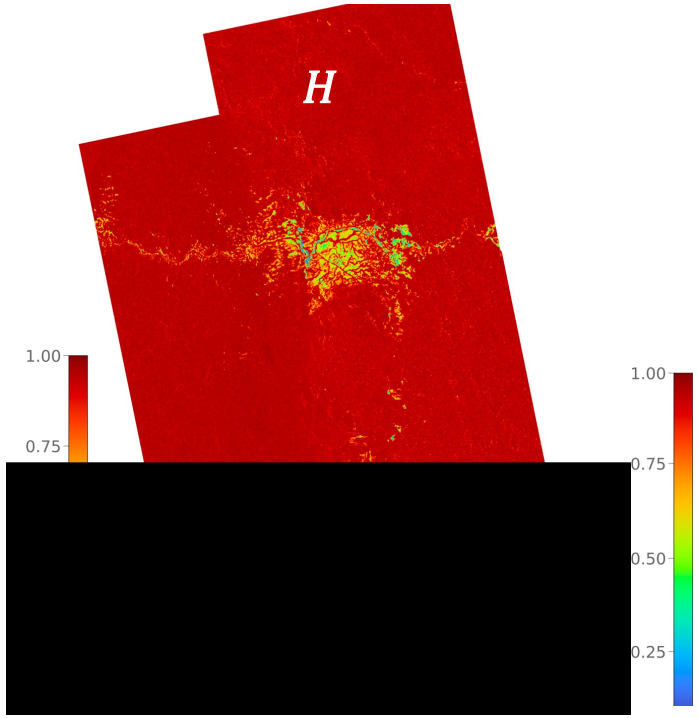
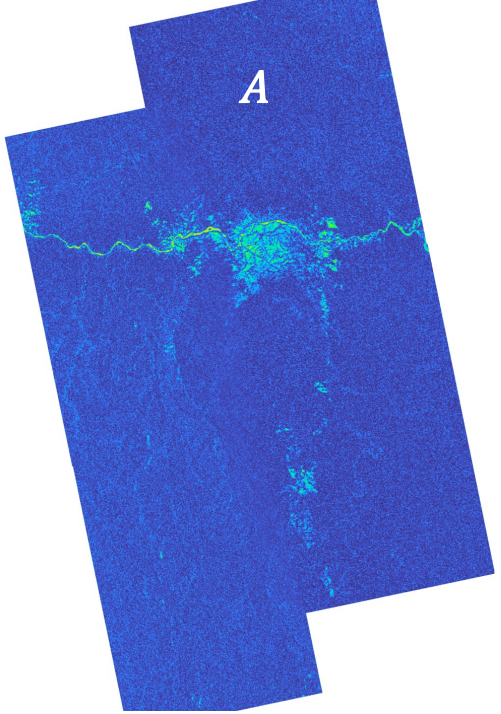






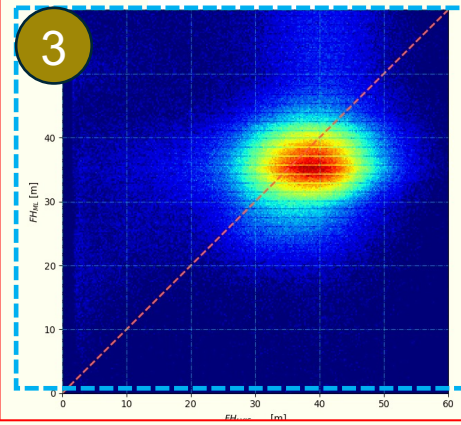
6

DATA INTEGRATION

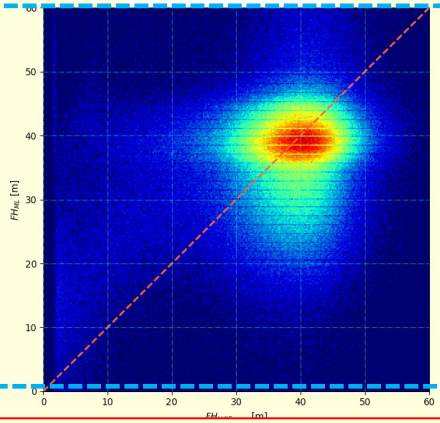
- Use of ALOS2 Data
  - $H, A, Alpha$
- Use of Landsat
  - Spectral bands

HoA: 52.45 | HoA: -65.22 | HoA: 86.34 | HoA: 94.89 | HoA: 95.41

3



Height estimates Model (ML)



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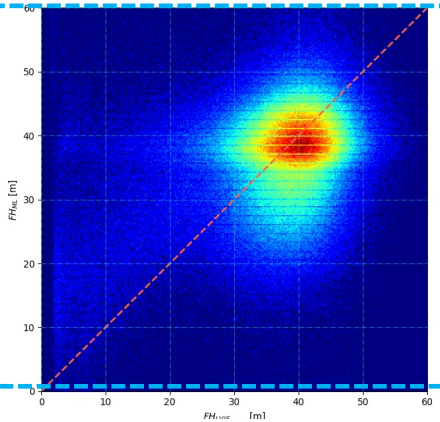

Height estimates Model (ML)

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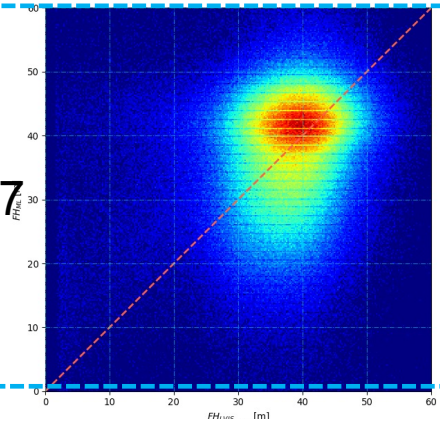
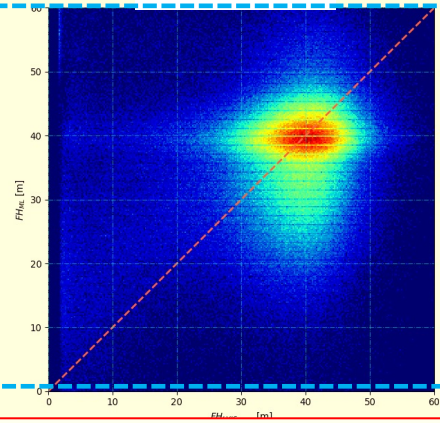
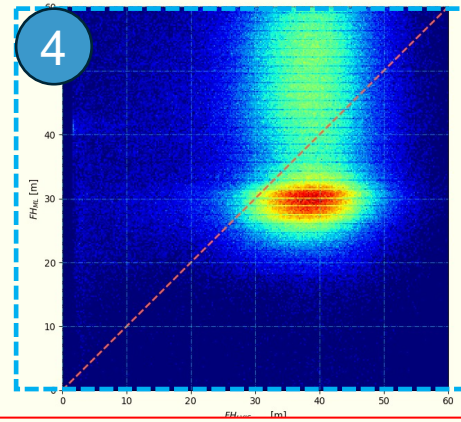


Height estimates Model (ML)

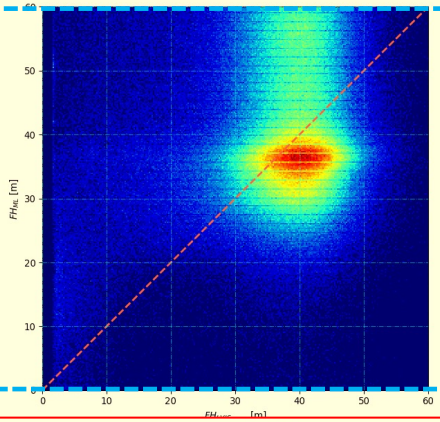


Height estimates Model (ML)

4



Height estimates Model (ML)



