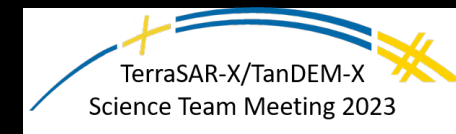
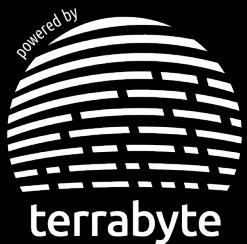


# Synergizing AI and Physical Models for TanDEM-X InSAR Forest Height Estimation: A Hybrid Approach over the Gabon

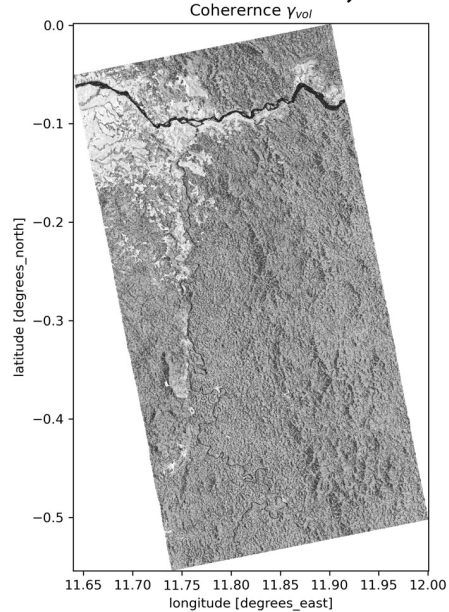
Islam Mansour, Ronny Hänsch,  
Irena Hajsek and Kostas Papathanassiou



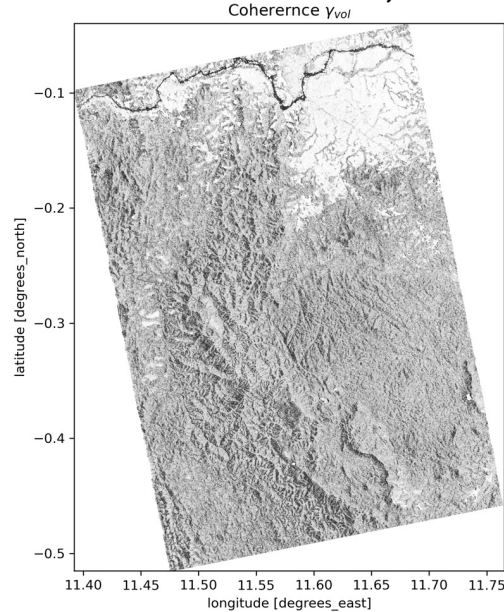
**ETH** zürich



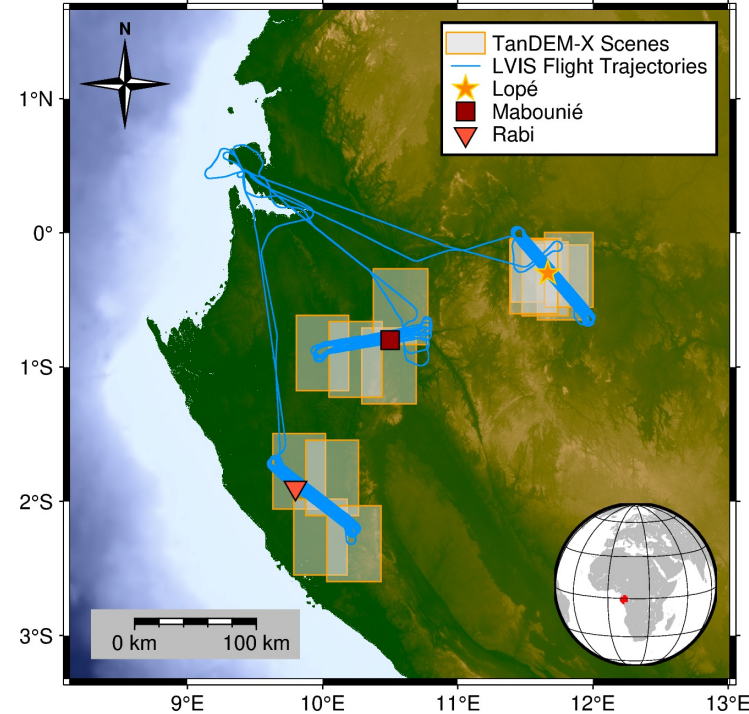
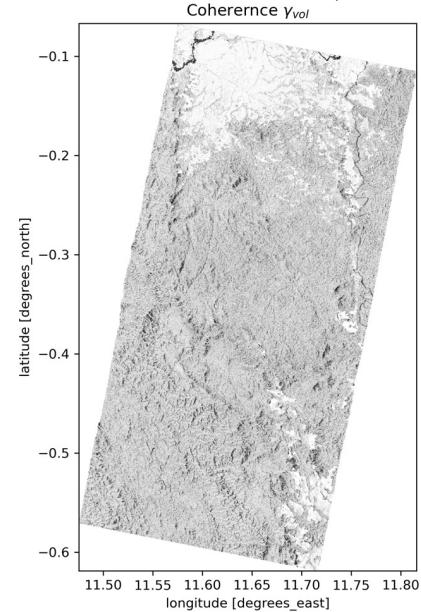
HoA: 52.45, D



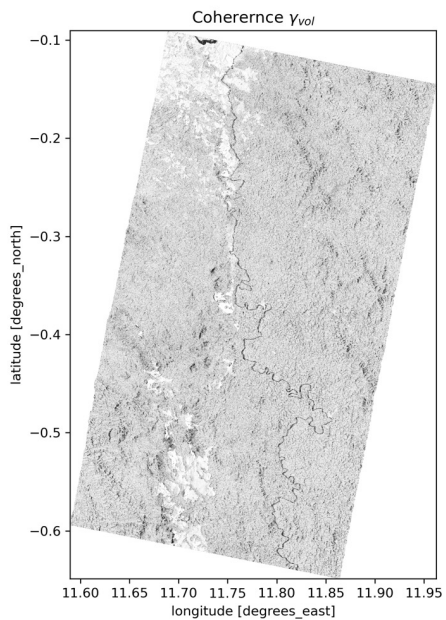
HoA: -65.22, A



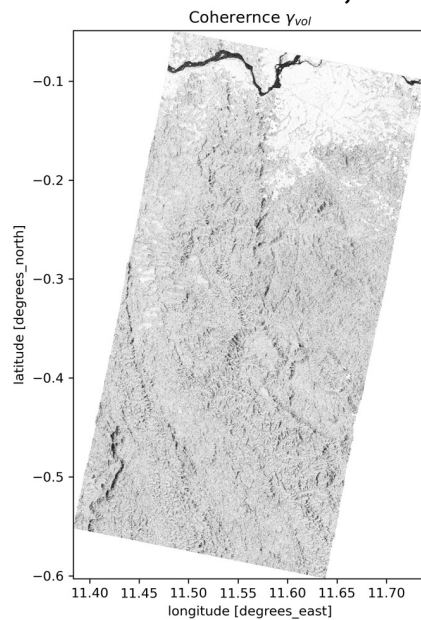
HoA: 86.34, D



HoA: 94.89, D



HoA: 95.41, D



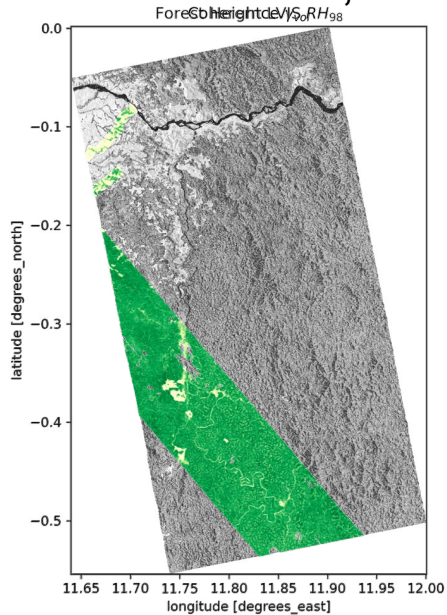
The interferometric coherence model:

$$\gamma_{vol} = \left| \frac{\int_0^{h_v} f(z) e^{i\kappa_z z} dz}{\int_0^{h_v} f(z) dz} \right|$$

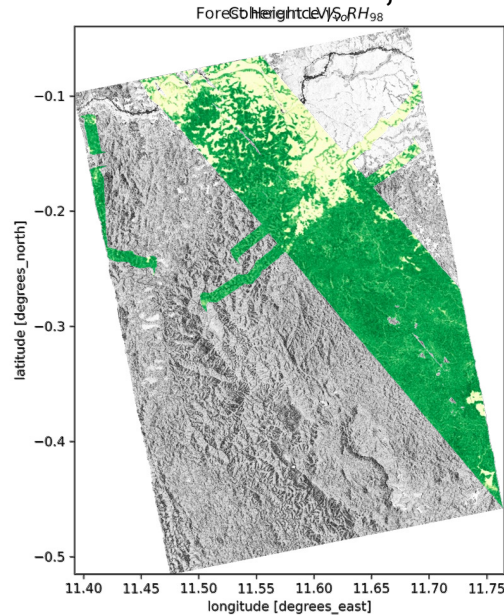
$f(z)$  ... vertical reflectivity function

$\kappa_z$  ... vertical wavenumber

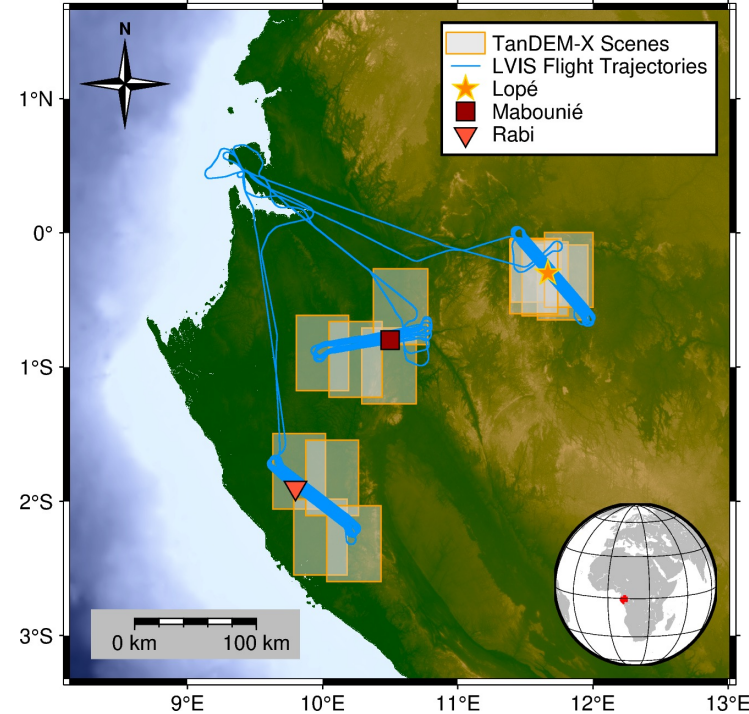
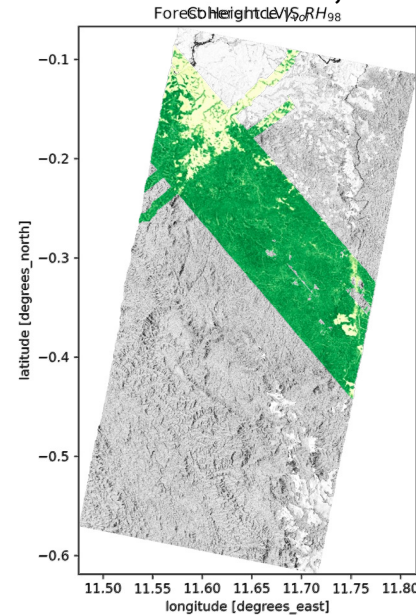
HoA: 52.45, D



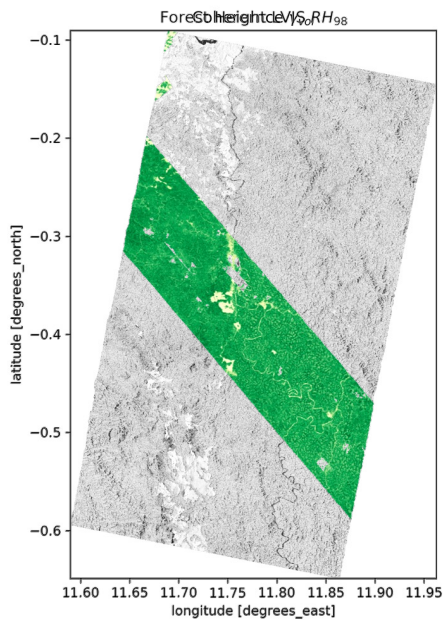
HoA: -65.22, A



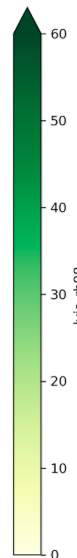
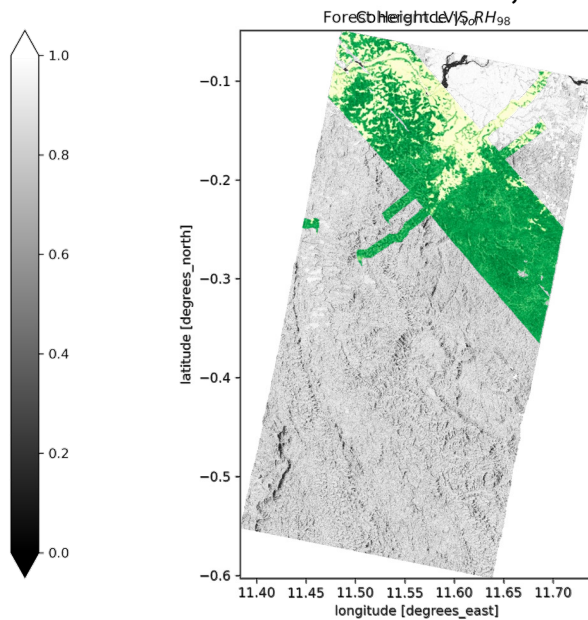
HoA: 86.34, D



