



Turbulent flow predictions of MHK turbine arrays using physics-informed convolutional neural networks

Zexia Zhang and Ali Khosronejad

Civil Engineering Department, College of Engineering & Applied Sciences,
Stony Brook University



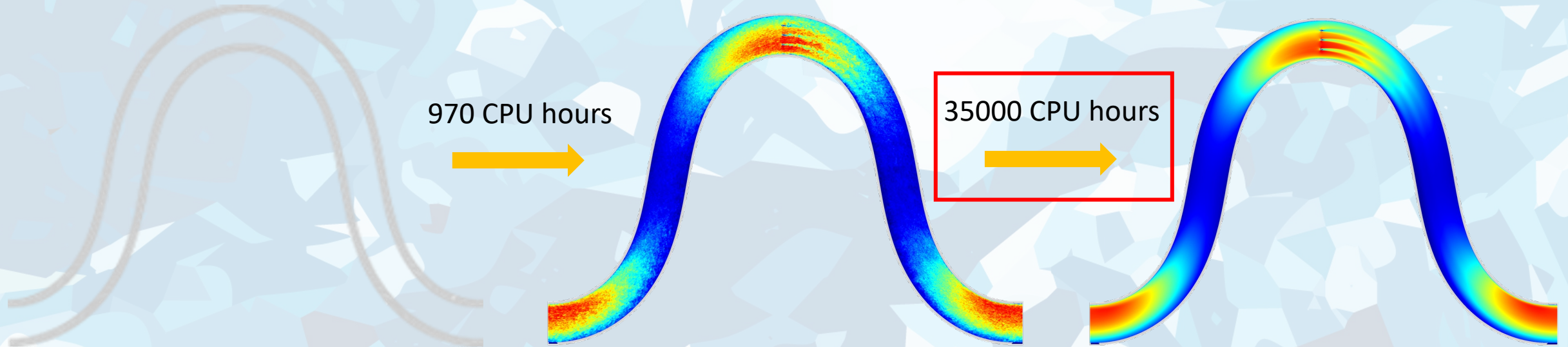
U.S. DEPARTMENT OF
ENERGY





Motivation

Large Eddy Simulations (LES) of large-scale rivers are very expensive, especially on calculating statistical properties, i.e. \bar{u} , \bar{v} , \bar{w} , $\overline{u'u'}$, $\overline{v'v'}$, $\overline{w'w'}$, etc.



Large- scale virtual meandering river

River size: 2110 m × 100 m × 3.3 m

Grid: 6601 × 501 × 21 = 6.9 × 10⁷

970 CPU hours

35000 CPU hours

Fully-converged instantaneous
turbulent flow field

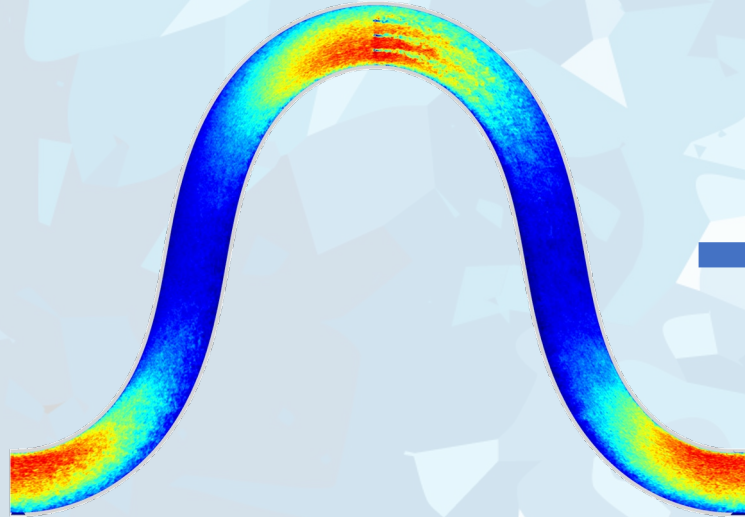
Time-averaged flow field



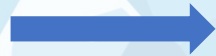
Motivation

Can we use artificial intelligence (AI) techniques to reduce the cost?