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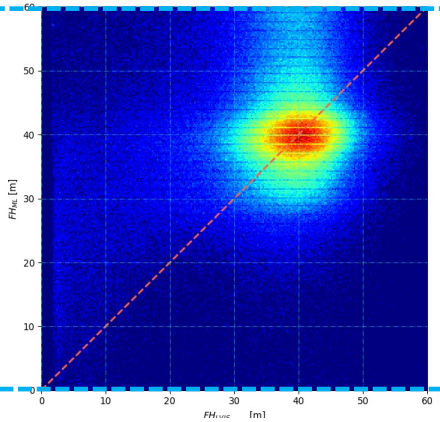

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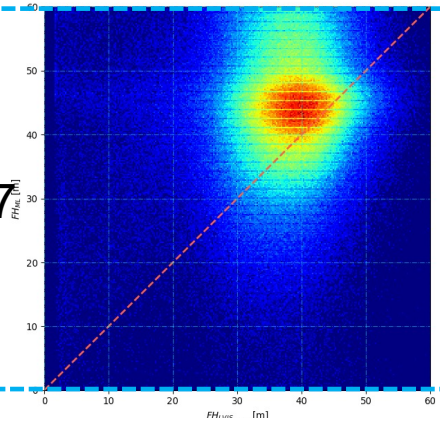

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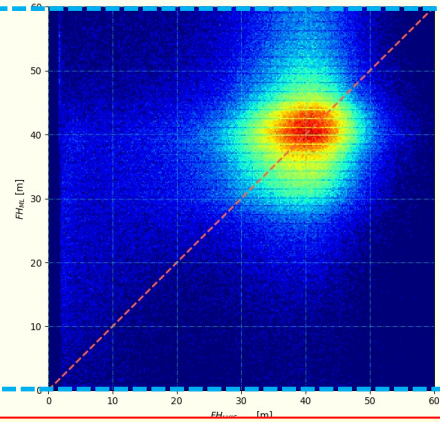
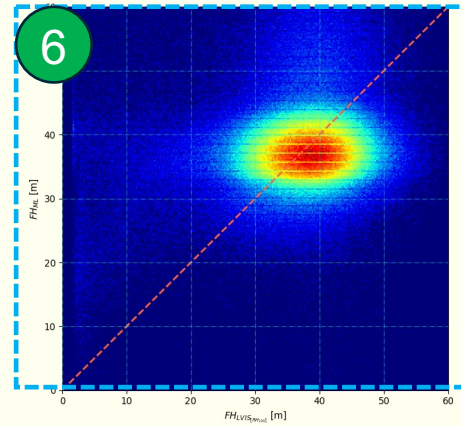
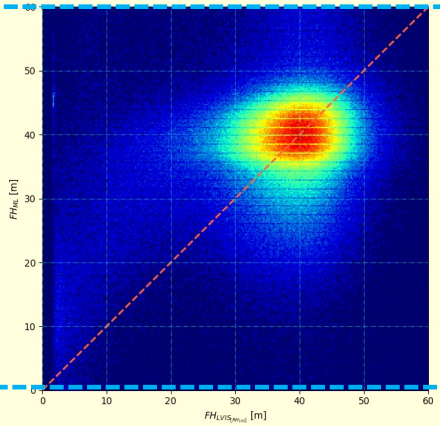
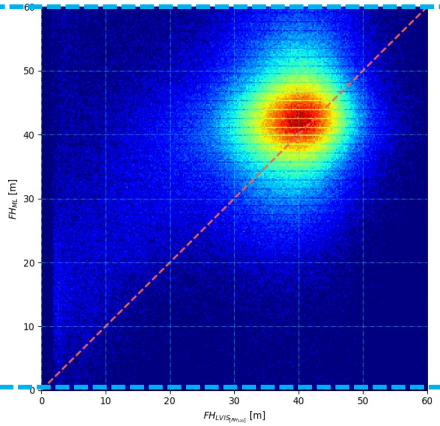


Height estimates Model (ML)

6







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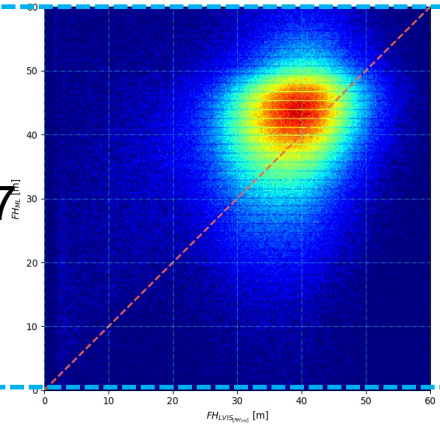
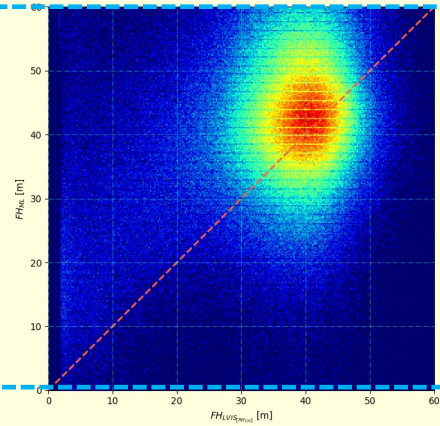




HoA: 52.45

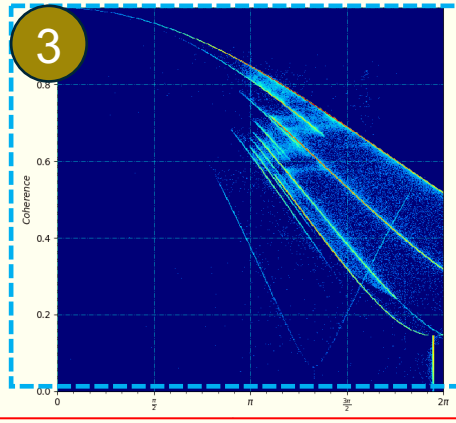
HoA: -65.22

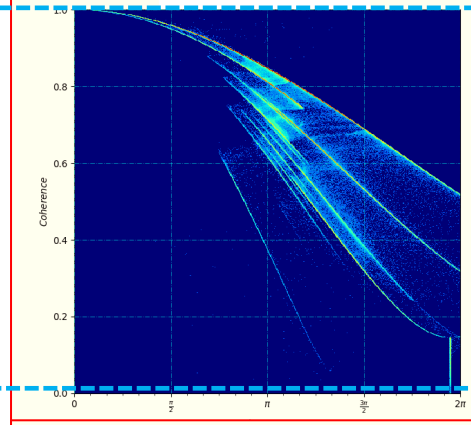
HoA: 86.34

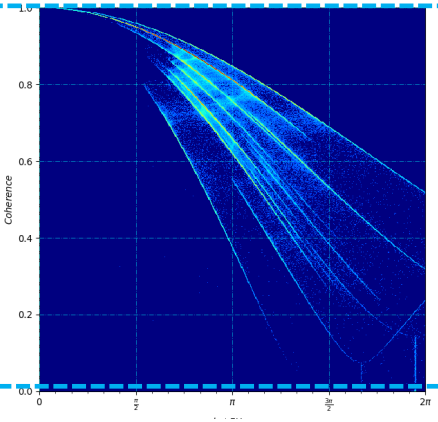
HoA: 94.89

HoA: 95.41

3







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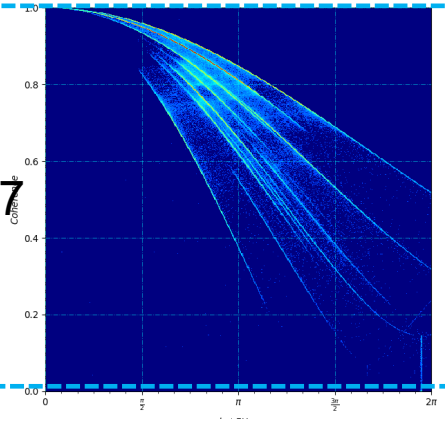