HoA: 94.89, D



HoA: 95.41, D



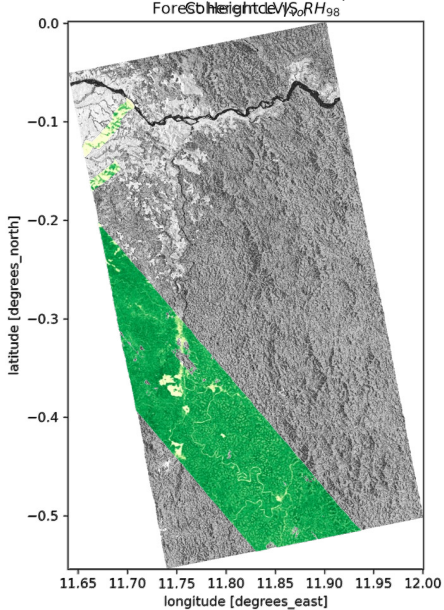
The interferometric coherence model:

$$\gamma_{vol} = \left| \frac{\int_0^{h_v} f(z) e^{i\kappa_z z} dz}{\int_0^{h_v} f(z) dz} \right|$$

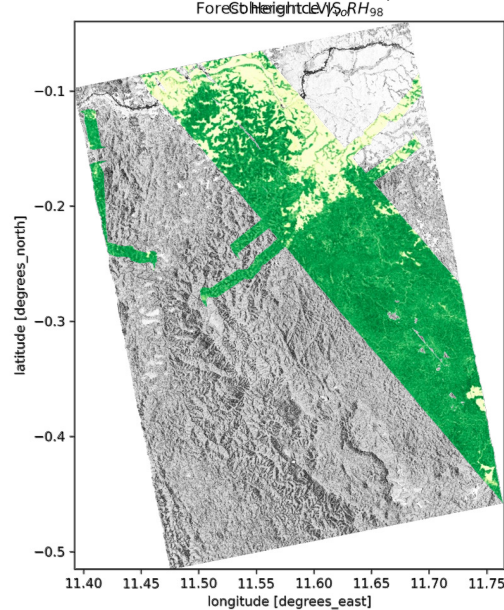
$f(z)$  ... vertical reflectivity function

$\kappa_z$  ... vertical wavenumber

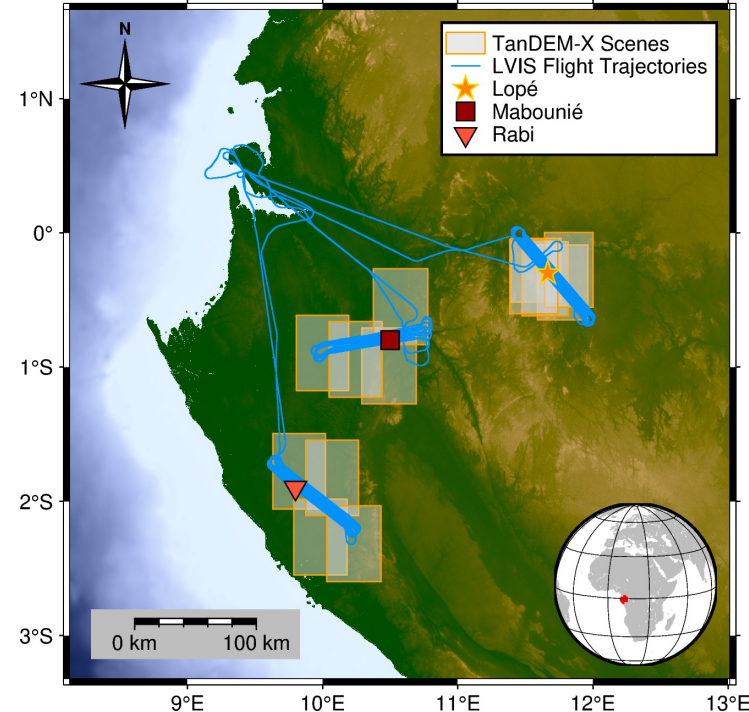
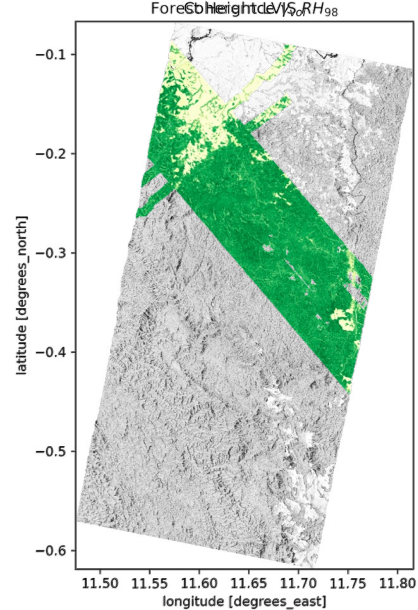
HoA: 52.45, D



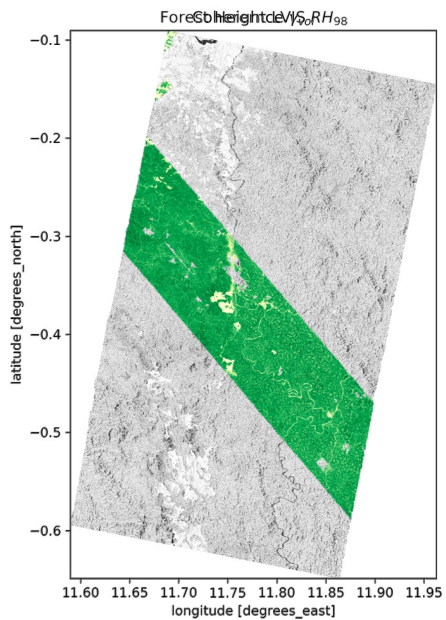
HoA: -65.22, A



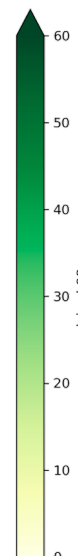
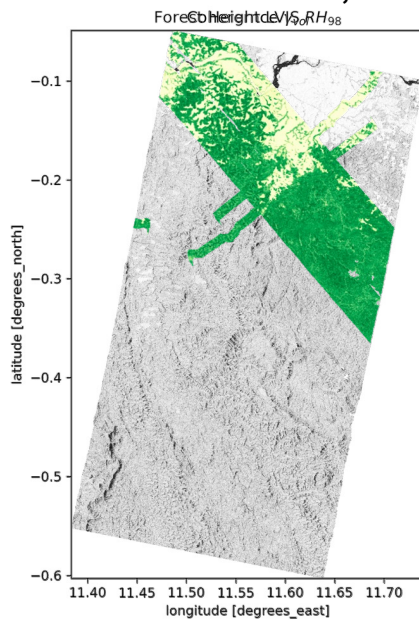
HoA: 86.34, D



HoA: 94.89, D

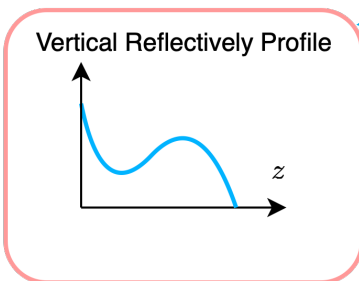


HoA: 95.41, D



The interferometric coherence model:

$$\gamma_{vol} = \frac{\left| \int_0^{h_v} f(z) e^{i\kappa_z z} dz \right|}{\int_0^{h_v} f(z) dz}$$



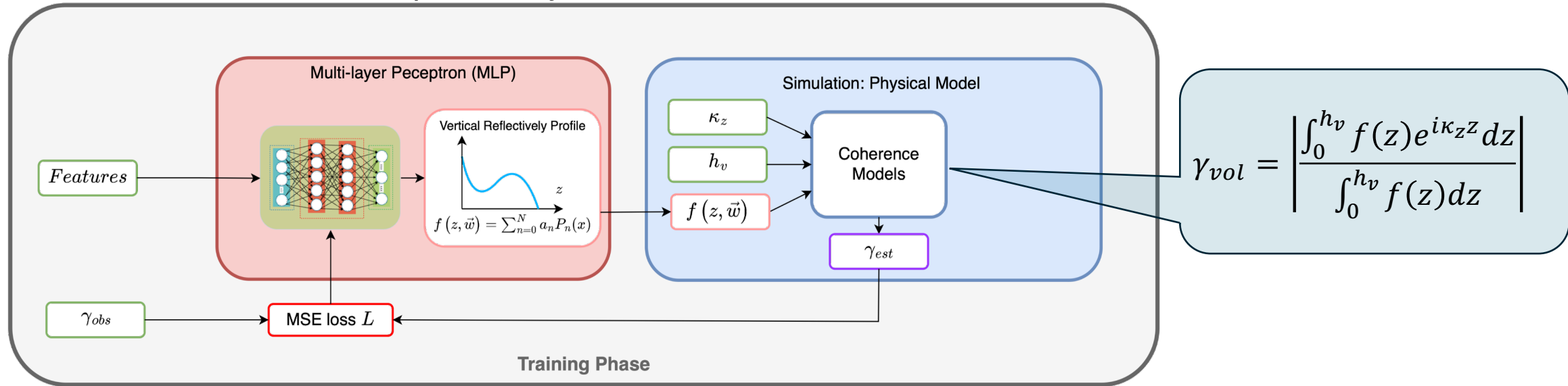
$f(z)$  ... vertical reflectivity function

$\kappa_z$  ... vertical wavenumber

Papathanassiou, K.P., and S.R. Cloud. "Single-Baseline Polarimetric SAR Interferometry." *IEEE Transactions on Geoscience and Remote Sensing* 39, no. 11 (November 2001): 2352–63. <https://doi.org/10.1109/36.964971>.

# Integration of Machine Learning and Physical Models

## Sequential Hybrid Model

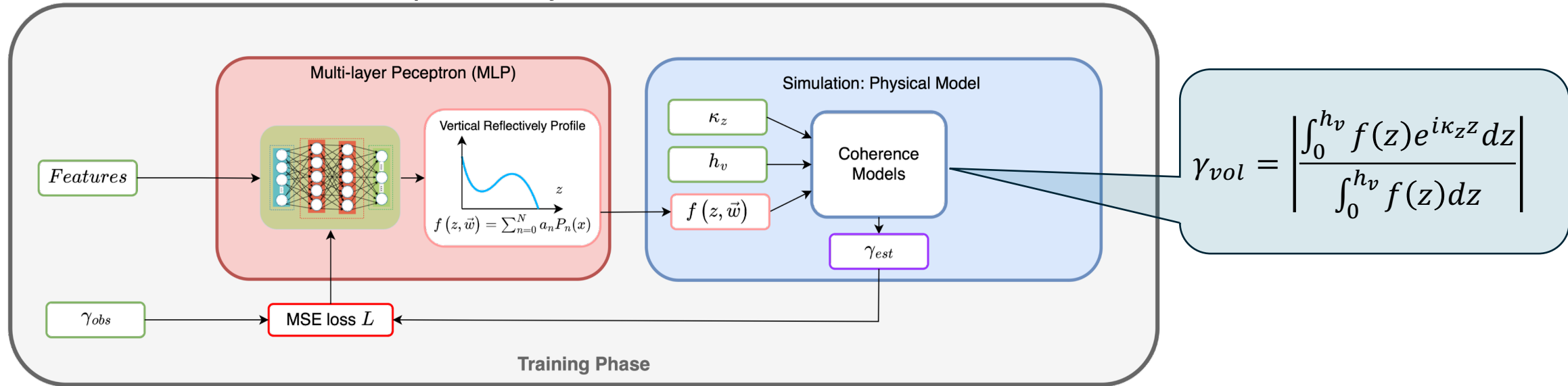


$$\gamma_{vol} = \left| \frac{\int_0^{h_v} f(z) e^{i\kappa_z z} dz}{\int_0^{h_v} f(z) dz} \right|$$