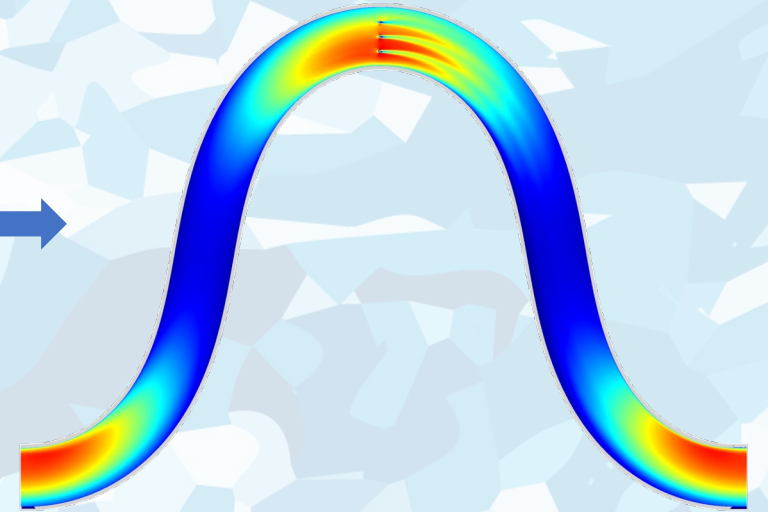
Strategy



Fully-converged instantaneous
turbulent flow field



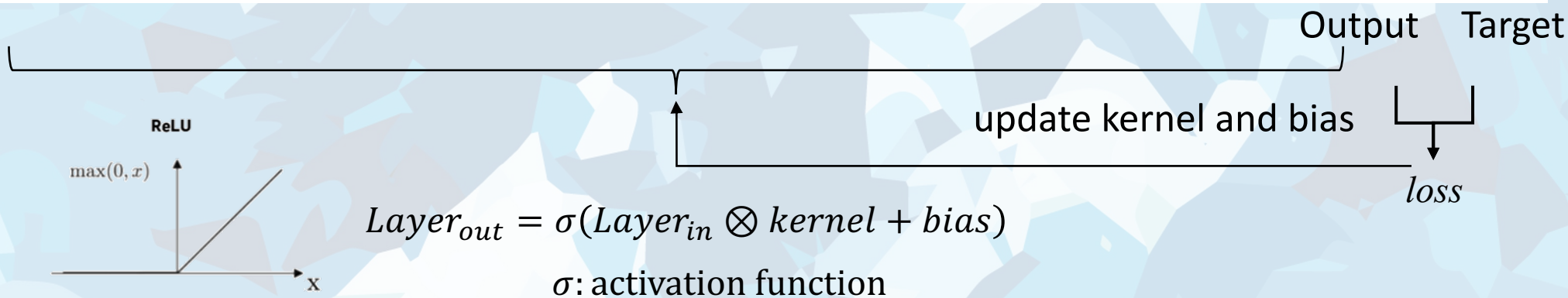
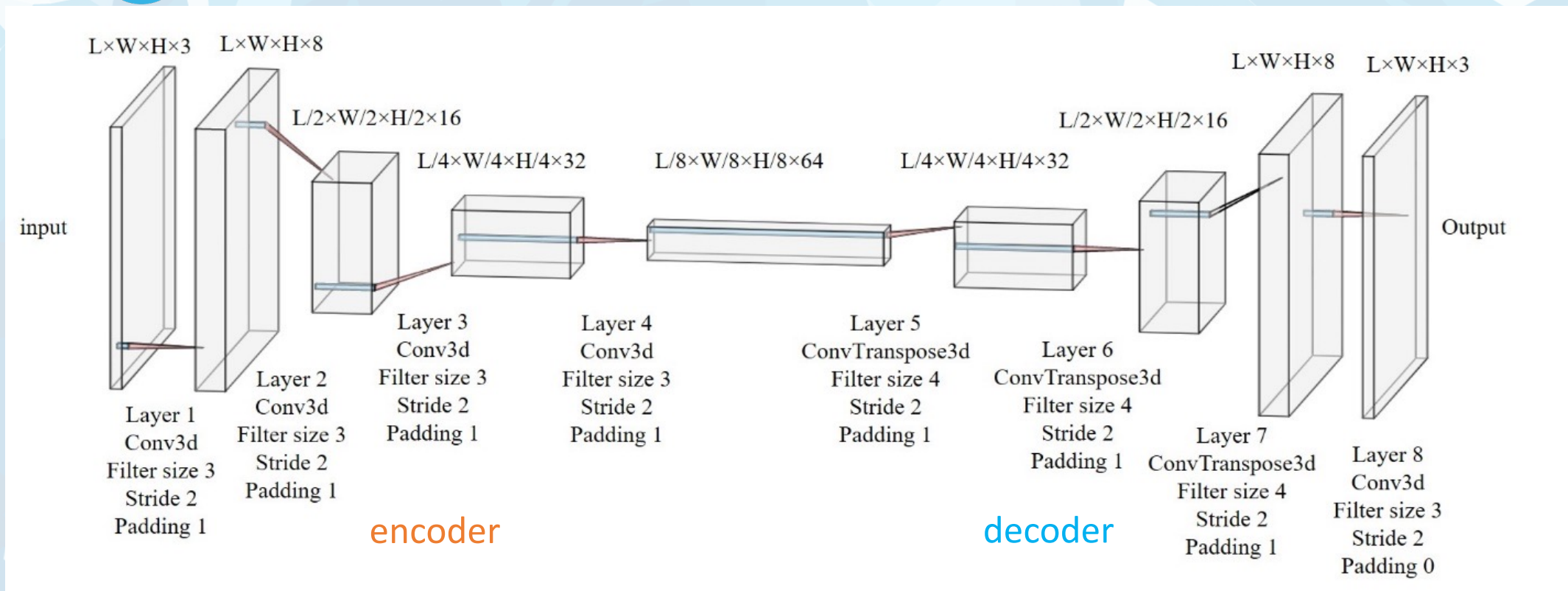
AI model



Time-averaged flow field



Convolutional Neural Network (CNN)





Loss function and Physics constraints

Governing equations for mean velocity:

$$\begin{aligned} \text{Div} &= 0 \\ M &= \text{Conv} + P + \text{Diff} + RS \end{aligned}$$

Difference between LES and CNN results:

$$\begin{aligned} \Delta \text{Div} &= \text{Div}_{\text{CNN}} - \text{Div}_{\text{LES}} \\ \Delta M &= M_{\text{CNN}} - M_{\text{LES}} \end{aligned}$$

Loss function of CNN:

CNN

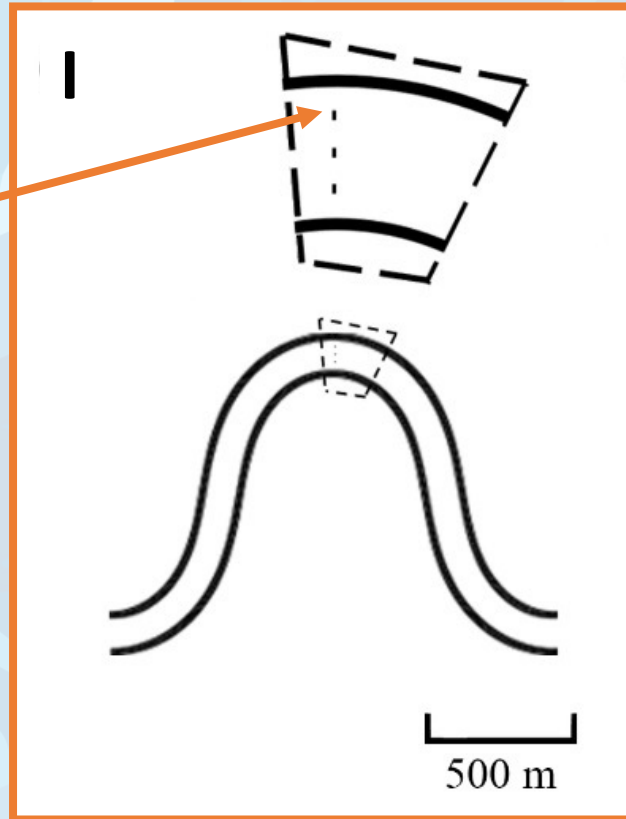
PICNN

$$\text{Loss} = \text{MSE}(\Phi_{\text{CNN}} - \Phi_{\text{LES}}) + \text{MSE}(\Delta \text{Div}) + \text{MSE}(\Delta M)$$

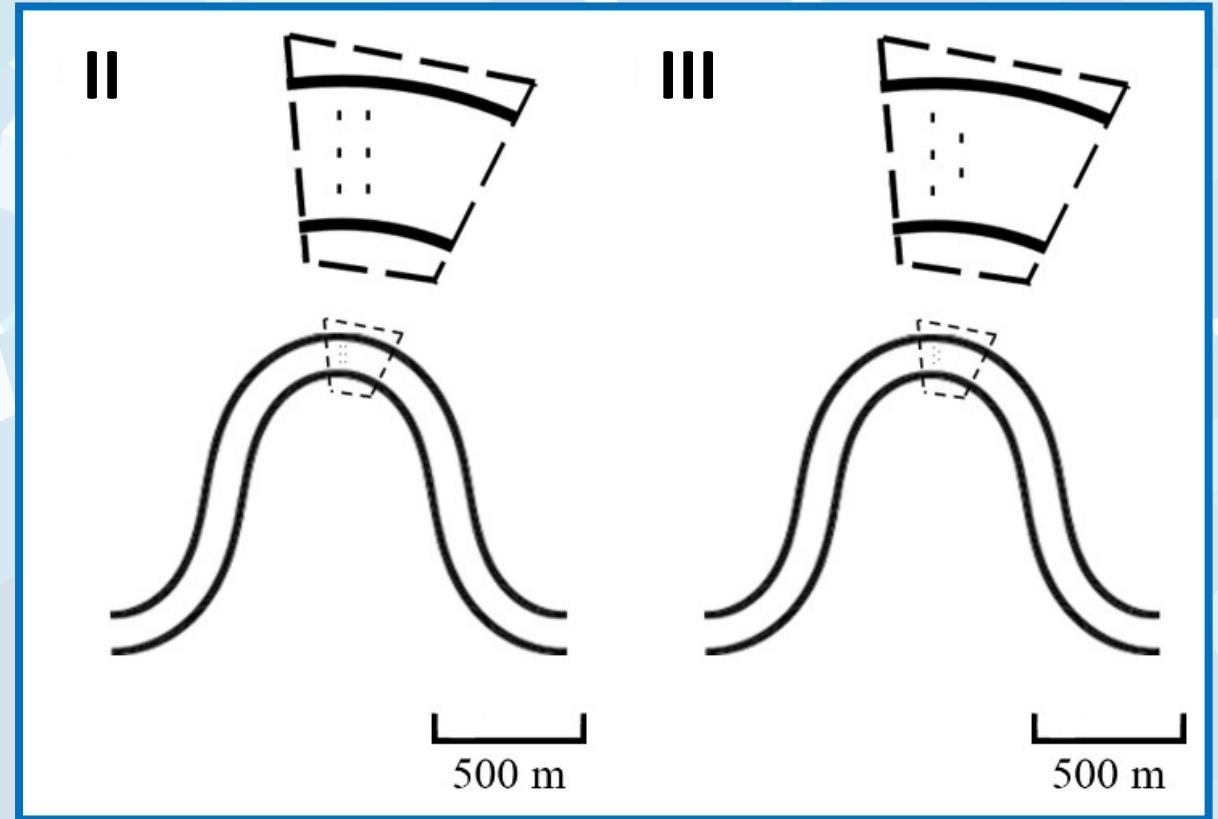


Training and validation cases

Turbines
 $D = 1.5 \text{ m}$



Training case



Validation cases

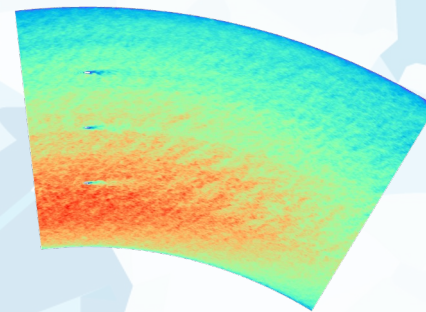
* Virtual Rivers are developed by Ajay B. Limaye from Department of Environmental Sciences, University of Virginia