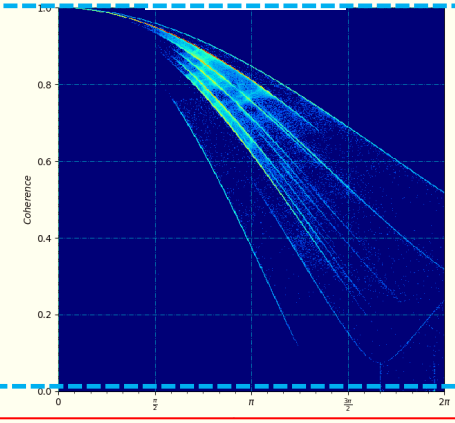

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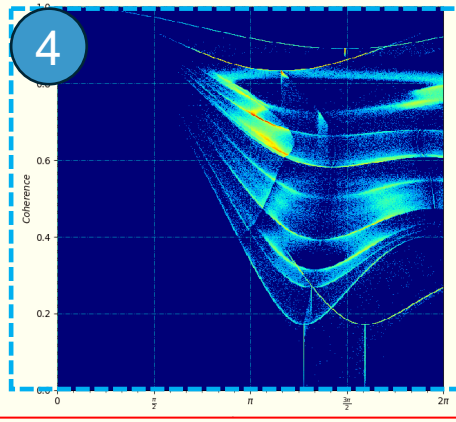

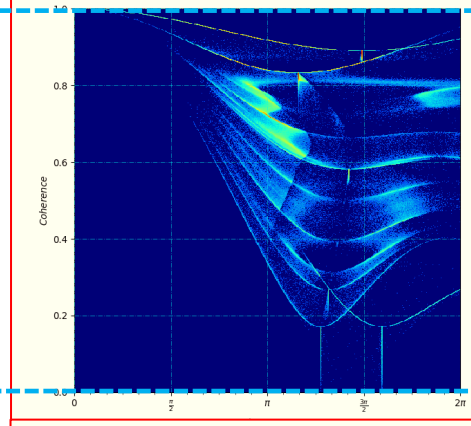

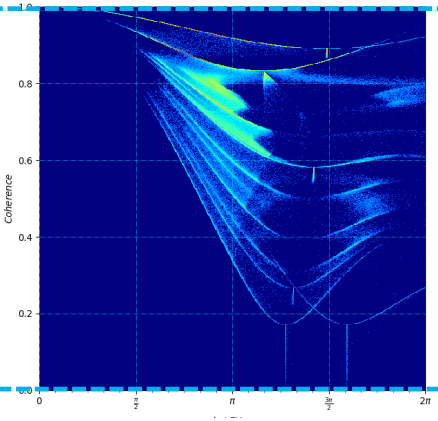

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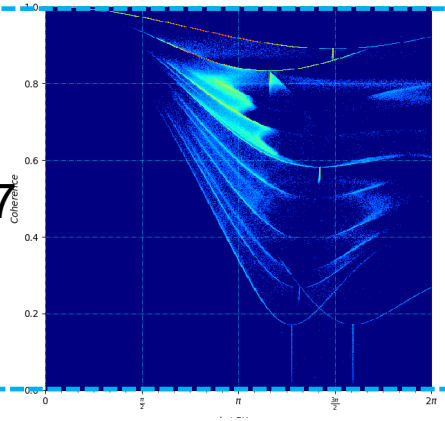

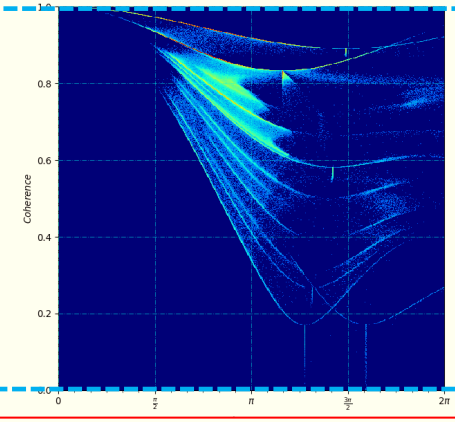

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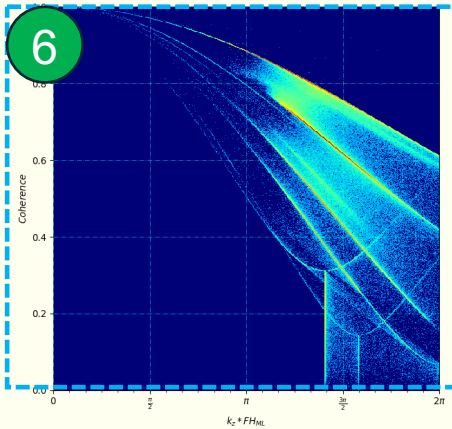

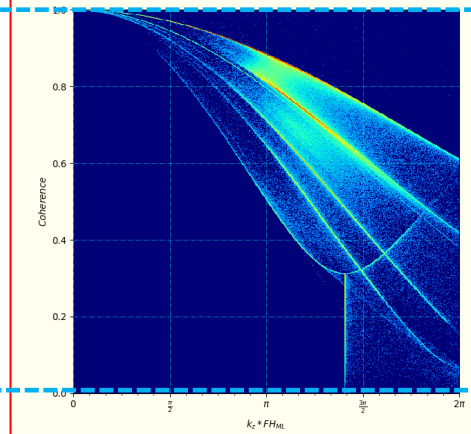

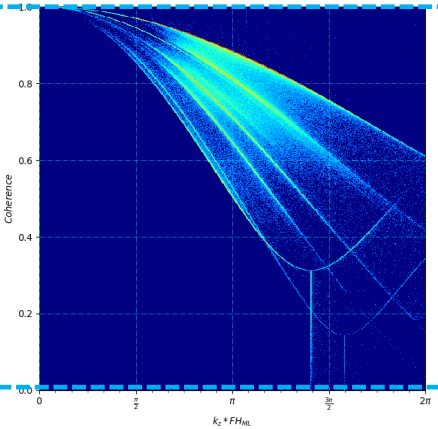

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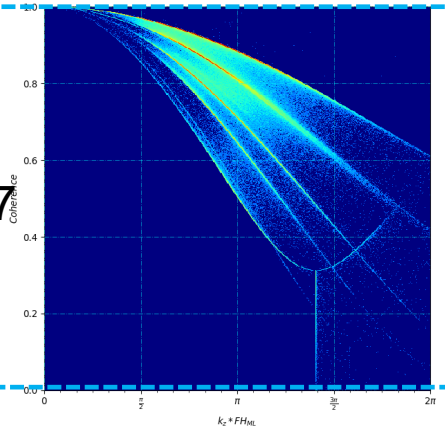
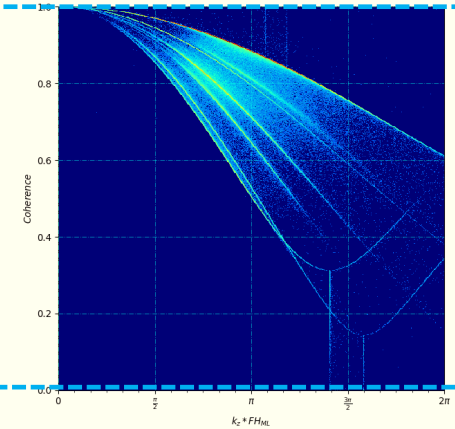
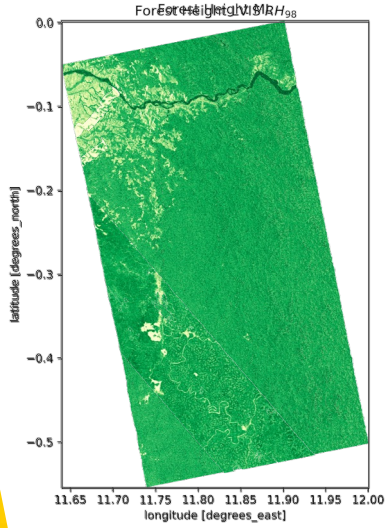
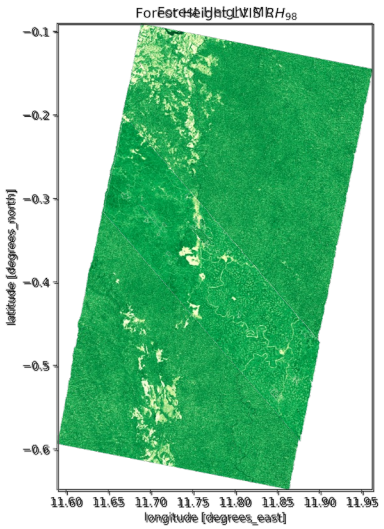