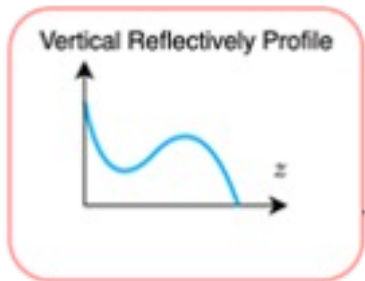
## Assumptions Correction Model

# Integration of Machine Learning and Physical Models

## Sequential Hybrid Model

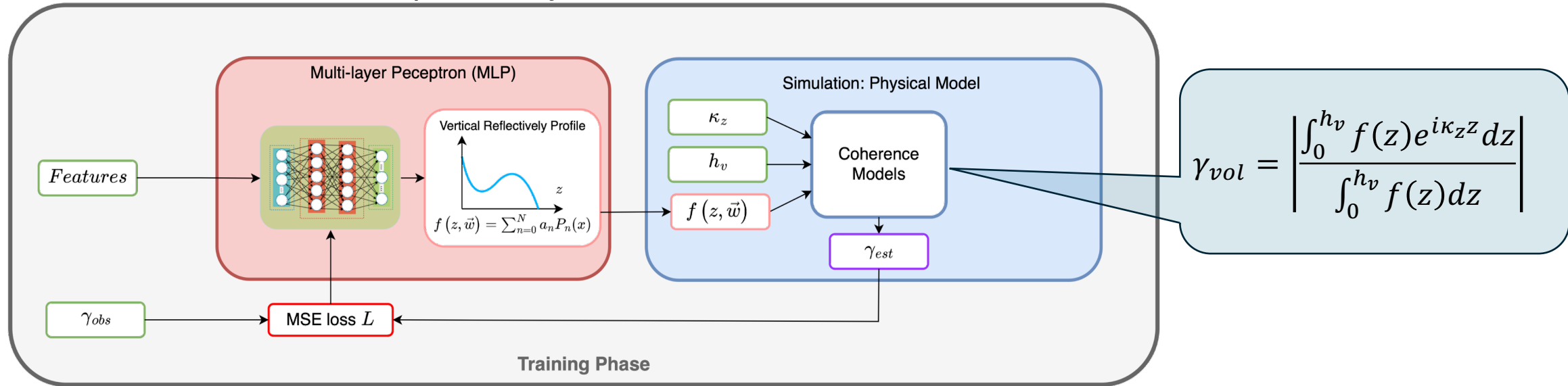


## Assumptions Correction Model

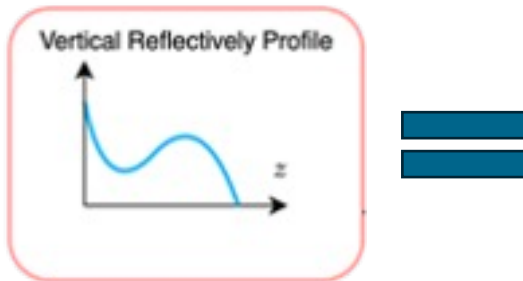


# Integration of Machine Learning and Physical Models

## Sequential Hybrid Model

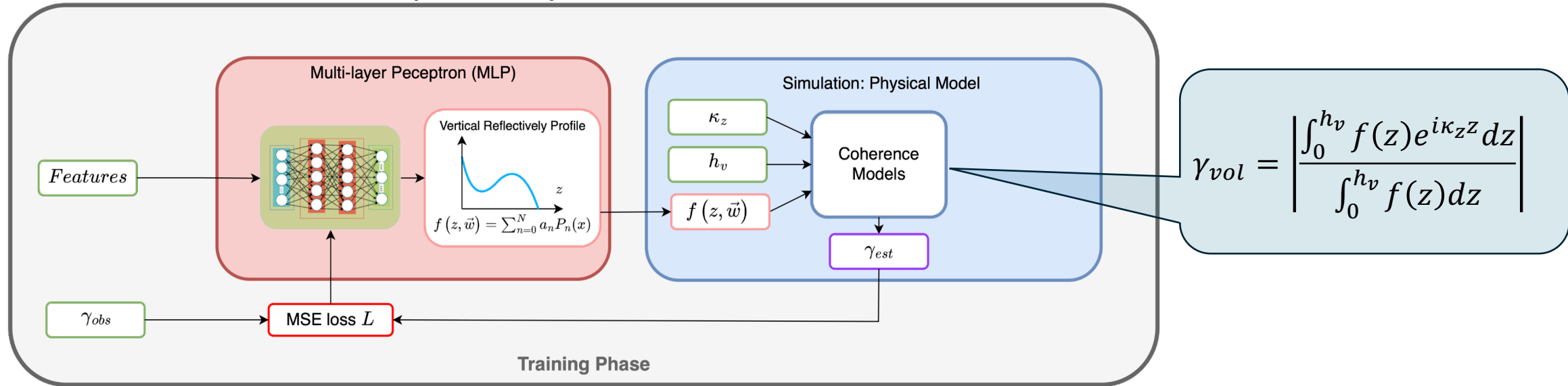


## Assumptions Correction Model

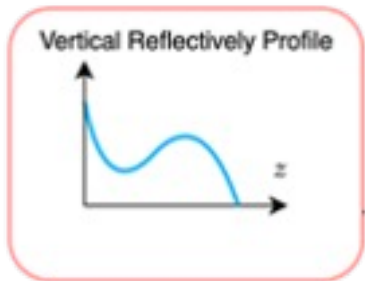


# Integration of Machine Learning and Physical Models

## Sequential Hybrid Model



## Assumptions Correction Model

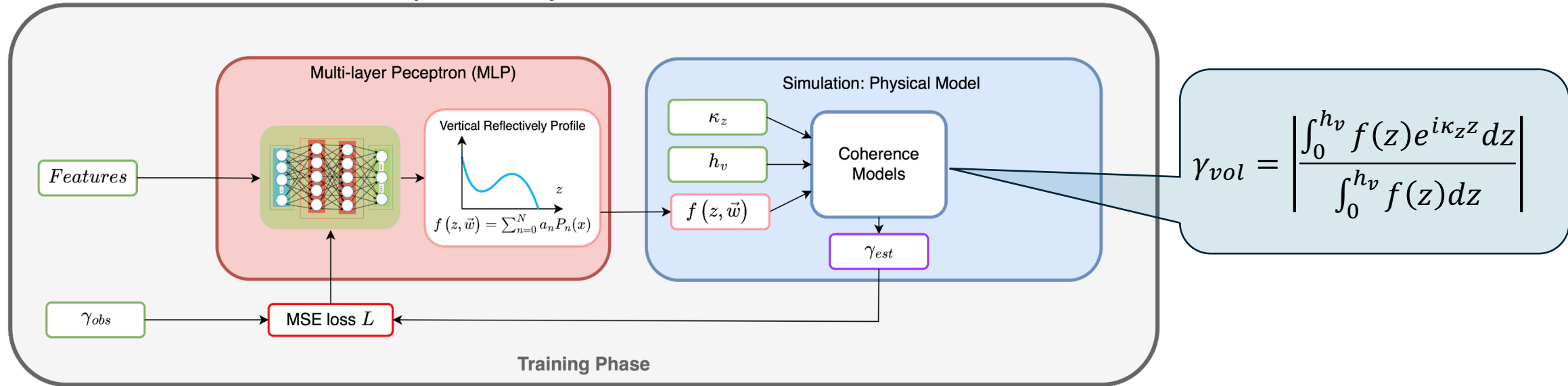


$$= f(z, \vec{w}) = \sum_{n=0}^N a_n P_n(z) \approx a_0 P_0(z) + a_1 P_1(z) + a_2 P_2(z) + a_3 P_3(z) + a_4 P_4(z) + \dots$$

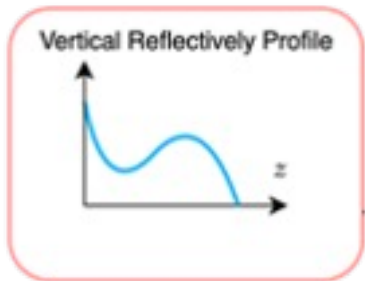


# Integration of Machine Learning and Physical Models

## Sequential Hybrid Model



## Assumptions Correction Model

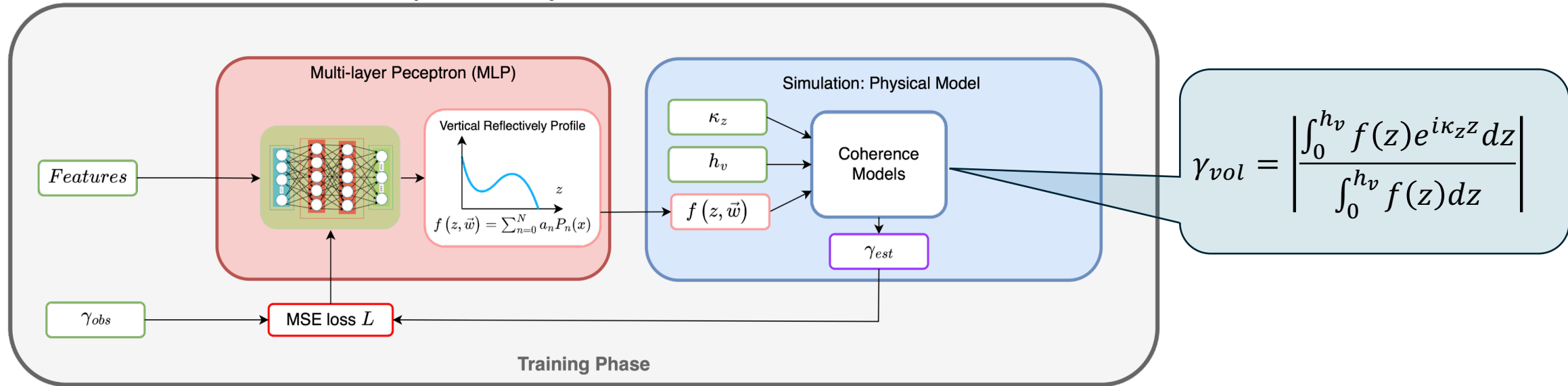


$$= f(z, \vec{w}) = \sum_{n=0}^N a_n P_n(z) \approx a_0 P_0(z) + a_1 P_1(z) + a_2 P_2(z) + a_3 P_3(z) + a_4 P_4(z) + \dots$$

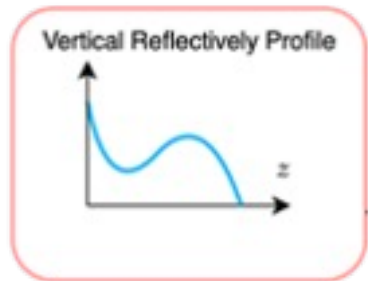
where  $P_n(z)$  : Legendre Polynomials

# Integration of Machine Learning and Physical Models

## Sequential Hybrid Model



## Assumptions Correction Model



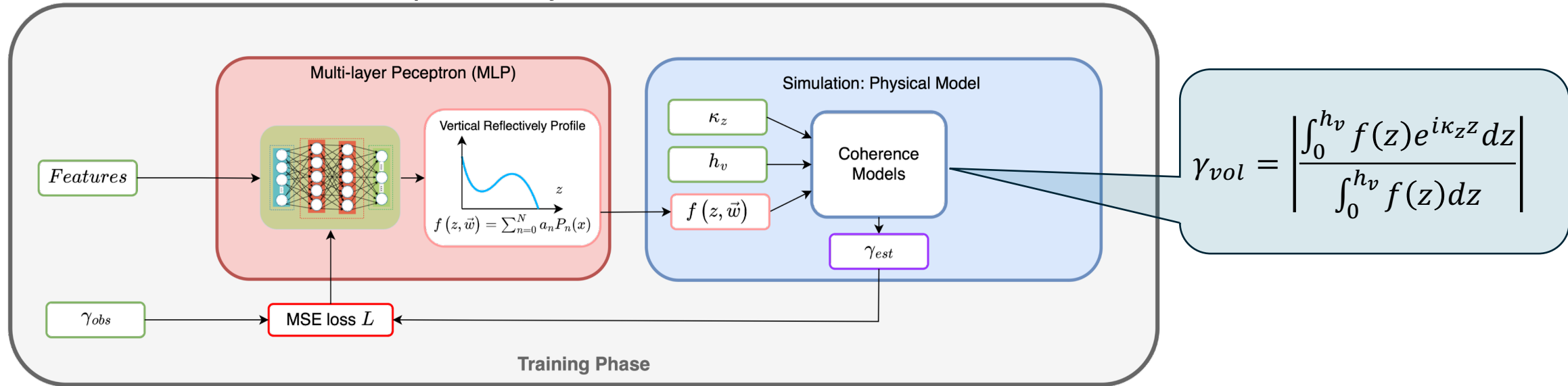
$$= f(z, \vec{w}) = \sum_{n=0}^N a_n P_n(z) \approx a_0 P_0(z) + a_1 P_1(z) + a_2 P_2(z) + a_3 P_3(z) + a_4 P_4(z) + \dots$$

where  $P_n(z)$  : Legendre Polynomials

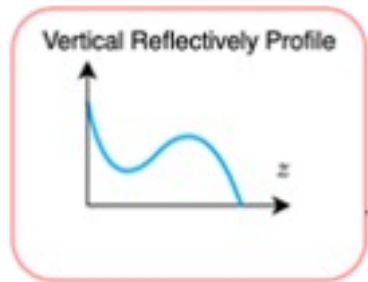


# Integration of Machine Learning and Physical Models

## Sequential Hybrid Model

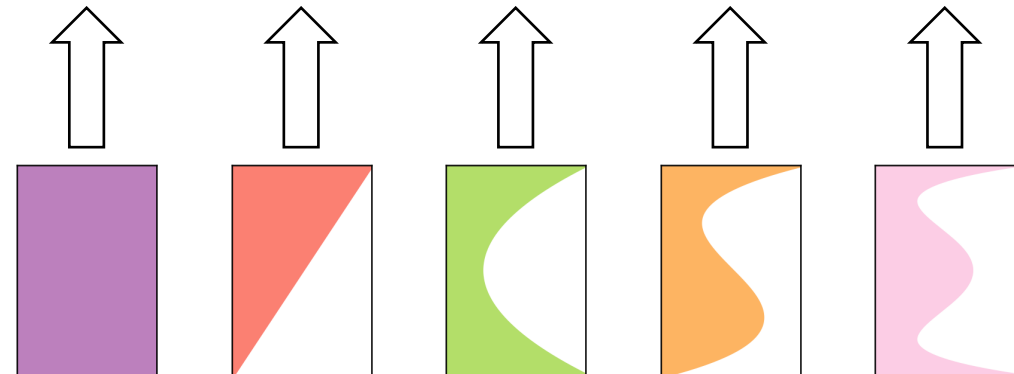


## Assumptions Correction Model



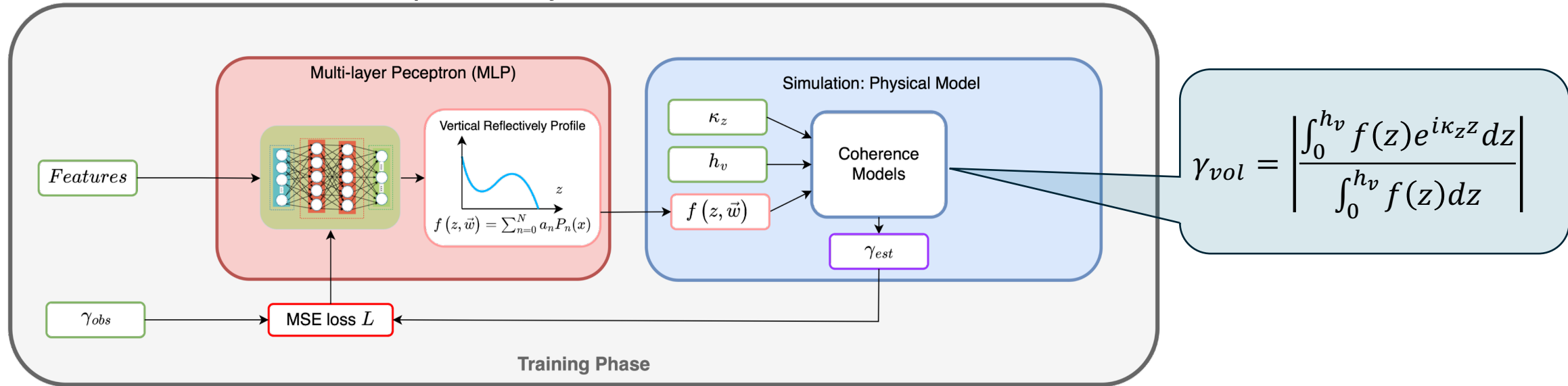
$$= f(z, \vec{w}) = \sum_{n=0}^N a_n P_n(z) \approx a_0 P_0(z) + a_1 P_1(z) + a_2 P_2(z) + a_3 P_3(z) + a_4 P_4(z) + \dots$$

where  $P_n(z)$  : Legendre Polynomials



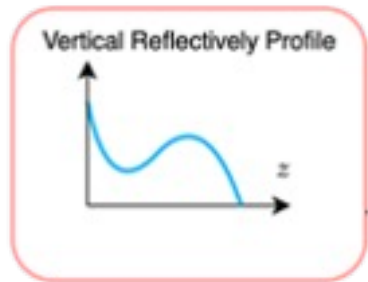
# Integration of Machine Learning and Physical Models