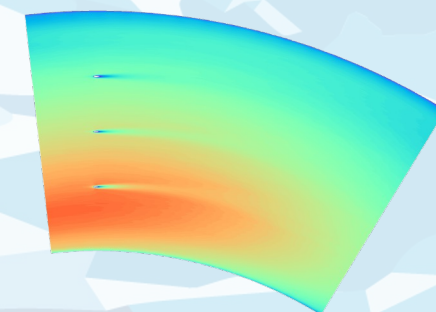
Training- mean velocity

- Run LES to produce training data
 - Instantaneous velocity fields
 - Time-averaged velocity fields
- Train the AI model
 - Learning rate: 0.001
 - Optimizer: Adam
 - Converge Epochs: 1400

Training sample



Inputs: instantaneous 3D flow fields



Training target: time-averaged 3D flow field

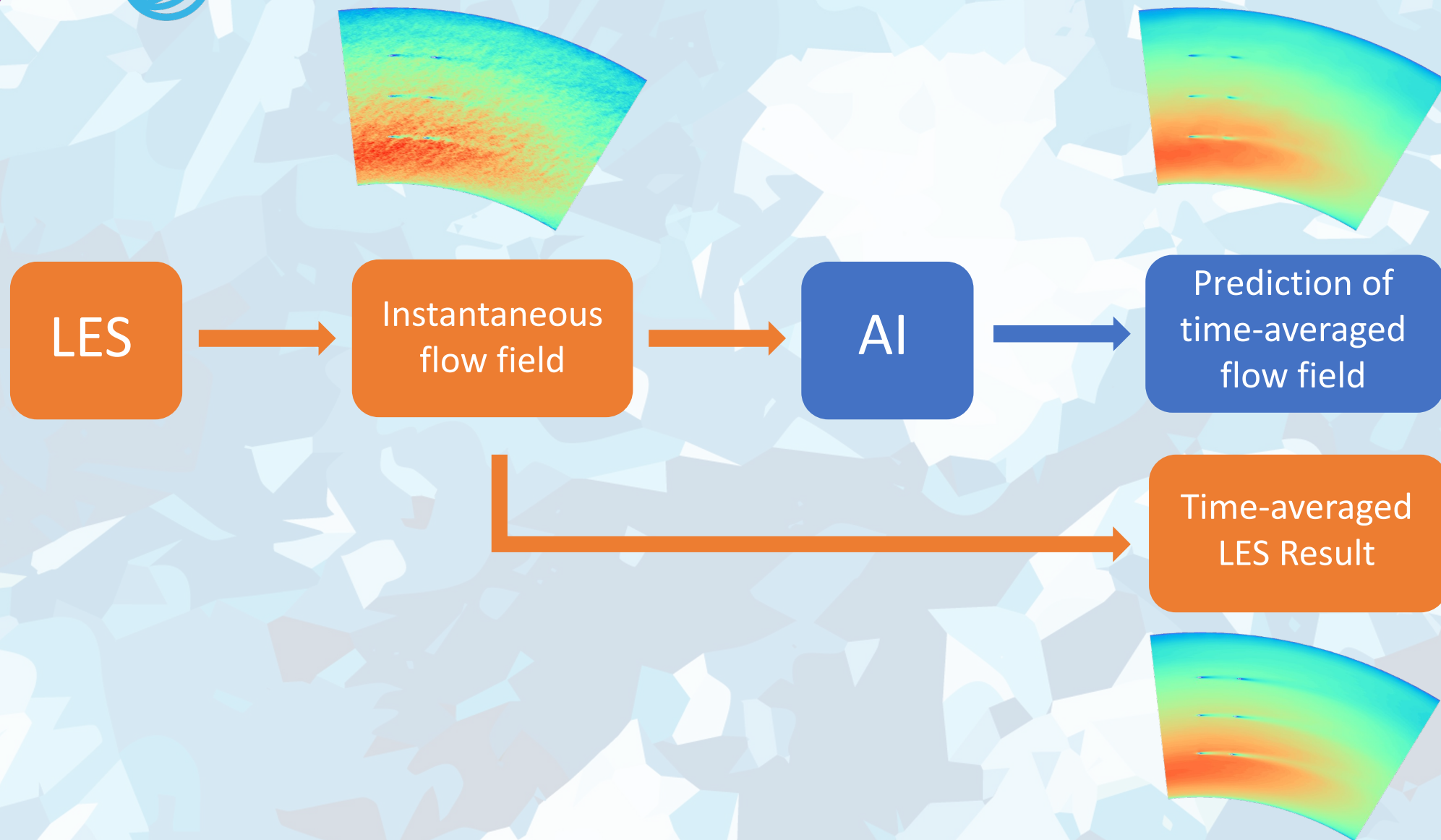
77 samples

-
-
-

Training dataset



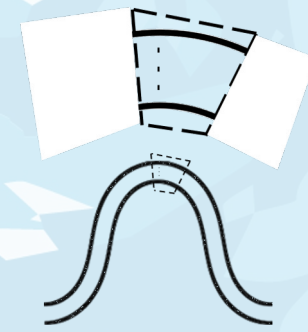
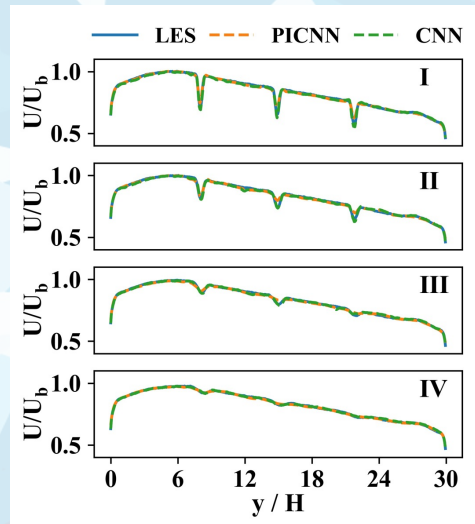
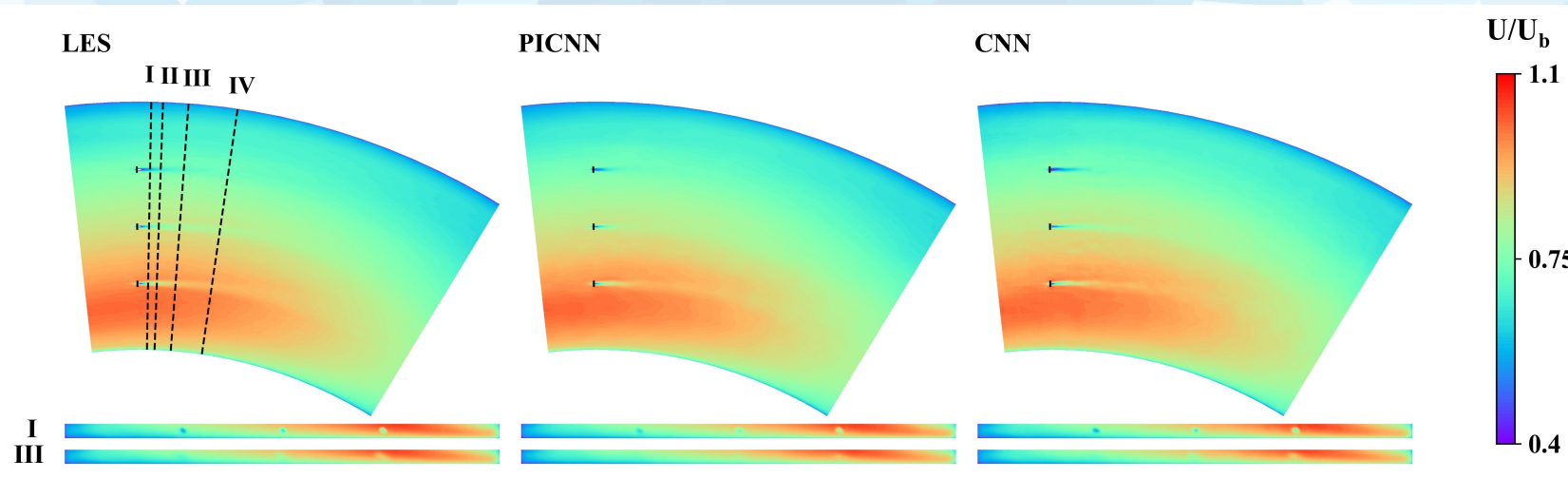
Validation- mean velocity



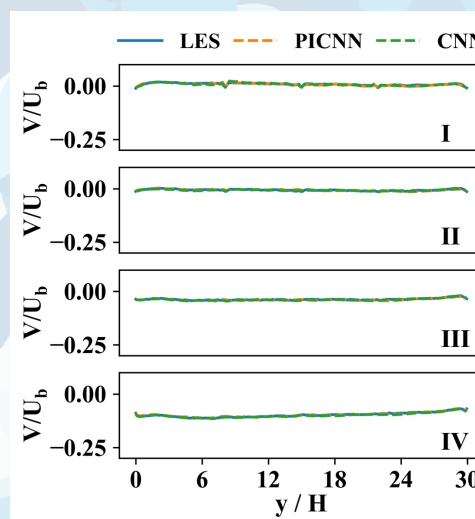
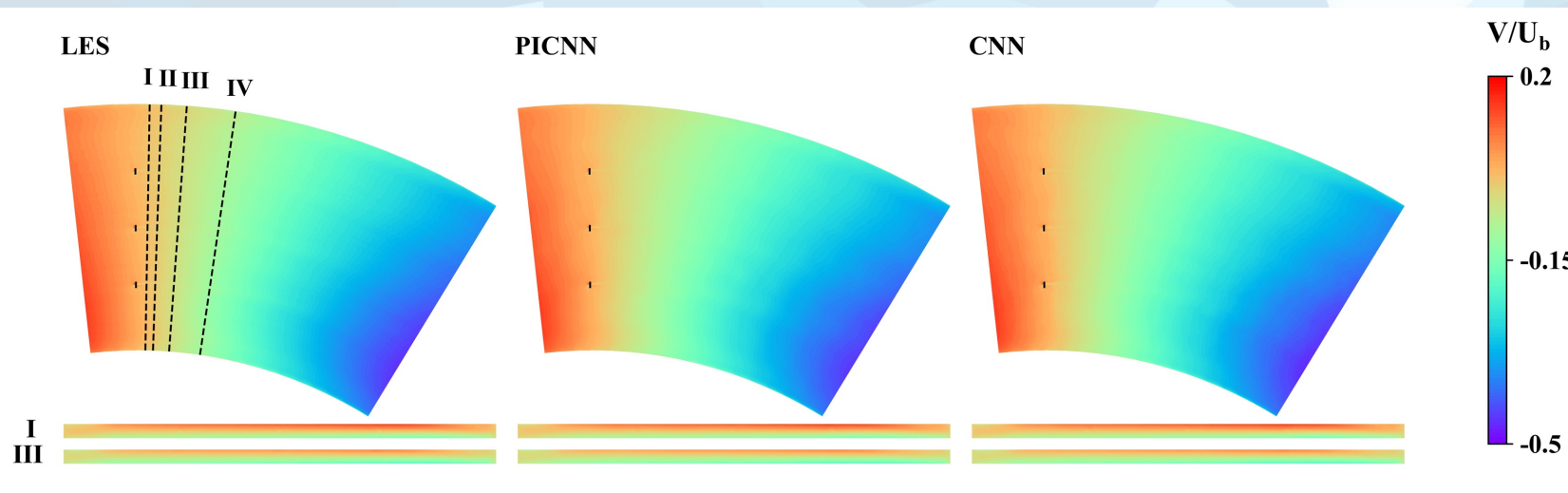