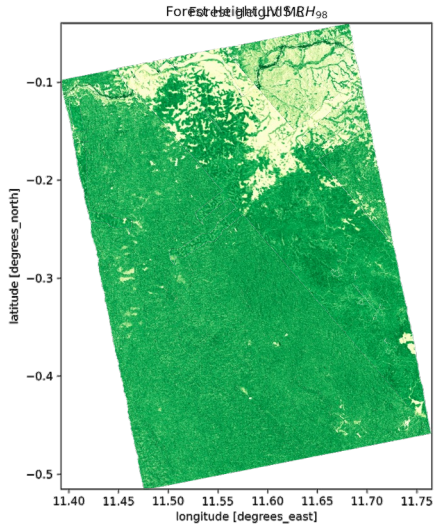


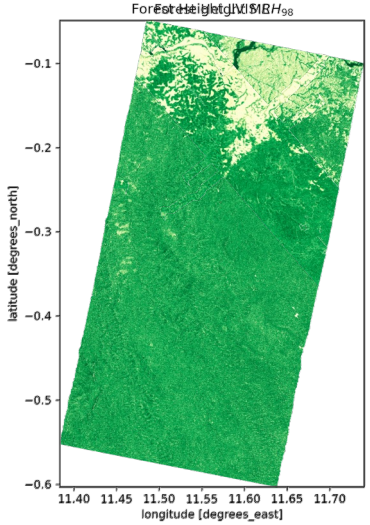
Summary of Key Points and Implications

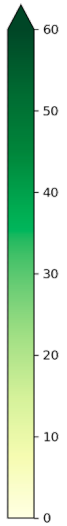
- **Hybrid Modeling Excellence:** Our novel hybrid modeling approach successfully integrates the domain-specific constraints of PM into ML. This enhances the model's robustness and generalizability while addressing the issue of explainability.
- **Importance of Legendre Coefficients:** The number (N) of Legendre coefficients is crucial for encapsulating the complexity of high-frequency components in the vertical reflectivity profile, thus playing a vital role in the model's performance.
- **Generalizability Enhancement:** To further improve the model's generalizability, the inclusion of diverse scenes with varying heights of ambiguity (vertical wavenumber) in the training dataset is imperative.
- **ALOS Data Analysis:** The ALOS data didn't lead to model improvement and even disrupted some underlying models. Overcoming this challenge might require expanding the dataset size and adopting a different strategy for ML data integration.
- **Landsat Data Contributions:** The inclusion of Landsat's multi-spectral images enriched our dataset, contributing to the diversity of the vertical reflectivity profile.





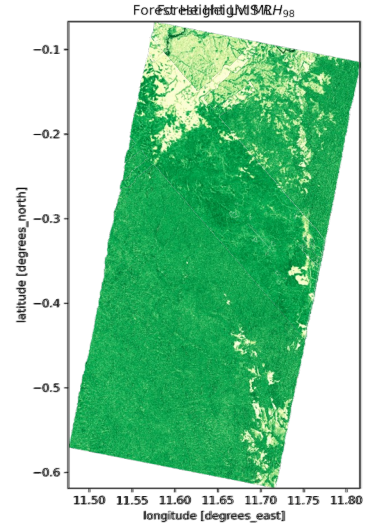






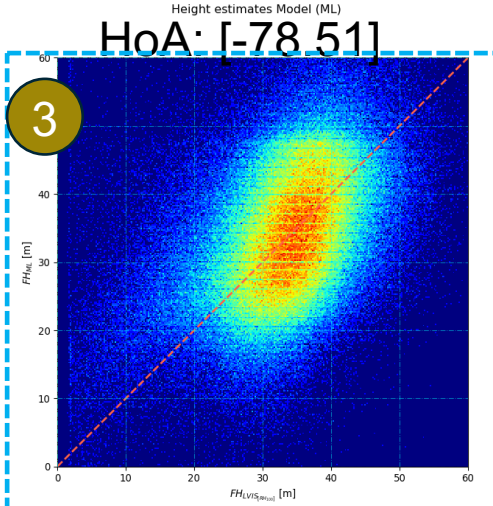
Thank You!

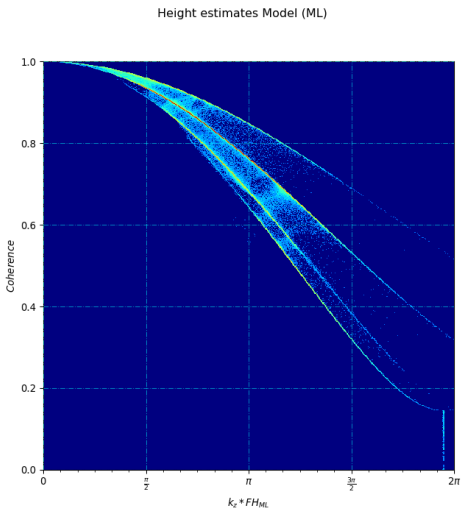
Looking forward for your questions!



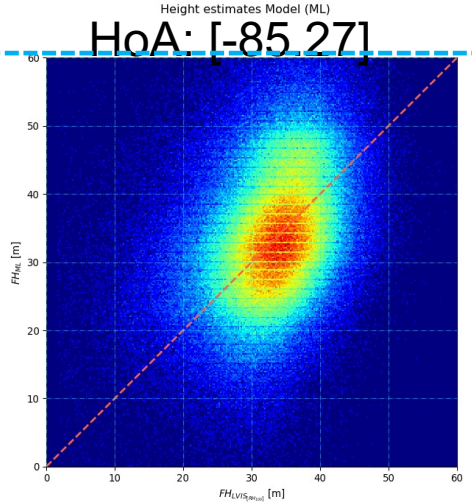
3

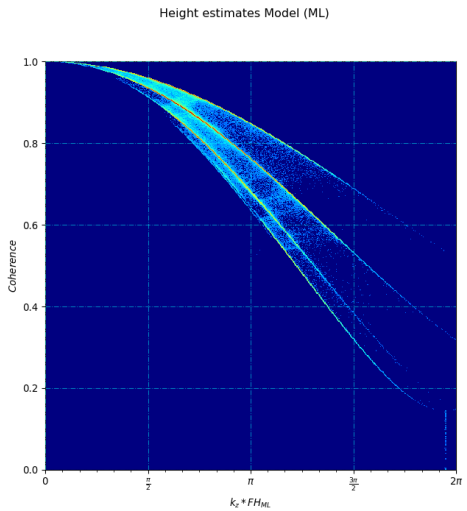
HoA: [-78.51]