## Sequential Hybrid Model

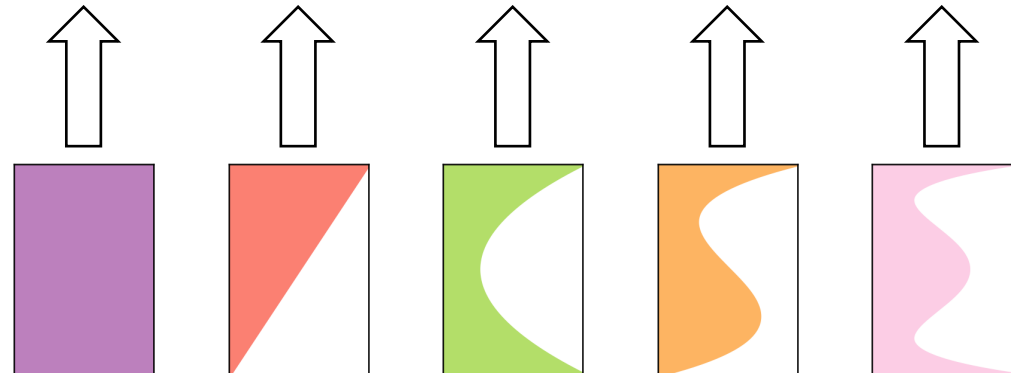


$$\gamma_{vol} = \left| \frac{\int_0^{h_v} f(z) e^{i\kappa_z z} dz}{\int_0^{h_v} f(z) dz} \right|$$

## Assumptions Correction Model



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

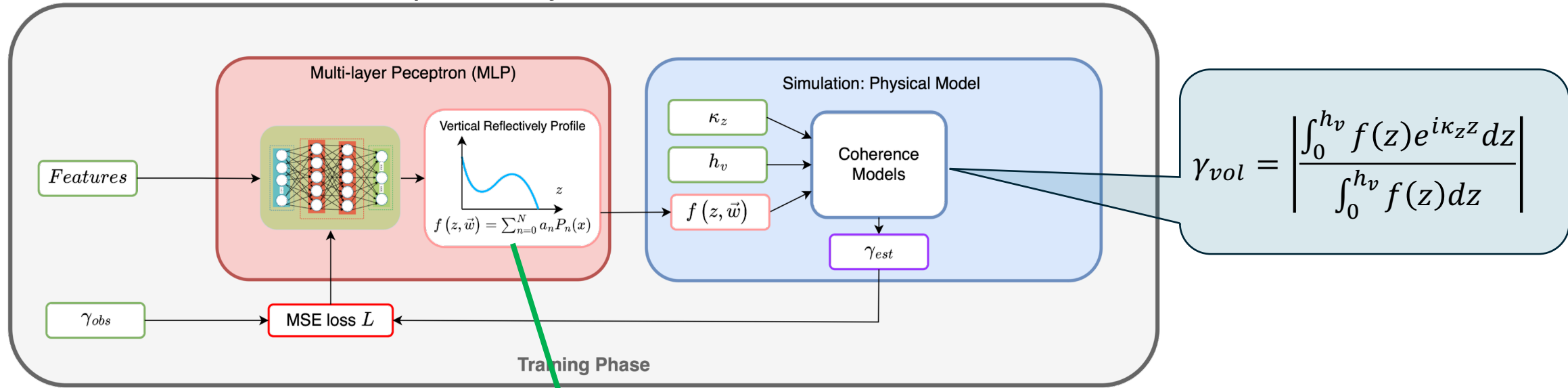


where  $P_n(z)$  : Legendre Polynomials

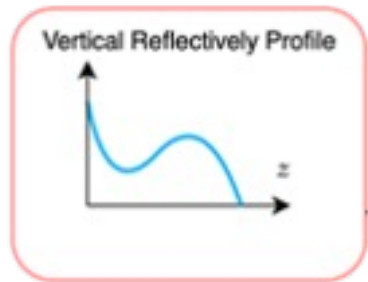


# Integration of Machine Learning and Physical Models

## Sequential Hybrid Model



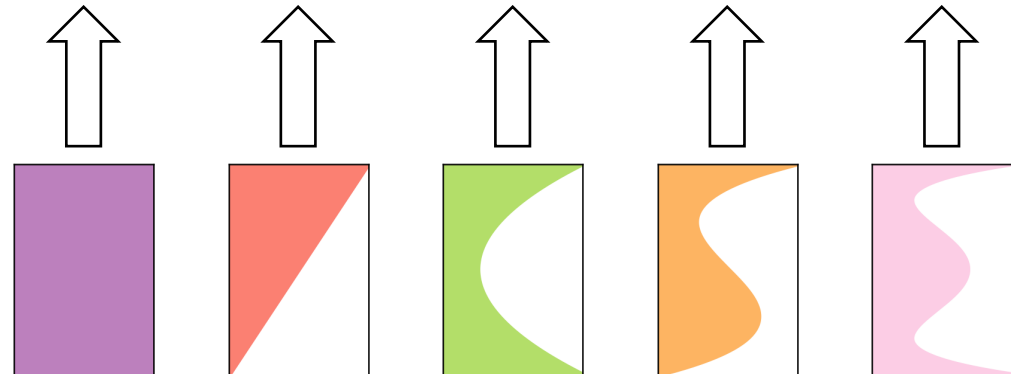
## Assumptions Correction Model



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

How many Legendre coefficients are required to approximate the function?

where  $P_n(z)$  : Legendre Polynomials



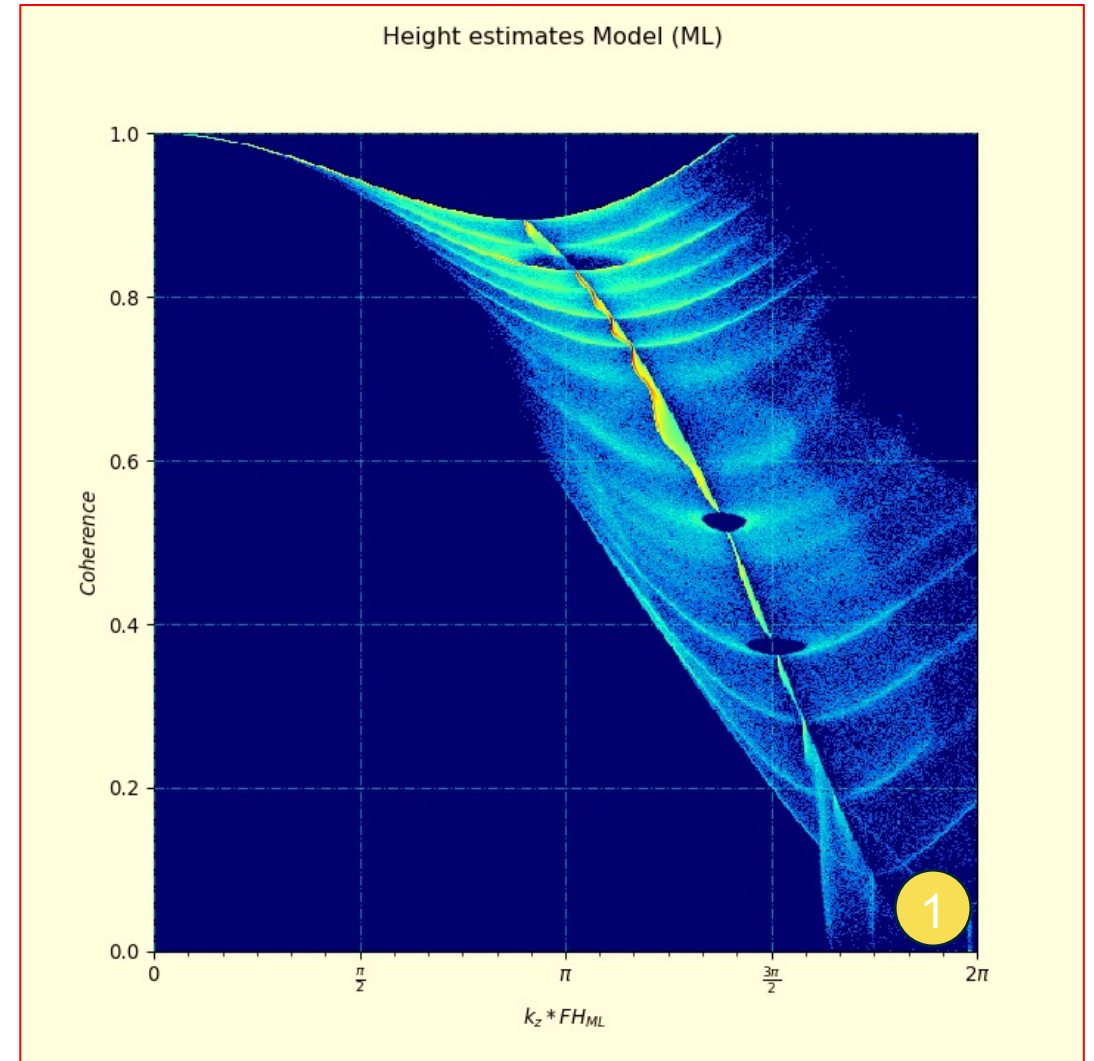
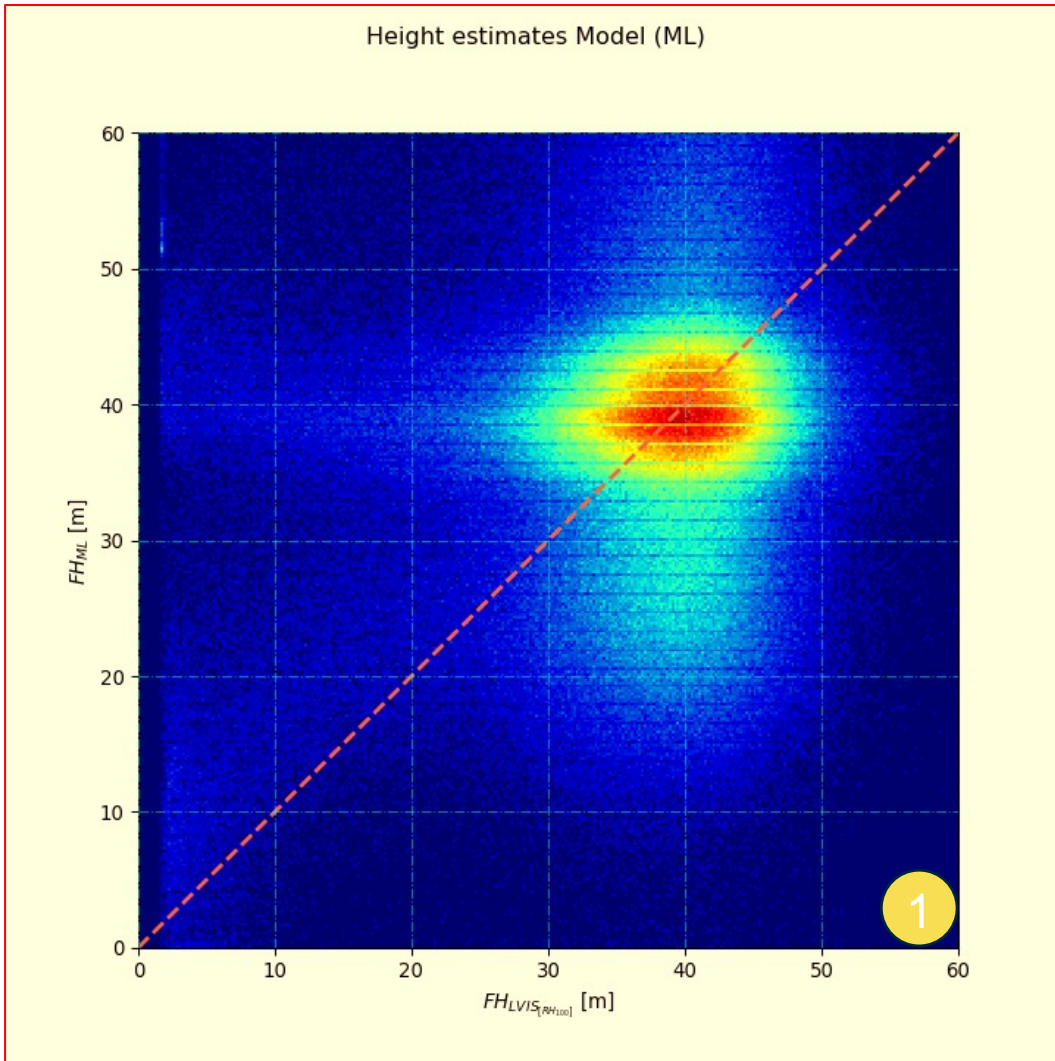
# Experiments Setup



| No. | Legendre coefficients (N) | HoA for Training         | Features (Inputs – Parameters)                              |
|-----|---------------------------|--------------------------|---|
|     |                           |                          | TanDEM-X  |
| 1   | 3                         | $[-65.22]$               | $\kappa_Z, \tilde{\gamma}_{vol}, \dots, \theta_O, \theta_T$ |
| 2   | 3                         | $[52.45, -65.22, 95.41]$ | $\kappa_Z, \tilde{\gamma}_{vol}, \dots, \theta_O, \theta_T$ |
| 3   | 7                         | $[52.45, -65.22, 95.41]$ | $\kappa_Z, \tilde{\gamma}_{vol}, \dots, \theta_O, \theta_T$ |

- a) Data Selection: Selection of **HoA** for training
- b) Coefficient Setup: A varying quantity (**N**) of Legendre coefficients
- } 1 2 3

# Results Explanation



HoA: 52.45

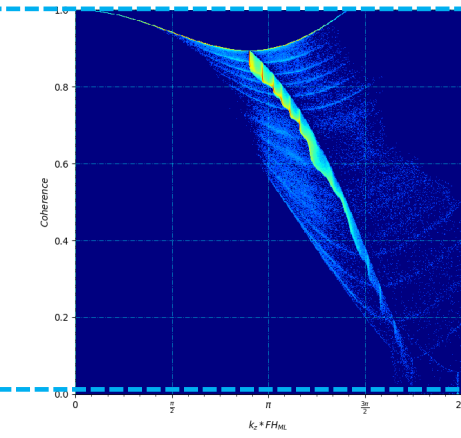
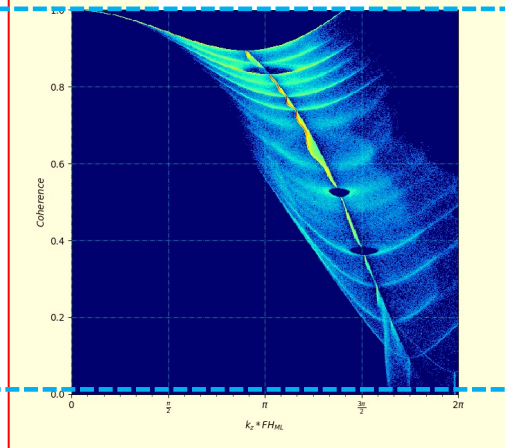
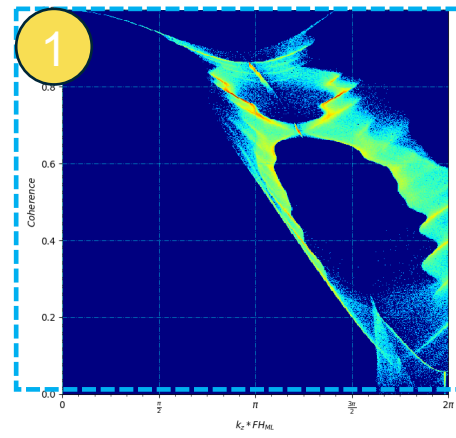
HoA: -65.22