Results- training case

$$\text{Percentage error} = \frac{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)} - \psi_{i(AI)}|}{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)}|}$$



Percentage error:
PICNN: 0.57%
CNN: 0.57%

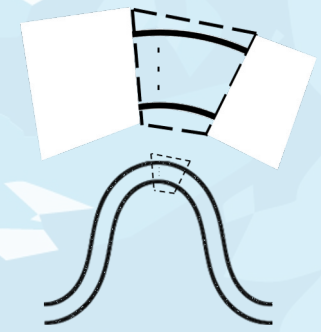
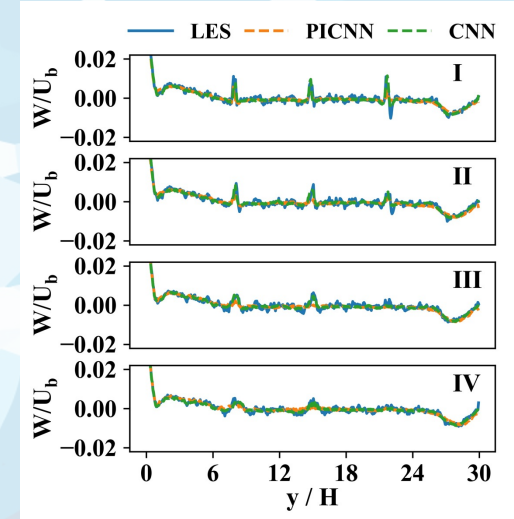
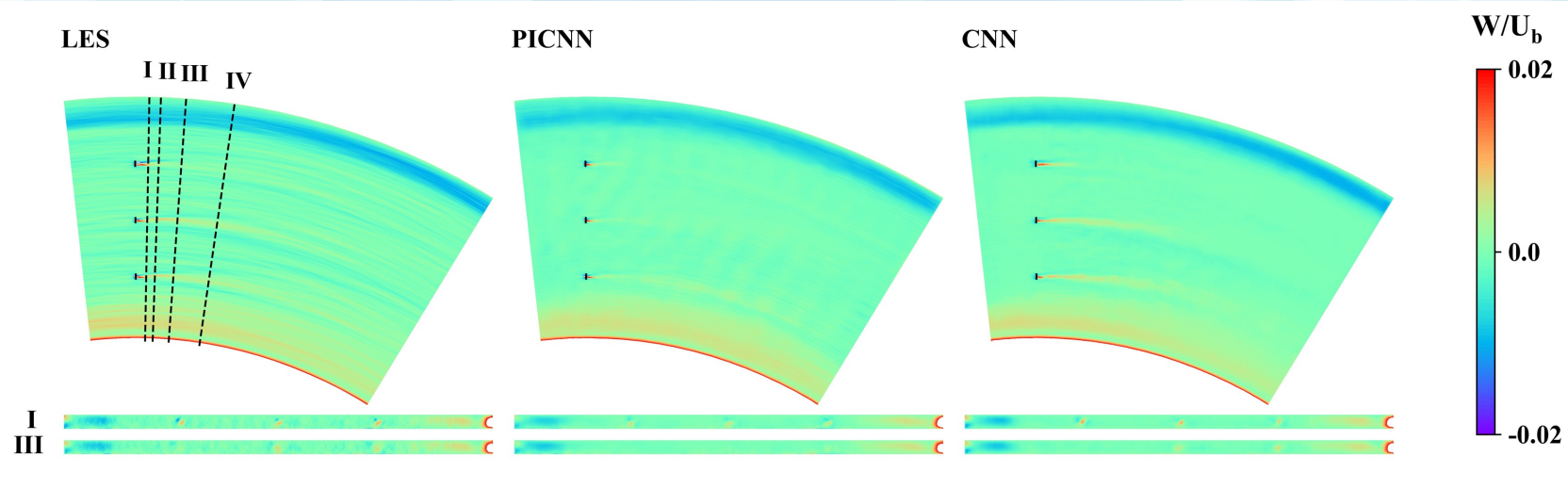