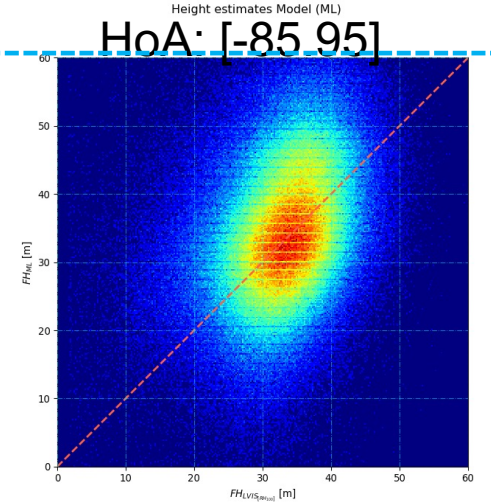


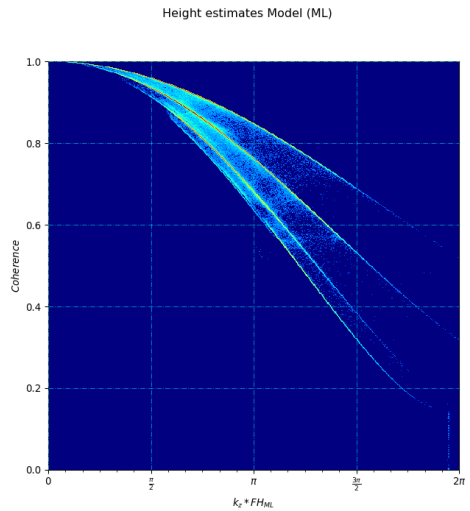
HoA: [-85.27]



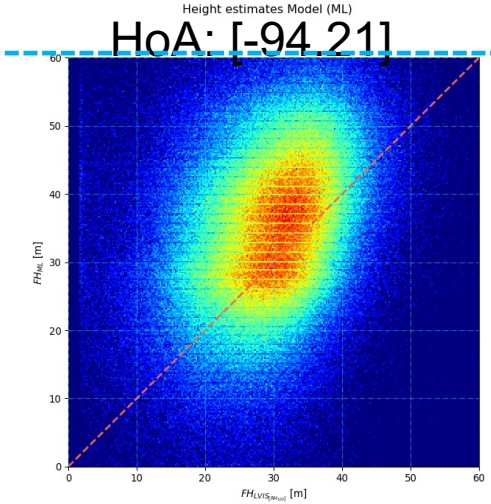


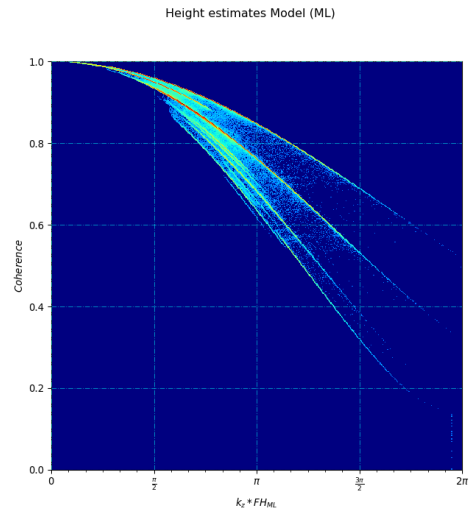
HoA: [-85.95]

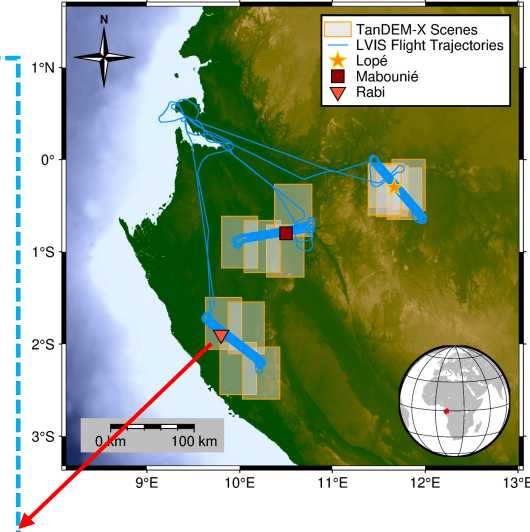




HoA: [-94.21]

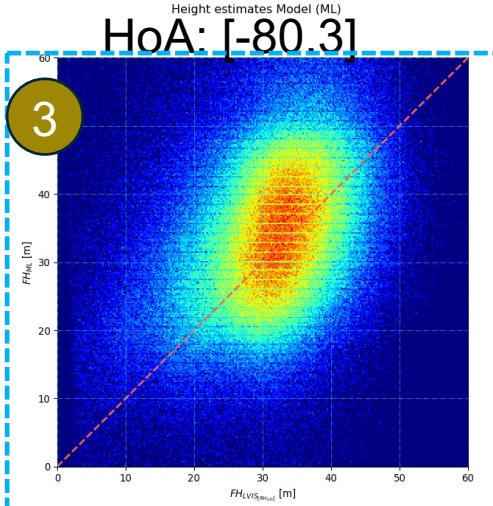


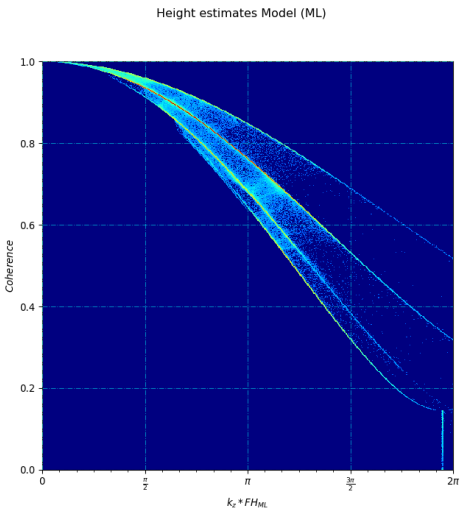




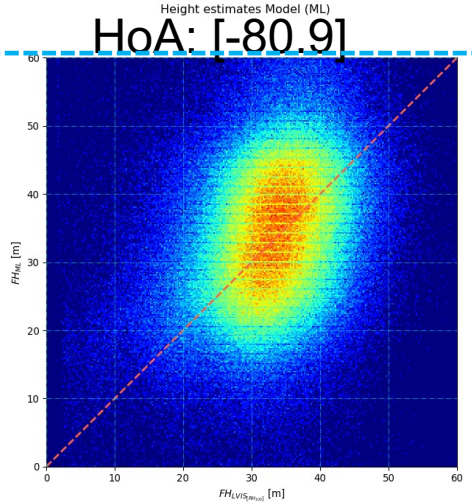
3

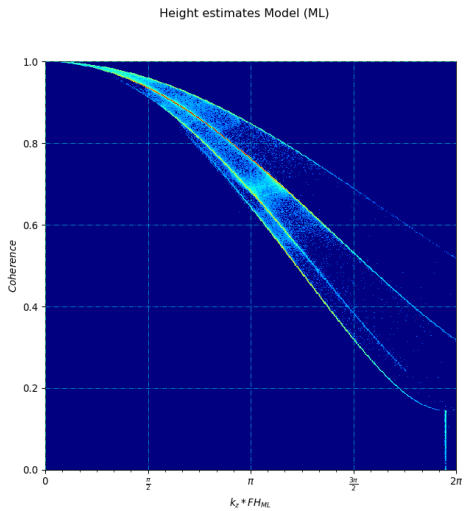
HoA: [-80.3]



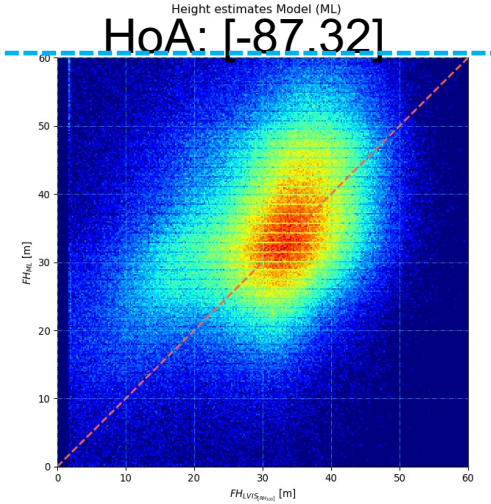


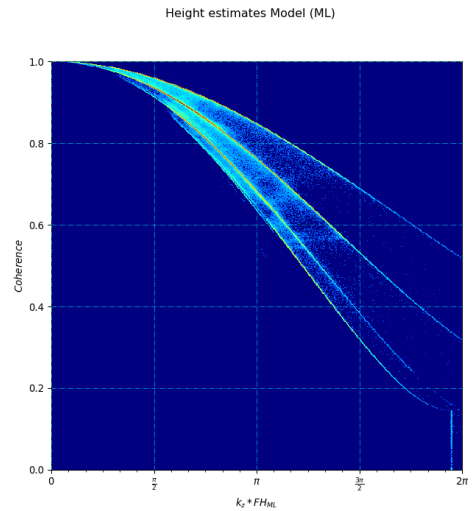
HoA: [-80.9]