HoA: 86.34

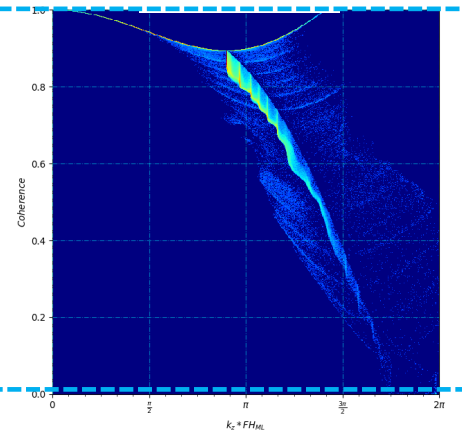
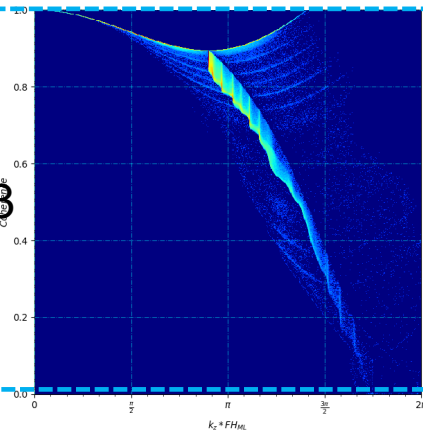
HoA: 94.89

HoA: 95.41

1



$N=3$





HoA: 52.45

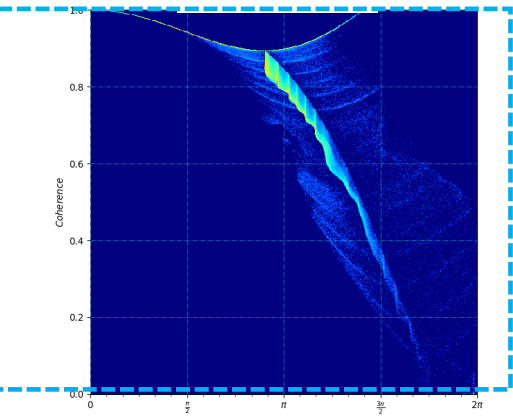
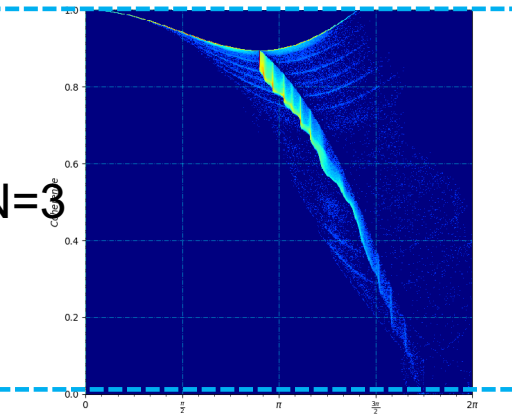
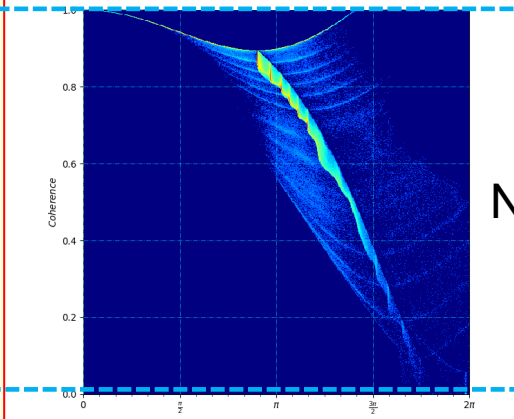
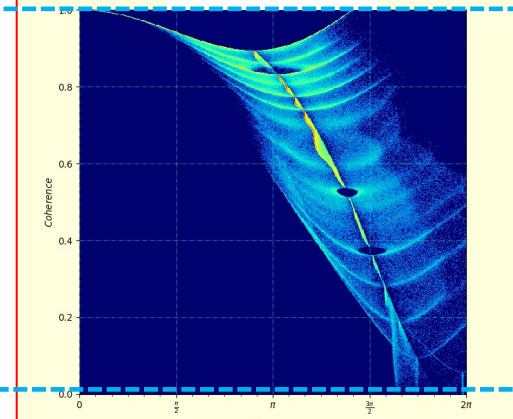
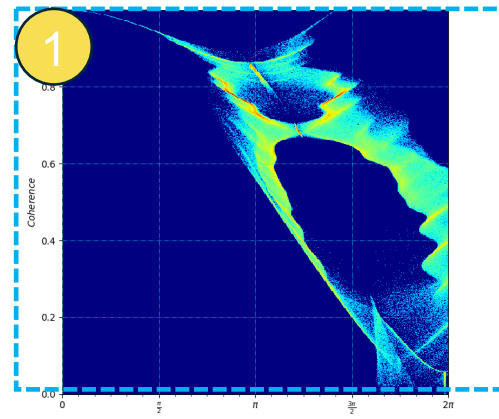
HoA: -65.22

HoA: 86.34

HoA: 94.89

HoA: 95.41

1



$N=3$

Height estimates Model (ML)

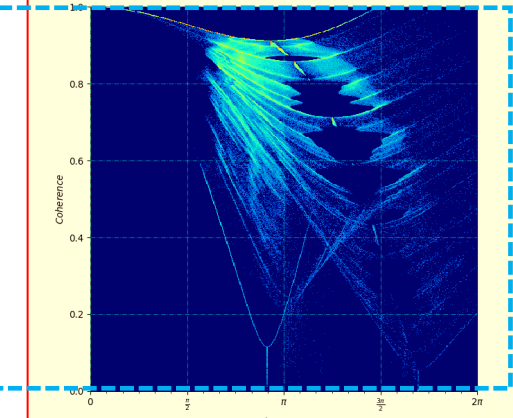
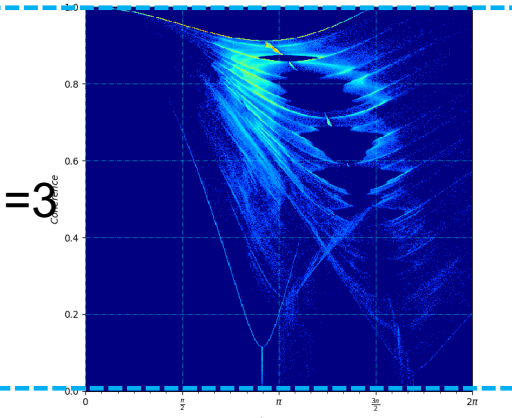
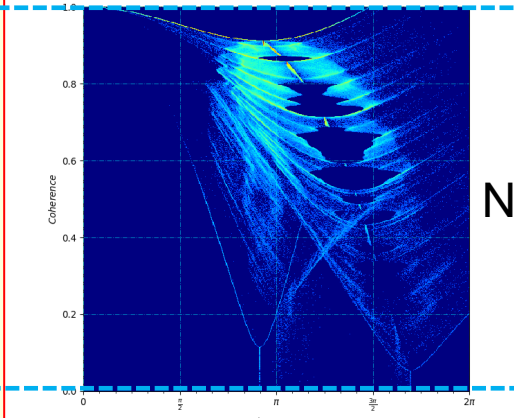
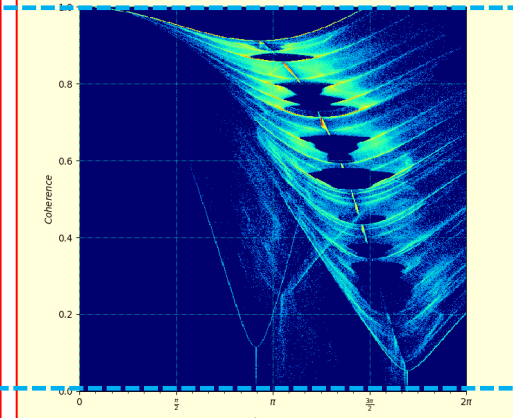
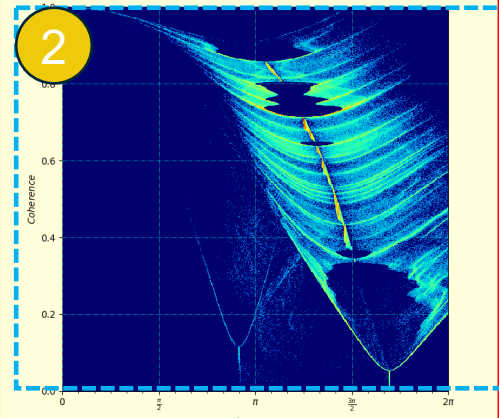
Height estimates Model (ML)

Height estimates Model (ML)

Height estimates Model (ML)

Height estimates Model (ML)

2



$N=3$

HoA: 52.45

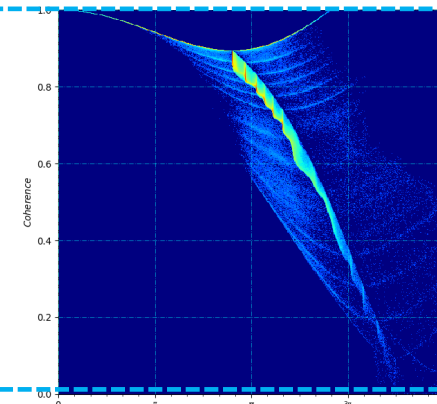
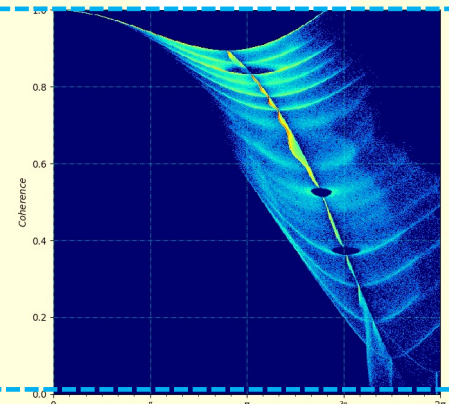
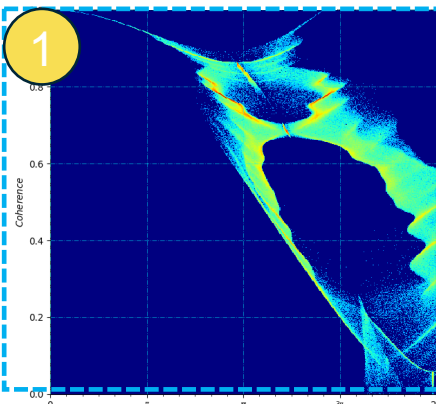
HoA: -65.22

HoA: 86.34

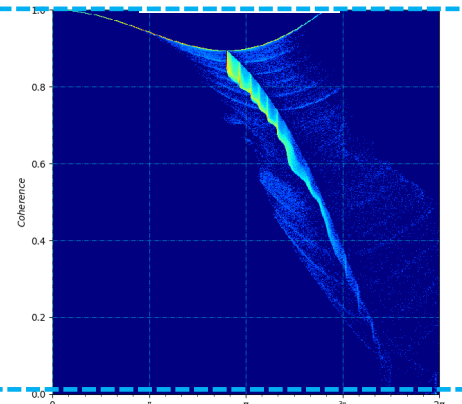
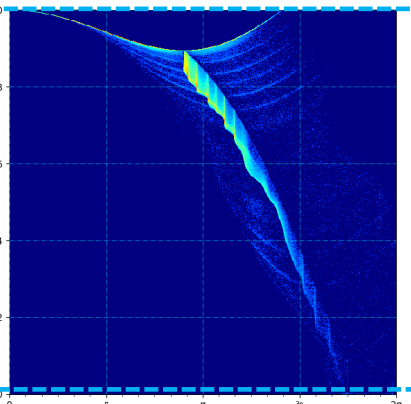
HoA: 94.89

HoA: 95.41

1



N=3



Height estimates Model (ML)

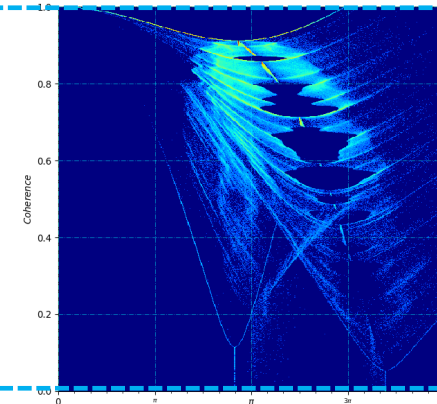
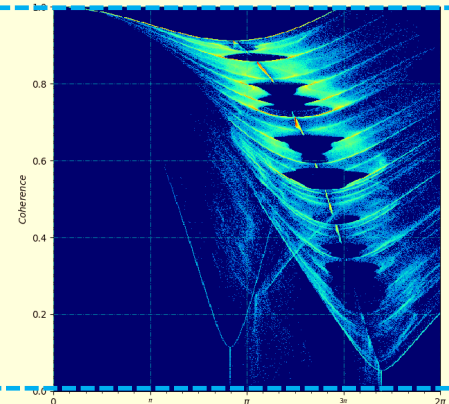
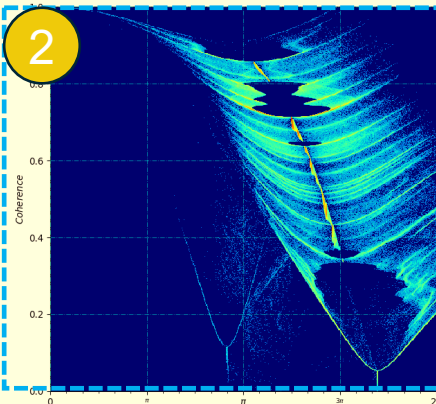
Height estimates Model (ML)

Height estimates Model (ML)

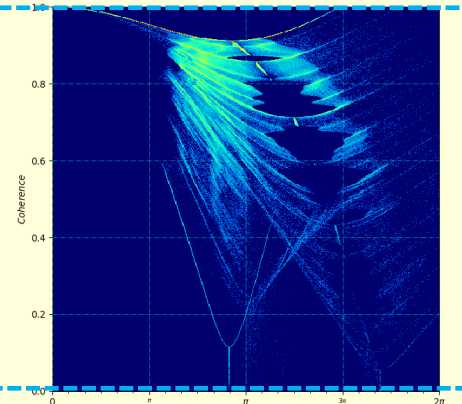
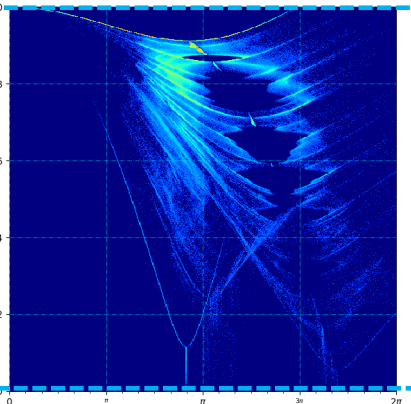
Height estimates Model (ML)