Percentage error:
PICNN: 1.23%
CNN: 1.79%

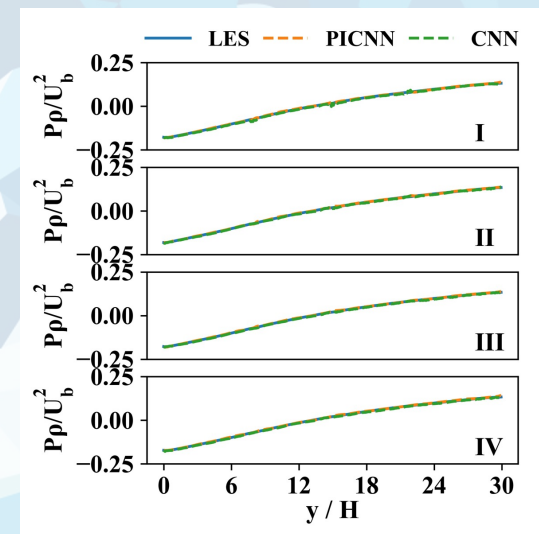
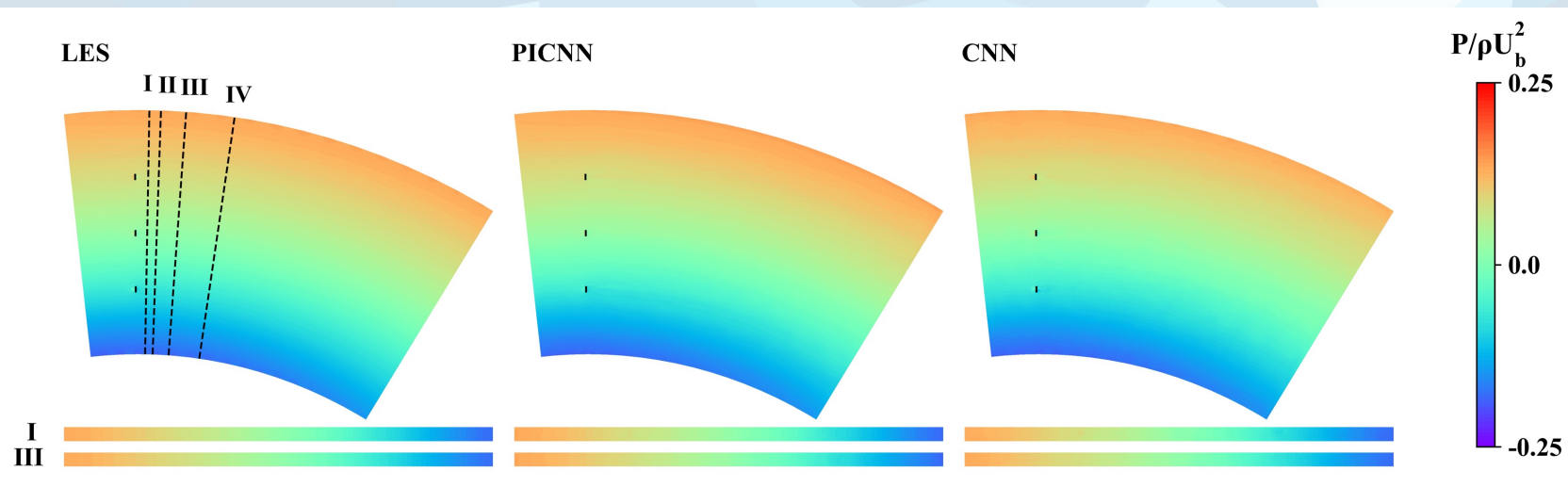


Results- training case

$$\text{Percentage error} = \frac{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)} - \psi_{i(AI)}|}{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)}|}$$



Percentage error:
PICNN: 22.22%
CNN: 38.65%

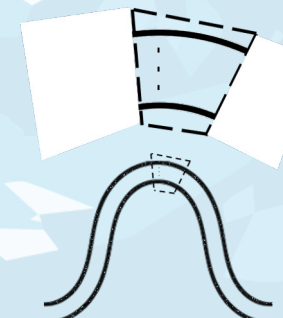
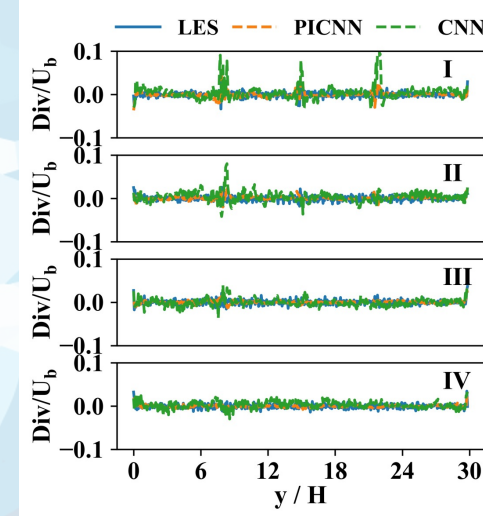
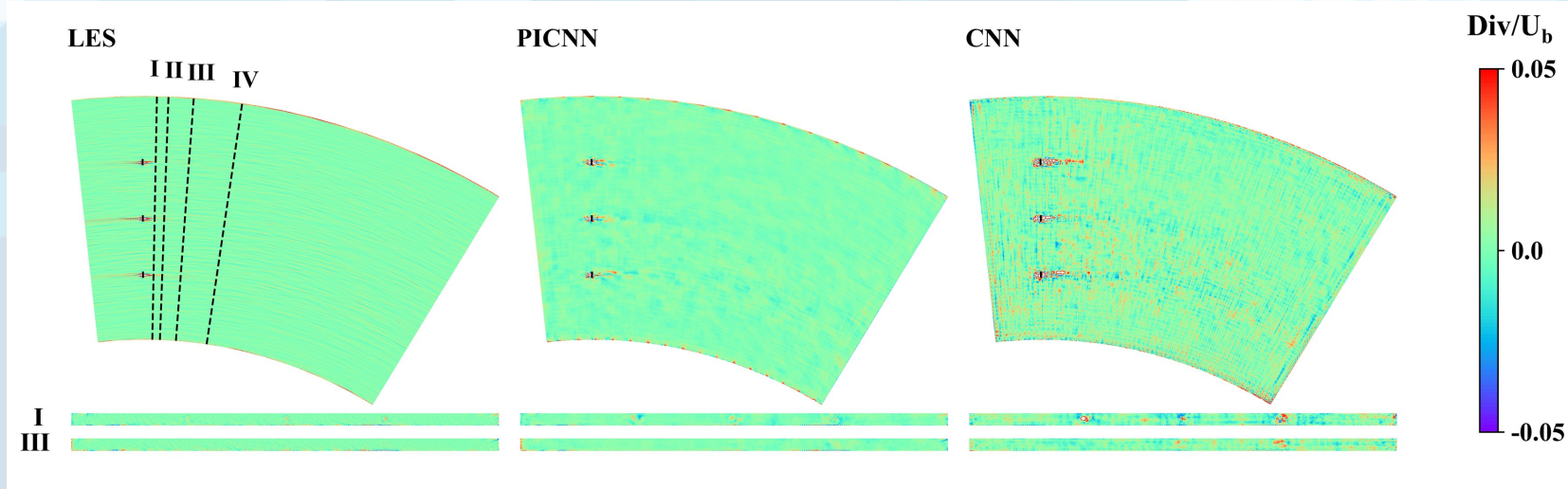