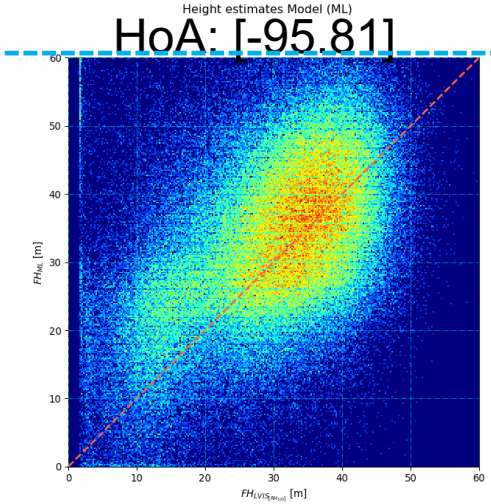


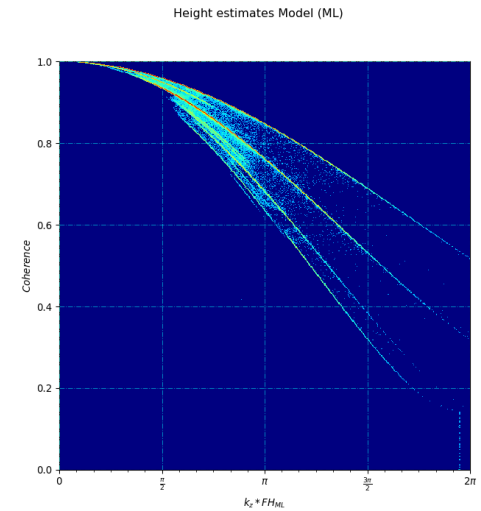
HoA: [-87.32]

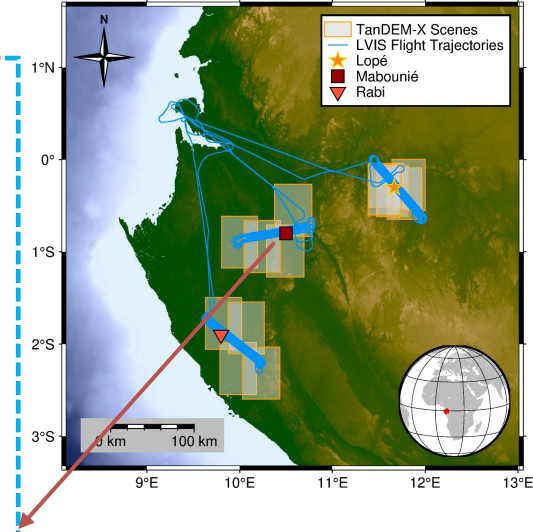




HoA: [-95.81]







Experiments Setup

No.	Legendre coefficients (N)	HoA for Training	Features (Inputs – Parameters)		
			TanDEM-X	ALOS2	Landsat
1	3	$[-65.22]$	$\kappa_z, \tilde{\gamma}_{vol}, \cdots, \theta_o, \theta_T$	–	–
2	3	$[-65.22]$	$\kappa_z, \tilde{\gamma}_{vol}, \cdots, \theta_o, \theta_T$	–	–
3	7	$[52.45, -65.22, 95.41]$	$\kappa_z, \tilde{\gamma}_{vol}, \cdots, \theta_o, \theta_T$	–	–
4	7	$[52.45, -65.22, 95.41]$	$\kappa_z, \tilde{\gamma}_{vol}, \cdots, \theta_o, \theta_T$	$H, A, Alpha$	–
5	7	$[52.45, -65.22, 95.41]$	$\kappa_z, \tilde{\gamma}_{vol}, \cdots, \theta_o, \theta_T$	$H, A, Alpha, e_1, e_2, e_3$	–
6	7	$[52.45, -65.22, 95.41]$	$\kappa_z, \tilde{\gamma}_{vol}, \cdots, \theta_o, \theta_T$	–	$spectral\ bands$