Height estimates Model (ML)

2



N=7



Height estimates Model (ML)

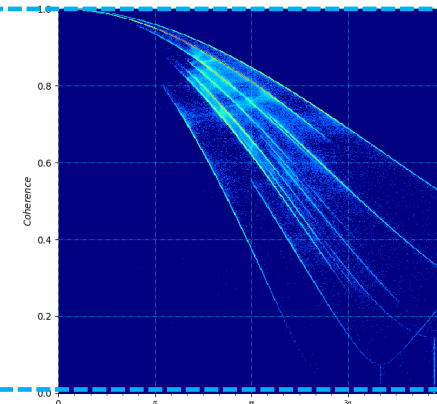
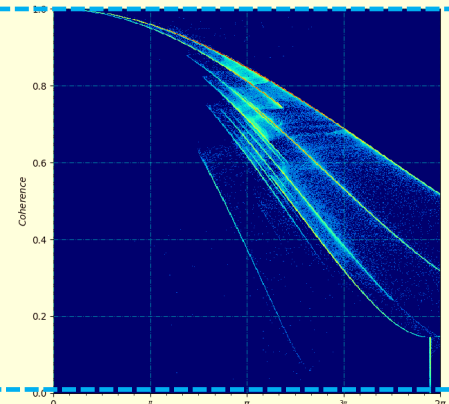
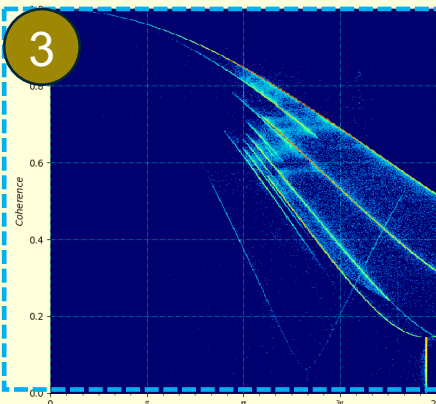
Height estimates Model (ML)

Height estimates Model (ML)

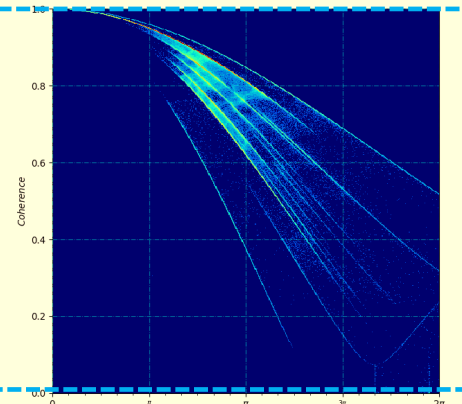
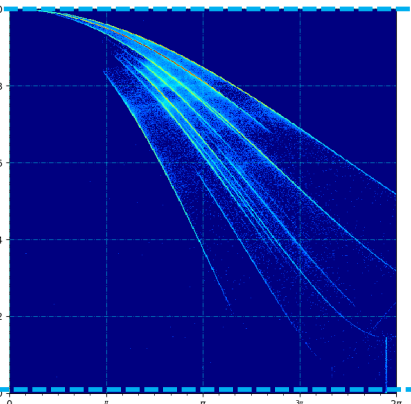
Height estimates Model (ML)

Height estimates Model (ML)

3



N=7



$k_z * FH_{ML}$

$k_z * FH_{ML}$

$k_z * FH_{ML}$

$k_z * FH_{ML}$

$k_z * FH_{ML}$

HoA: 52.45

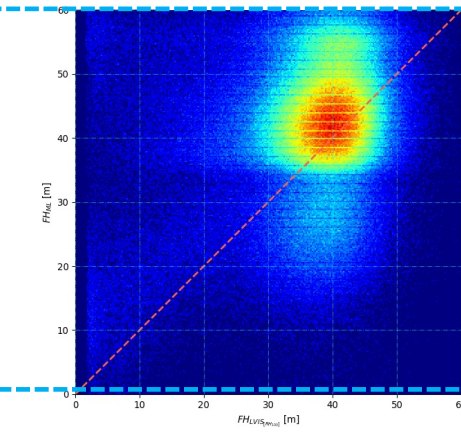
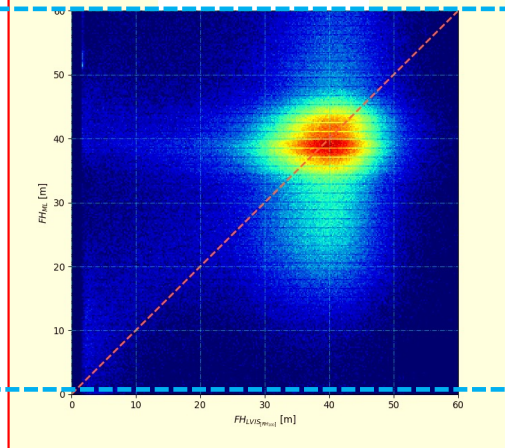
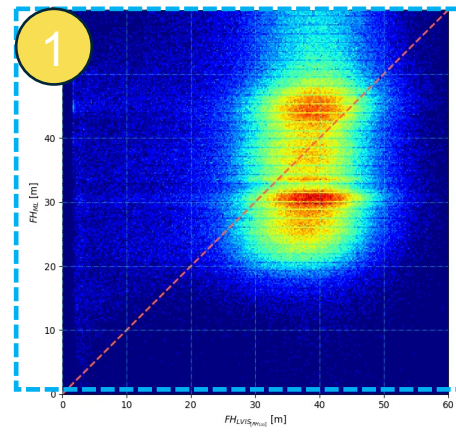
HoA: -65.22

HoA: 86.34

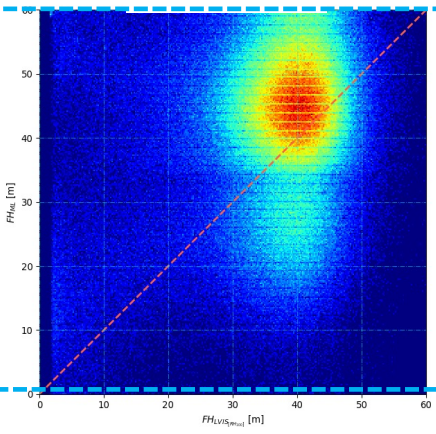
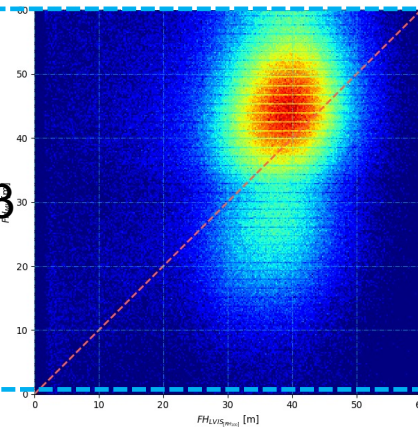
HoA: 94.89

HoA: 95.41

1



N=3



HoA: 52.45

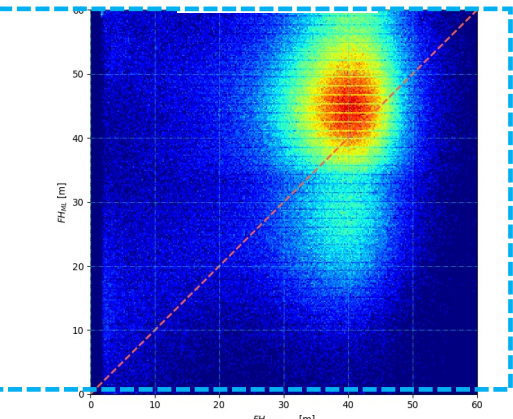
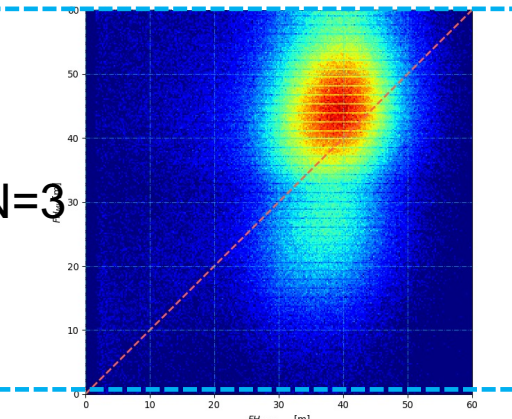
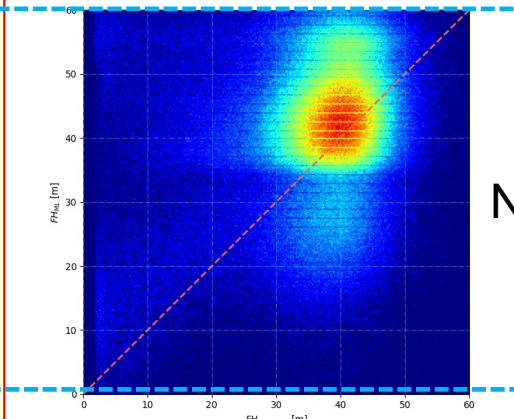
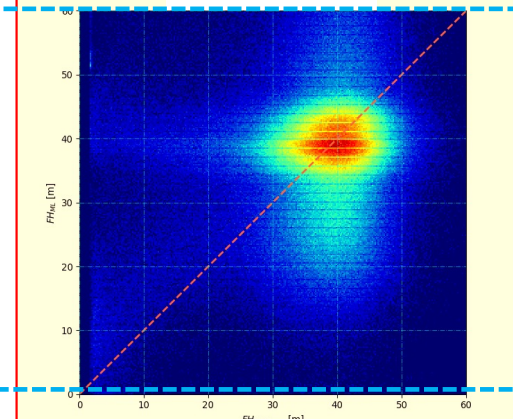
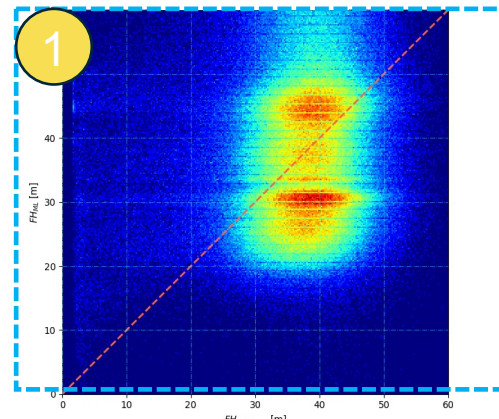
HoA: -65.22

HoA: 86.34

HoA: 94.89

HoA: 95.41

1



N=3

Height estimates Model (ML)

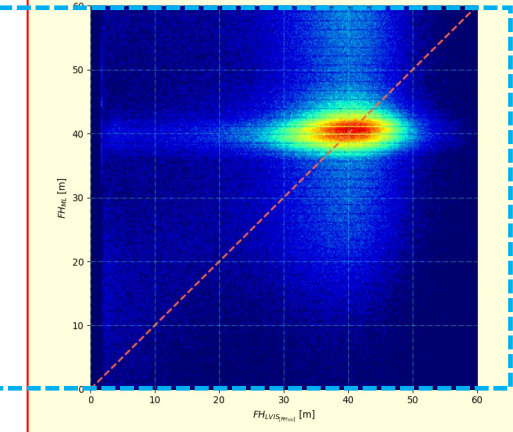
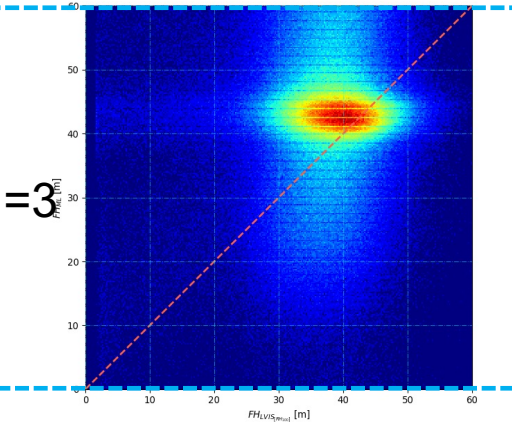
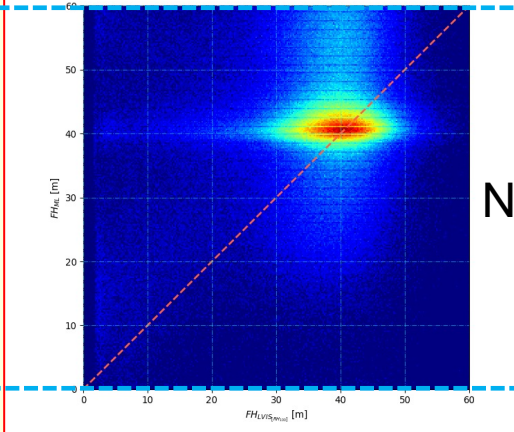
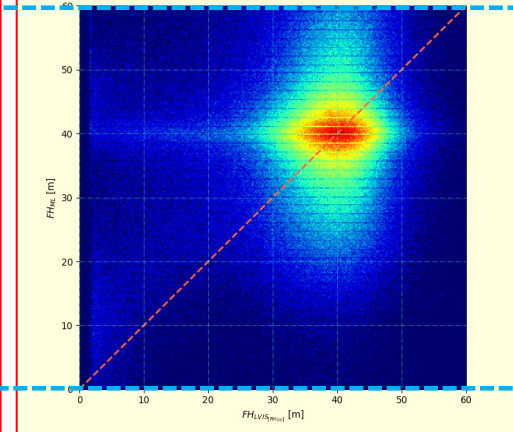
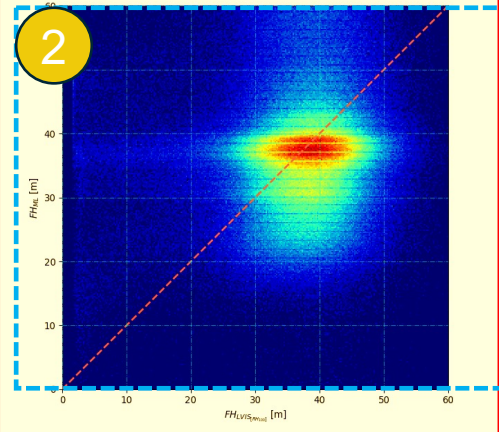
Height estimates Model (ML)