a) Data Selection: Selection of HoA for training

b) Coefficient Setup: A varying quantity (N) of Legendre coefficients

c) Data Integration: TanDEM-X, ALOS2, Landsat

1 2 3

4 5 6

HoA: 52.45

HoA: -65.22

HoA: 86.34

HoA: 94.89

HoA: 95.41

1

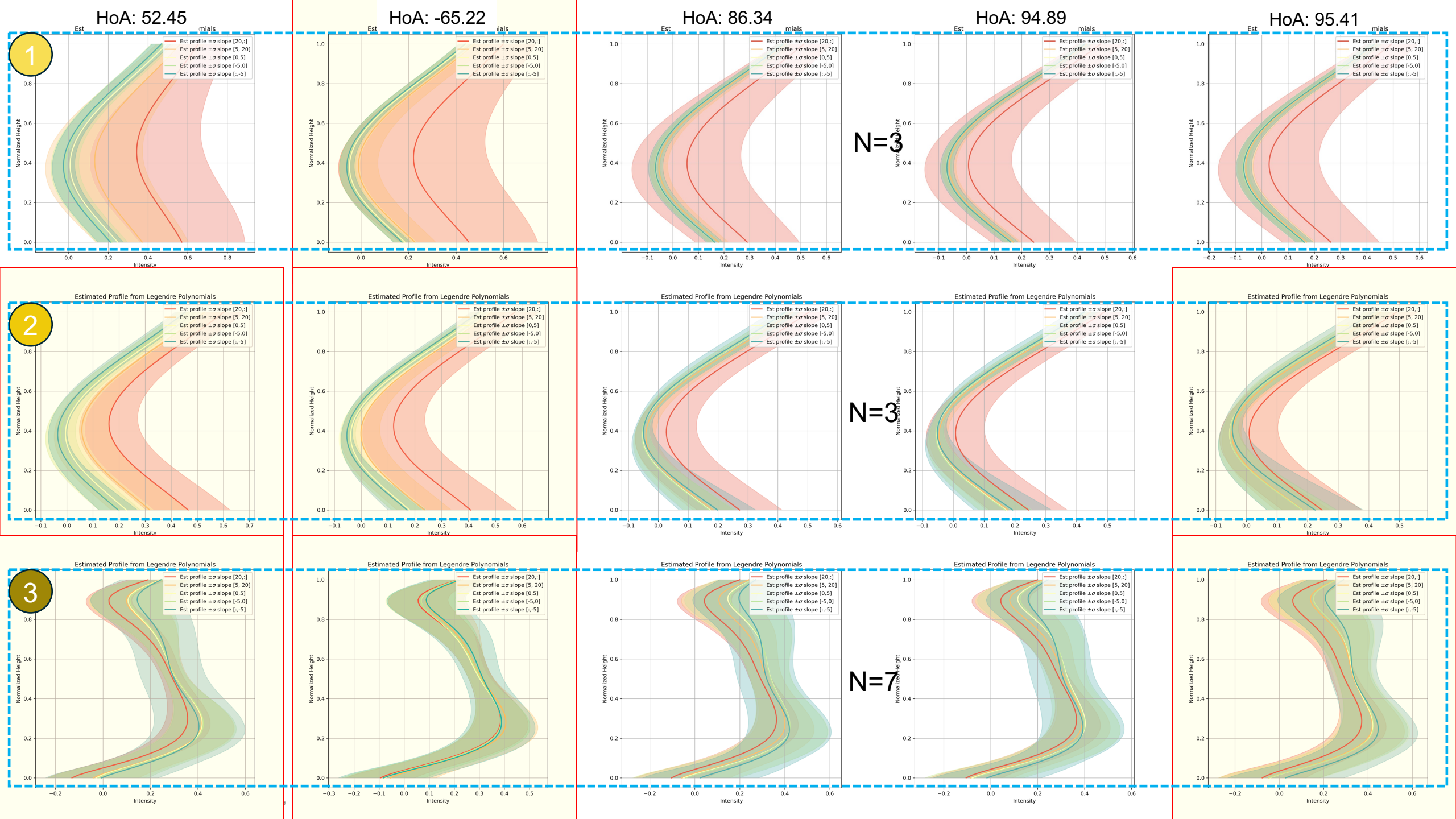
2

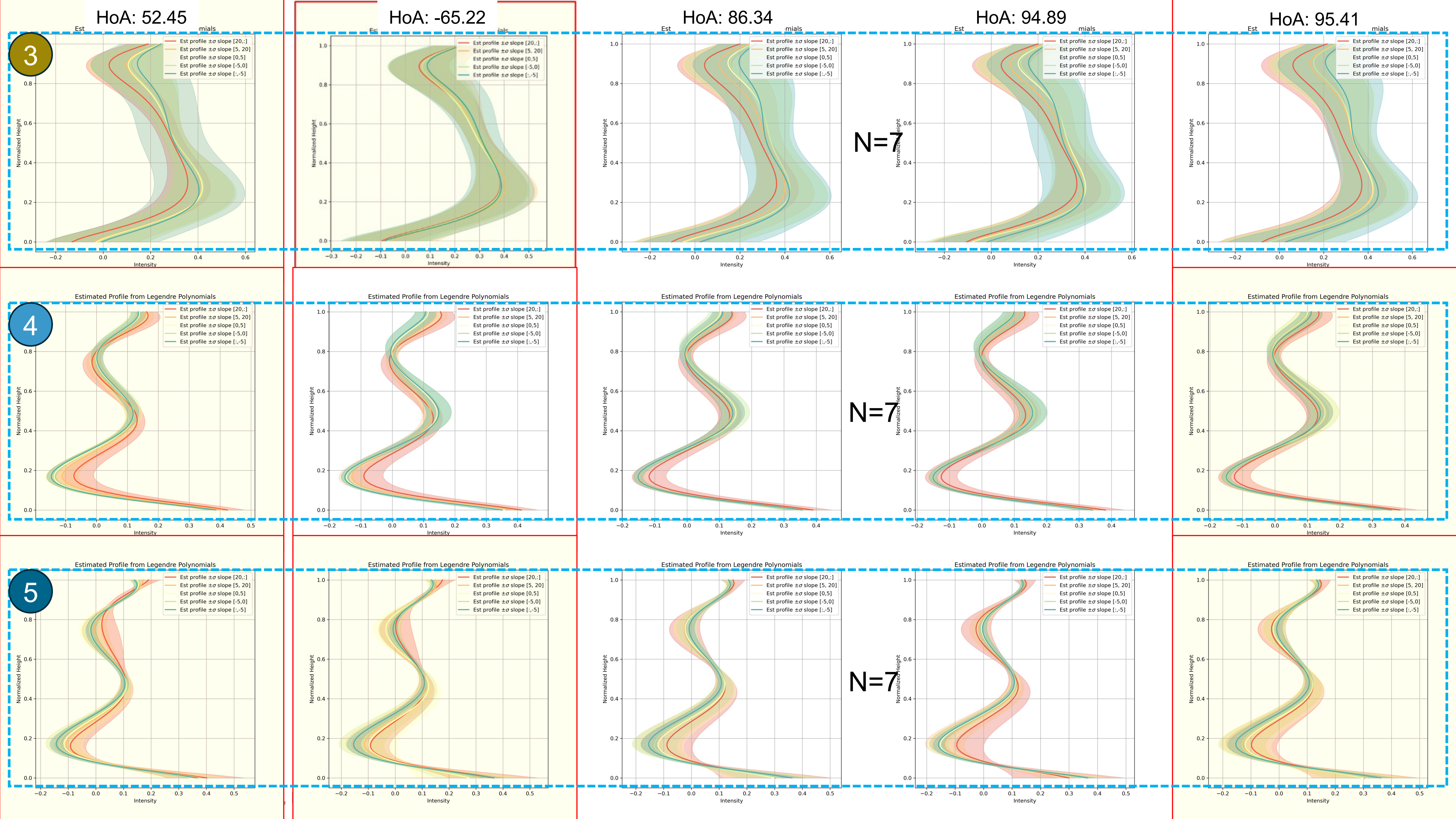
3

N=3

N=3

N=7





HoA: 52.45
HoA: -65.22
HoA: 86.34
HoA: 94.89
HoA: 95.41
3
4
5
N=7
N=7
N=7
Estimated Profile from Legendre Polynomials
Est profile ±σ slope [20,:]
Est profile ±σ slope [5, 20]
Est profile ±σ slope [0,5]
Est profile ±σ slope [-5,0]
Est profile ±σ slope [:,-5]
Normalized Height
Intensity

HoA: 52.45

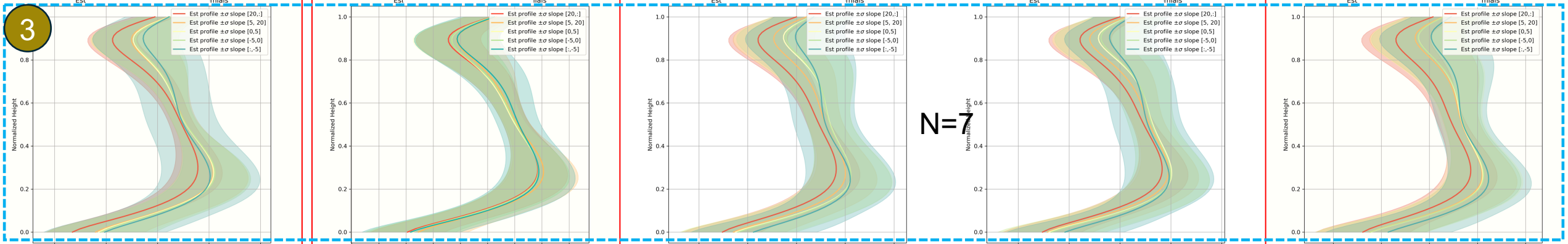
HoA: -65.22

HoA: 86.34

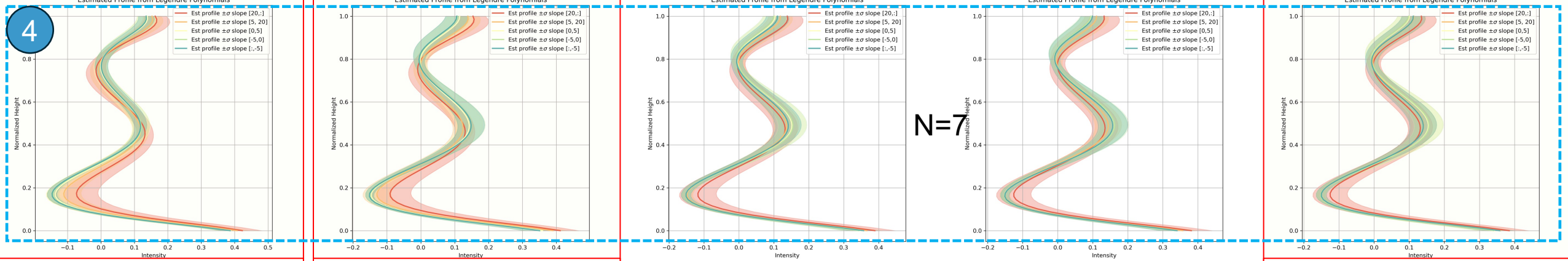
HoA: 94.89

HoA: 95.41

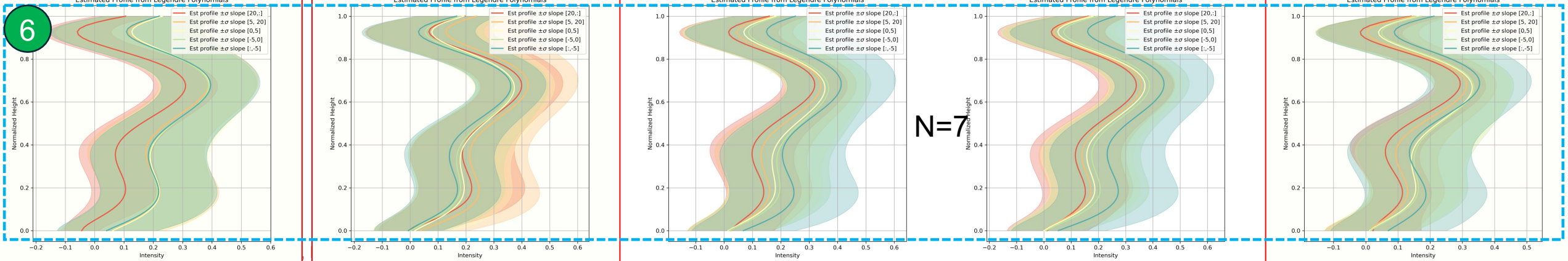
3



4



6

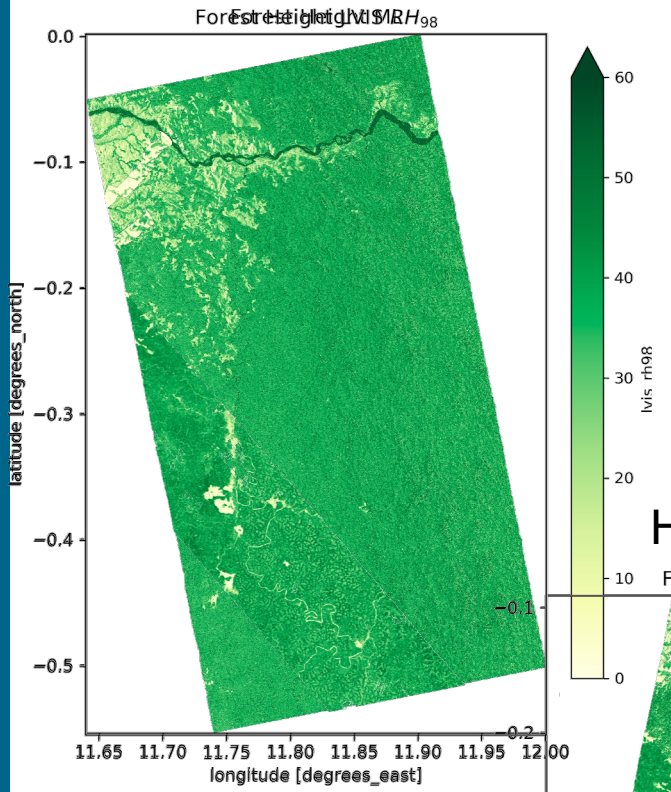


N=7

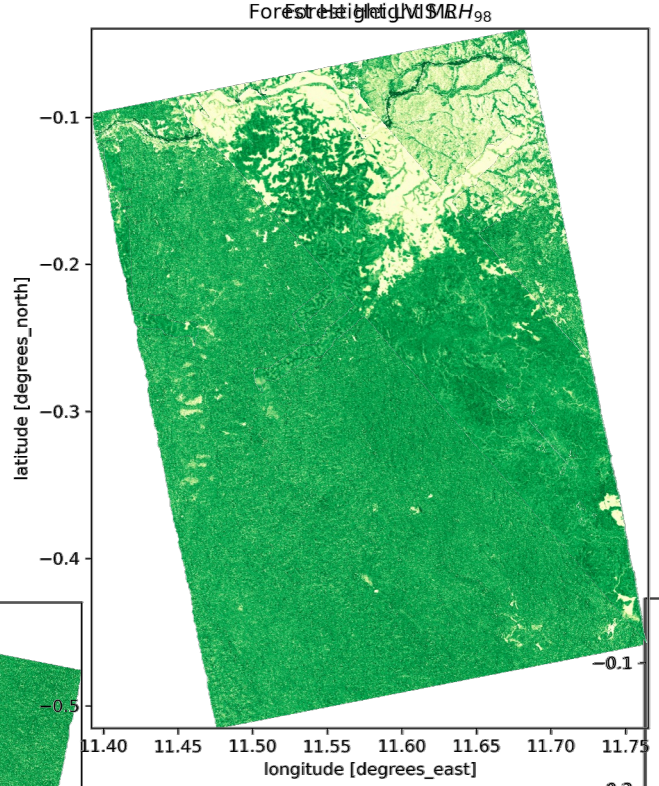
N=7

N=7

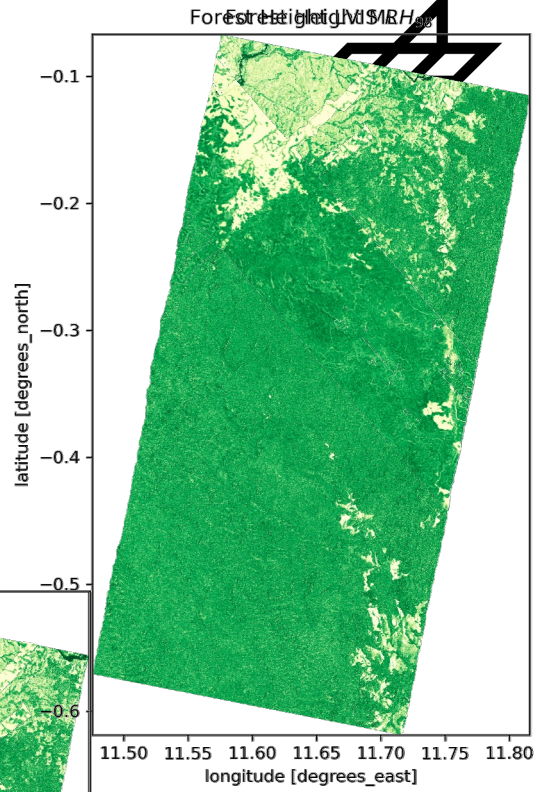
HoA: 52.45



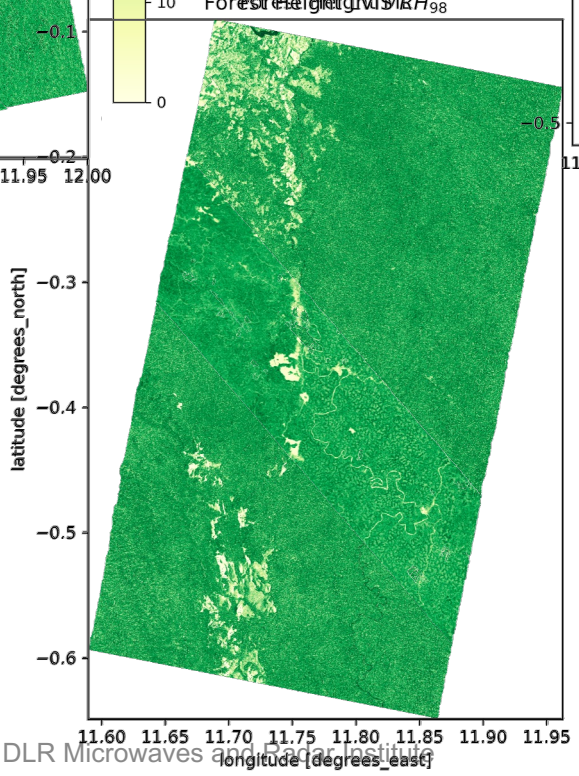
HoA: -65.22



HoA: 86.34



HoA: 94.89



HoA: 95.41