Height estimates Model (ML)

Height estimates Model (ML)

Height estimates Model (ML)

2



N=3

HoA: 52.45

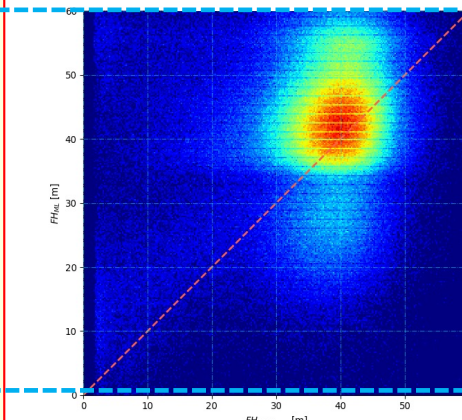
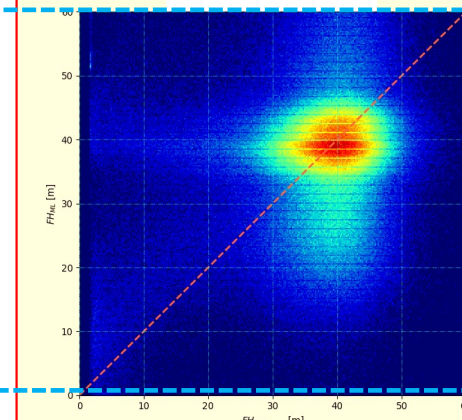
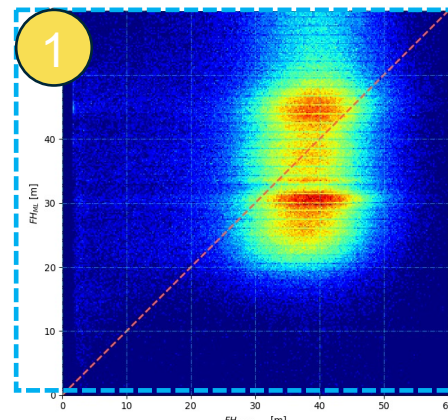
HoA: -65.22

HoA: 86.34

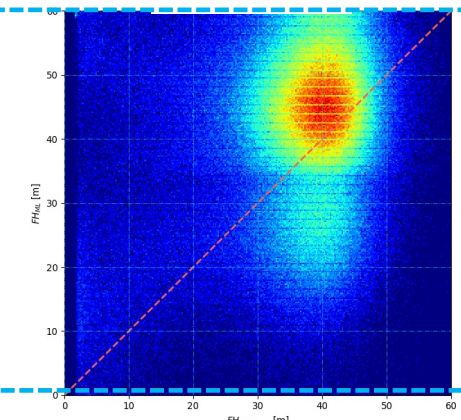
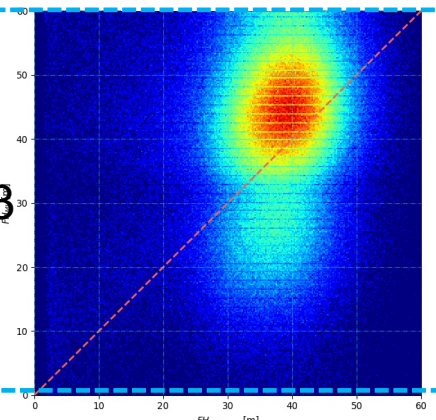
HoA: 94.89

HoA: 95.41

1



N=3



Height estimates Model (ML)

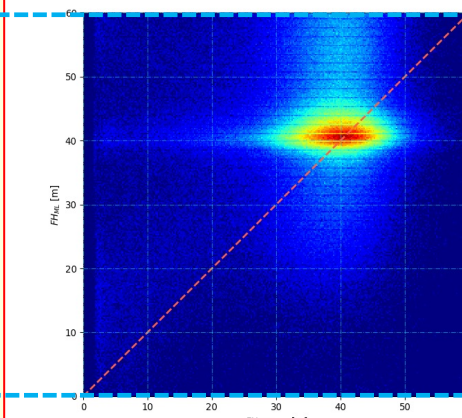
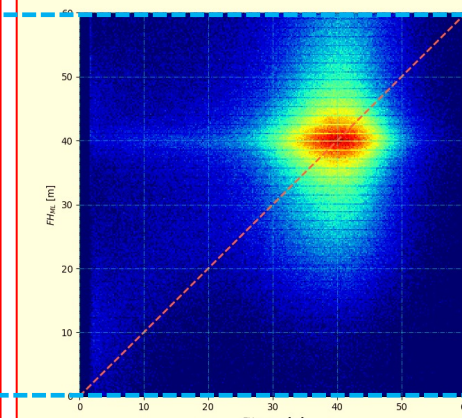
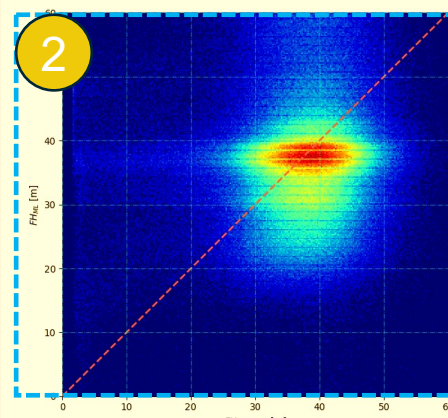
Height estimates Model (ML)

Height estimates Model (ML)

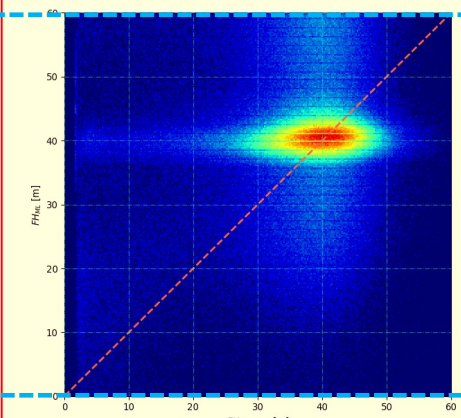
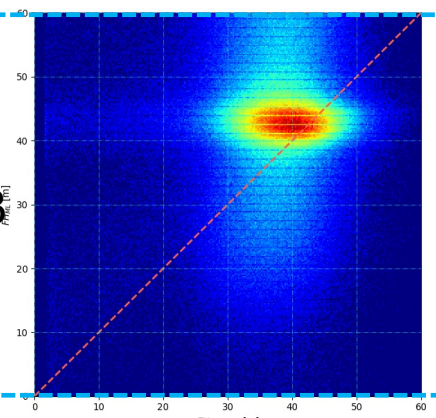
Height estimates Model (ML)

Height estimates Model (ML)

2



N=3



Height estimates Model (ML)

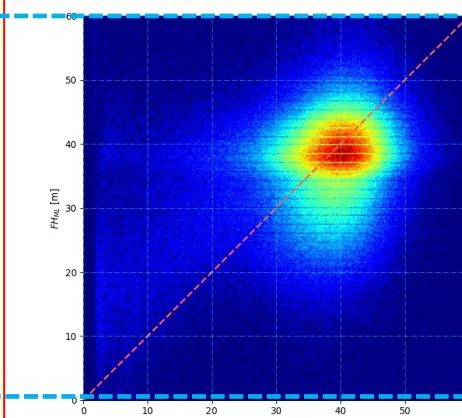
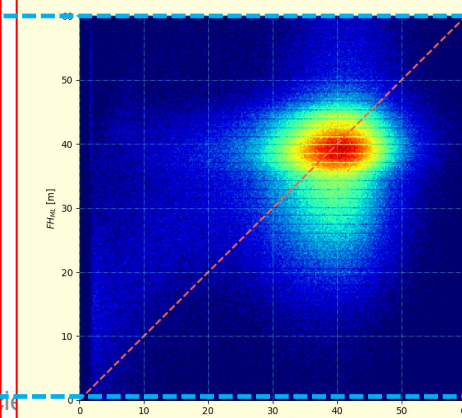
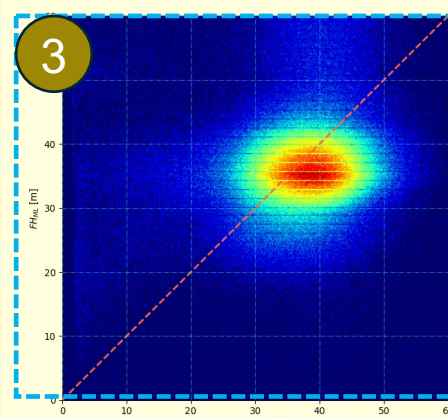
Height estimates Model (ML)

Height estimates Model (ML)

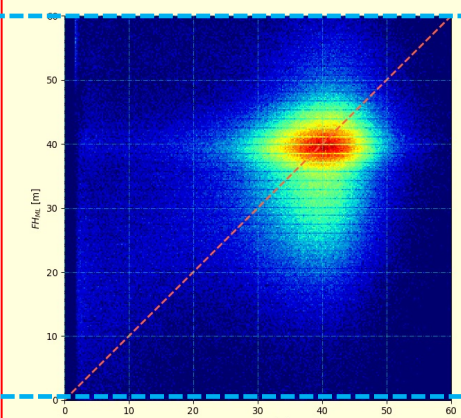
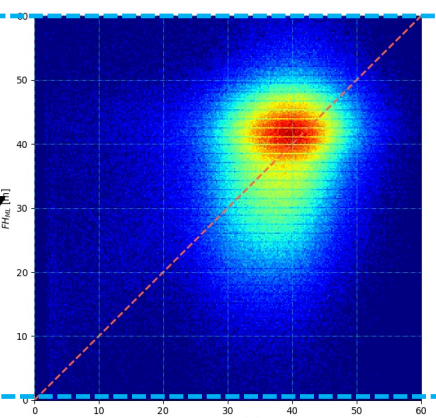
Height estimates Model (ML)

Height estimates Model (ML)

3



N=7



Height estimates Model (ML)

Height estimates Model (ML)

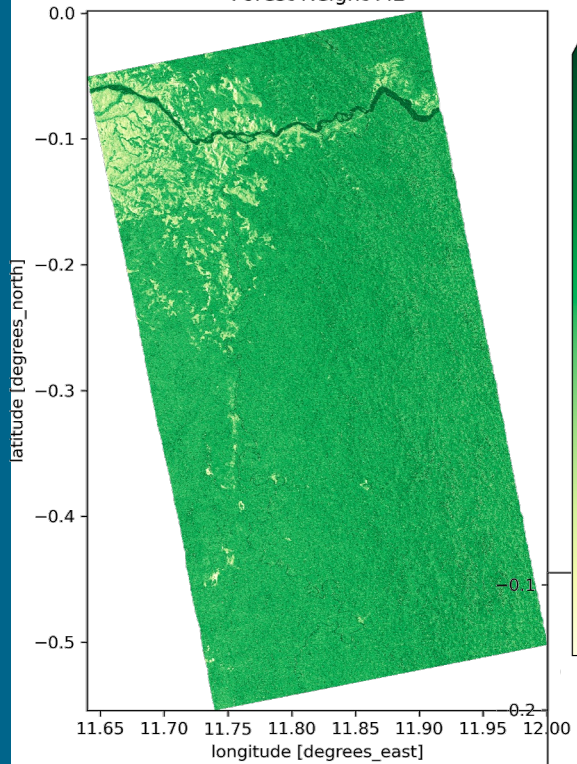
Height estimates Model (ML)

Height estimates Model (ML)

Height estimates Model (ML)

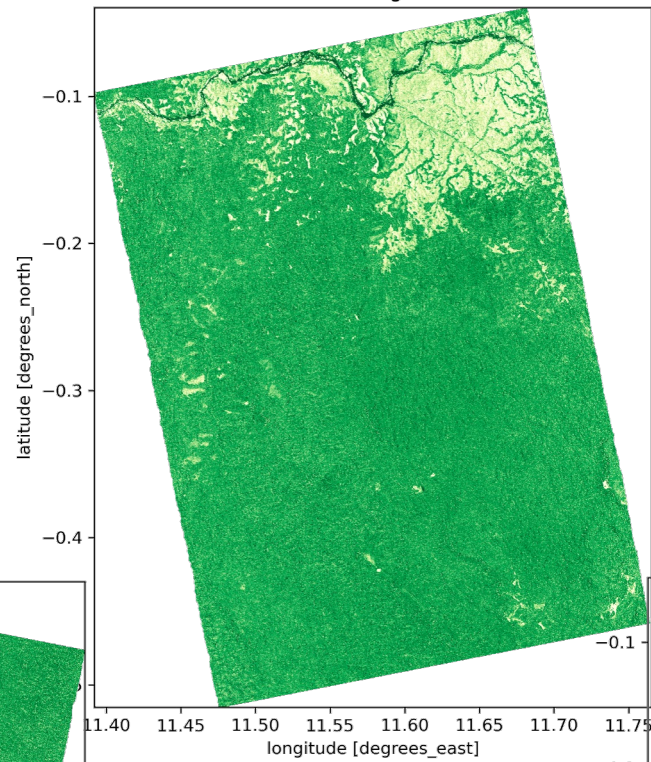
HoA: 52.45

Forest Height ML



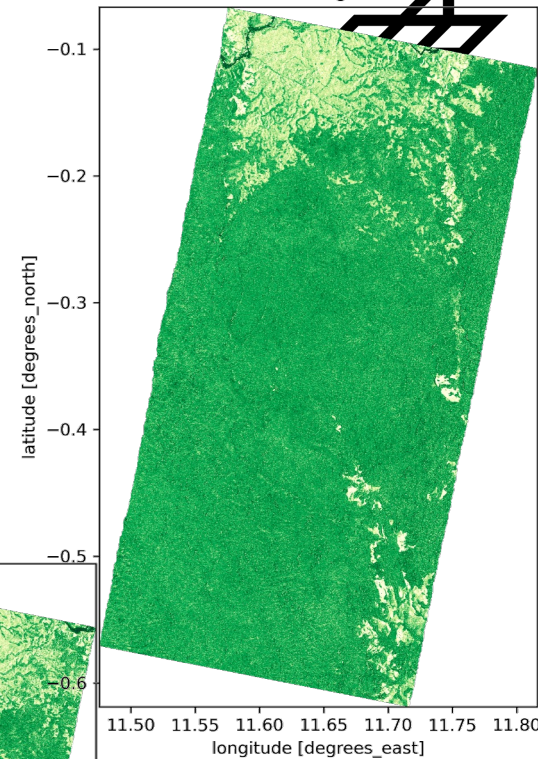
HoA: -65.22

Forest Height ML



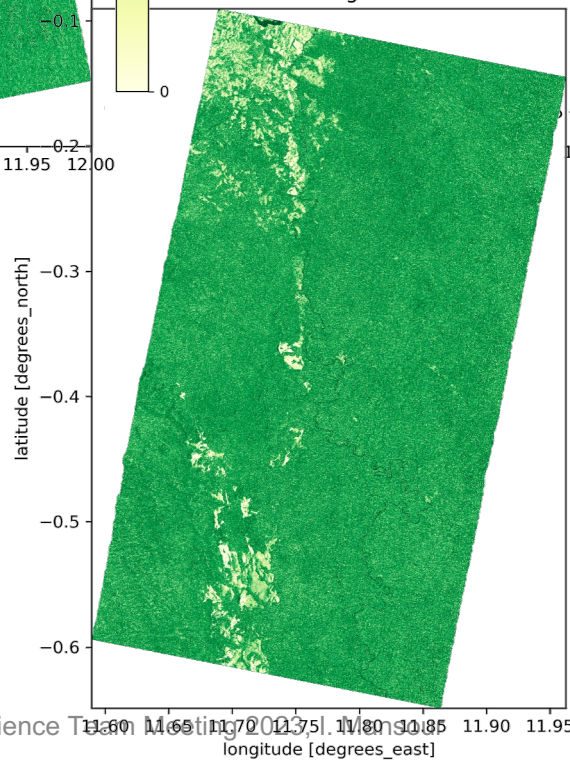
HoA: 86.34

Forest Height ML



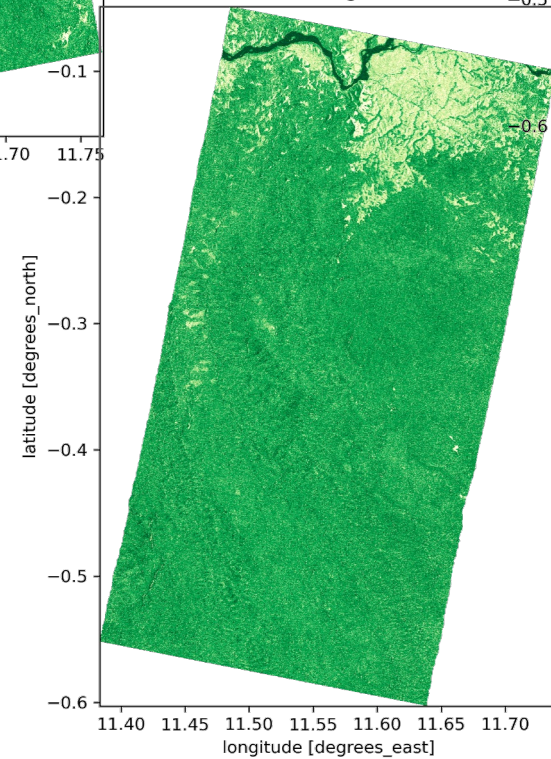
HoA: 94.89

Forest Height ML

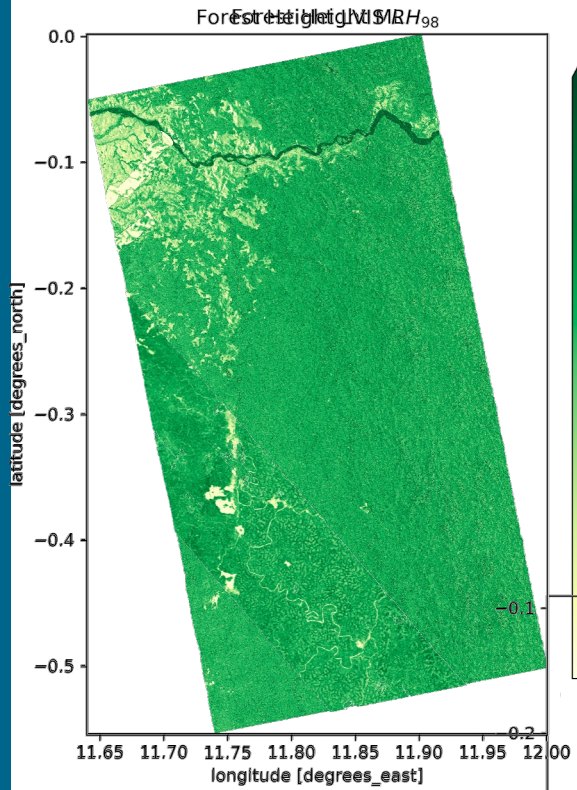


HoA: 95.41

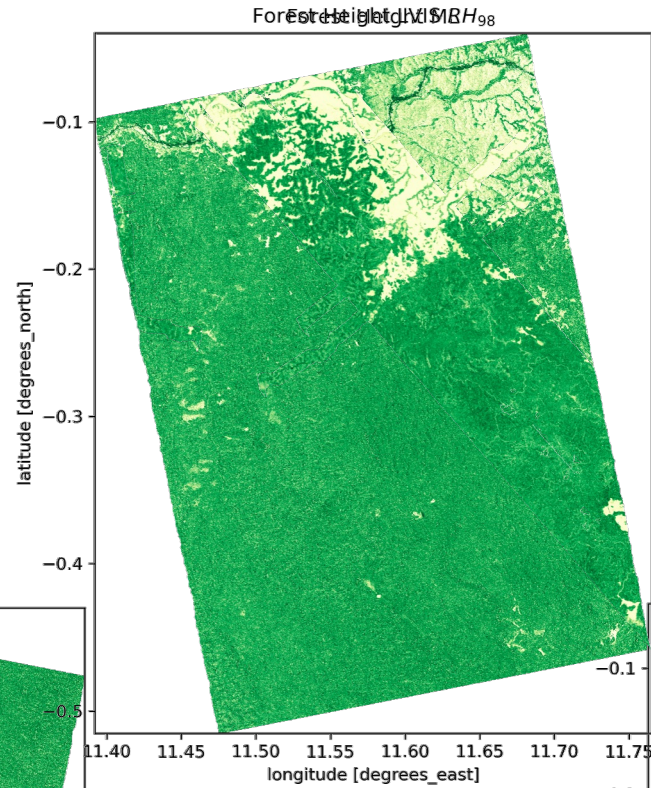
Forest Height ML



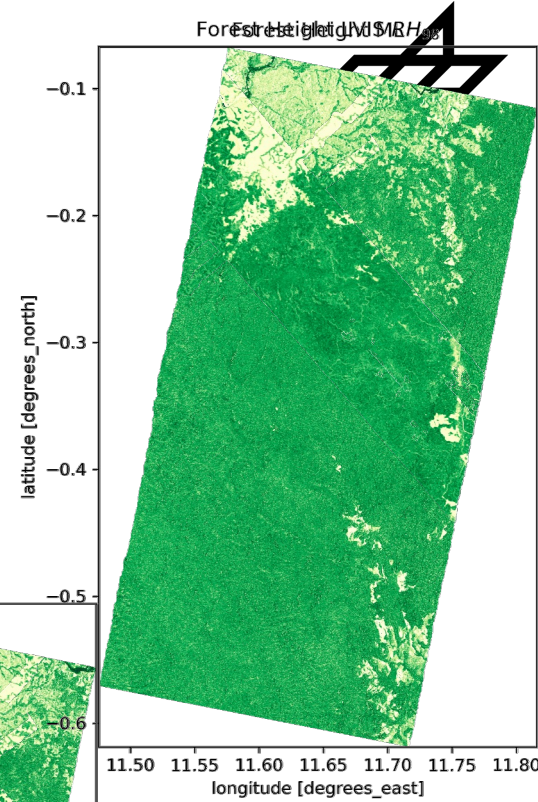
HoA: 52.45



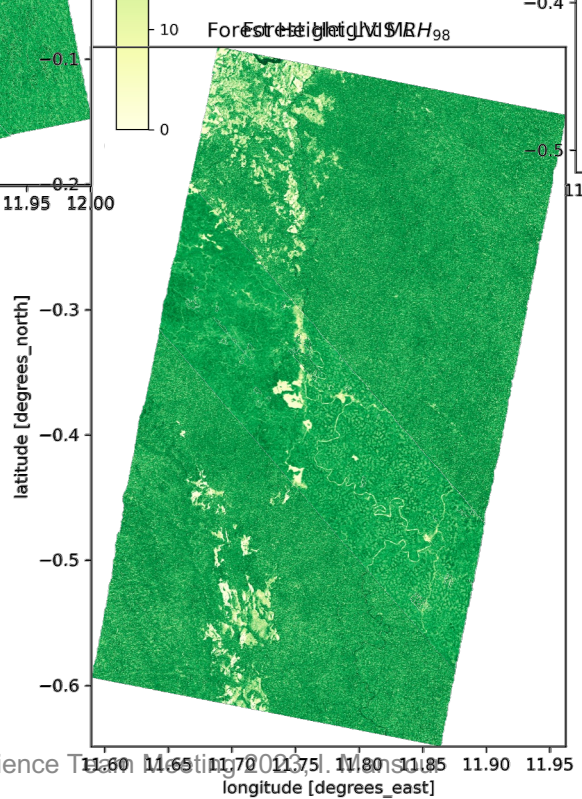
HoA: -65.22



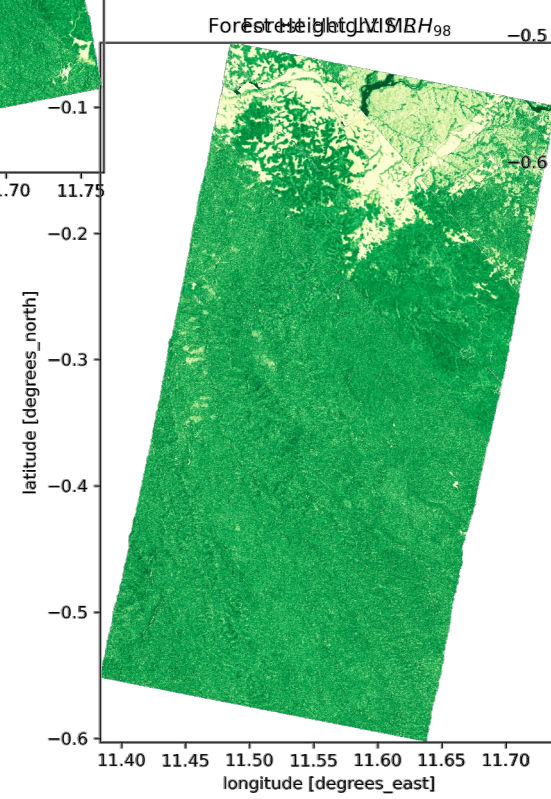
HoA: 86.34



HoA: 94.89



HoA: 95.41



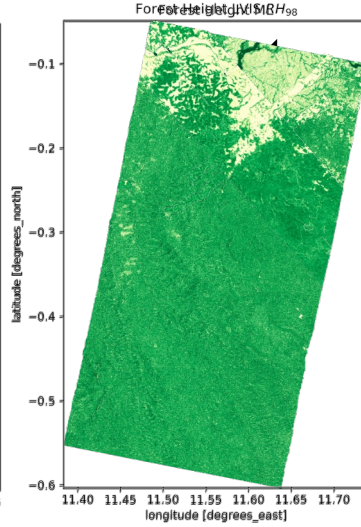
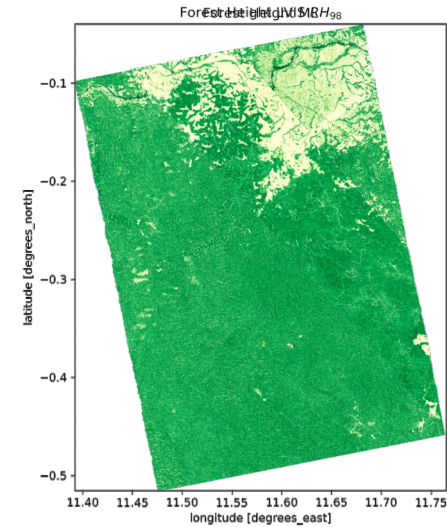
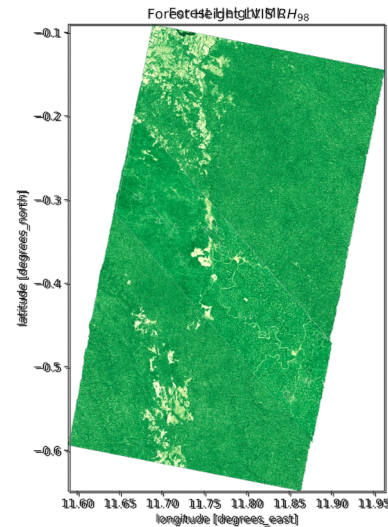
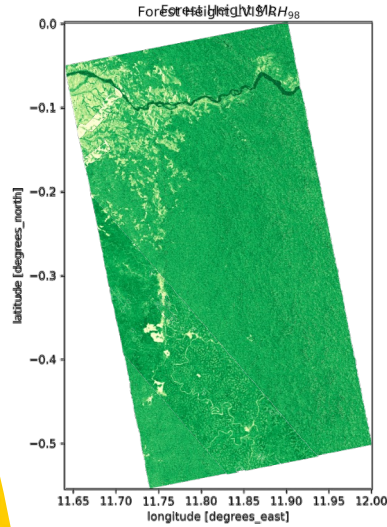
TerraSAR-X / TanDEM-X Science Team Meeting 2013, 11.80-11.85

# Summary of Key Points and Implications



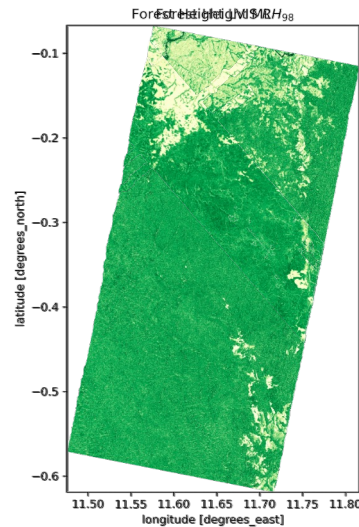
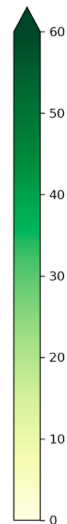
- **Hybrid Modeling Excellence:** Our novel hybrid modeling approach successfully integrates the domain-specific constraints of PM into ML. This enhances the model's robustness and generalizability while addressing the issue of explainability.
- **Importance of Legendre Coefficients:** The number ( $N$ ) 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.
- **Multi-Sensor and Multi-Data:** This approach also enables the integration of multi-sensor and multi-data sources (e.g., multi-spectral images, LandSAT, ALOS) as features for the ML model, expanding its capabilities beyond traditional physical models.





# Thank You!

Looking forward for your questions!



# Thank you



Looking forward for your questions!