Percentage error:
PICNN: 2.02%
CNN: 5.15%

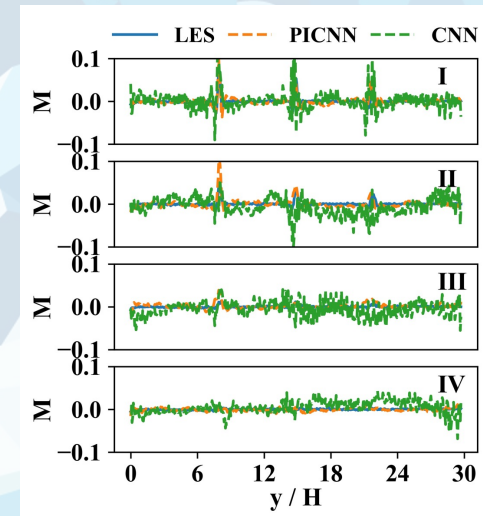
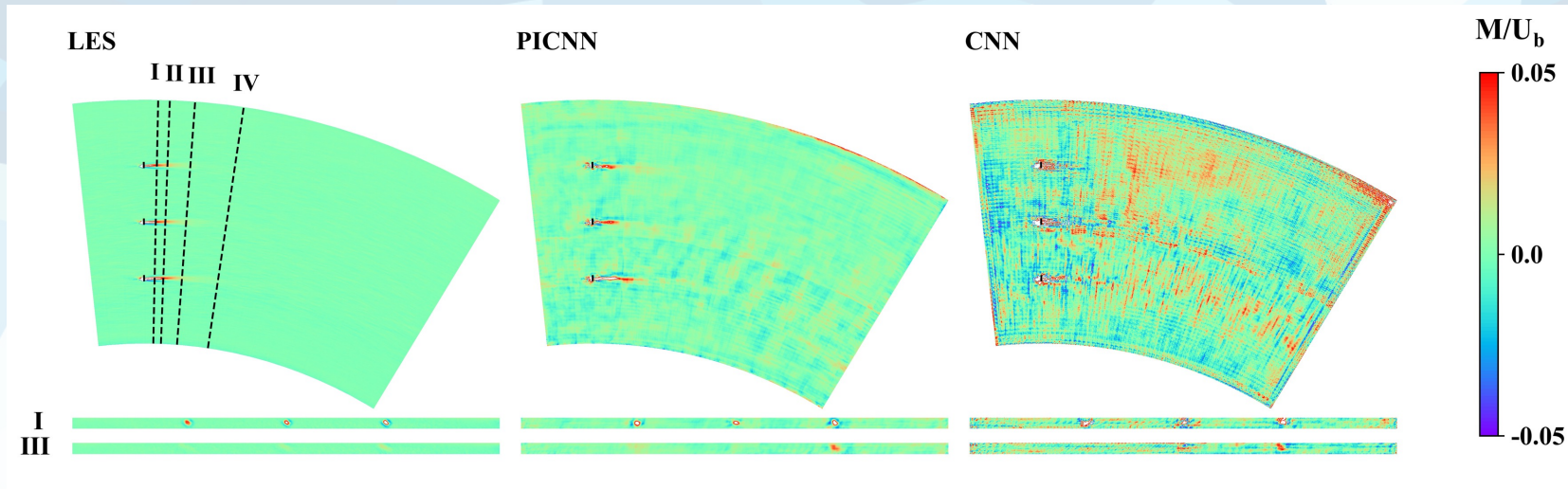


Results- training case

$$\|\Delta\psi\|_2 = \sqrt{\frac{1}{N} \sum_{i=1}^N (\psi_{i(LES)} - \psi_{i(AI)})^2}$$



$\|\Delta Div\|_2$:
PICNN: 0.0079
CNN: 0.0135

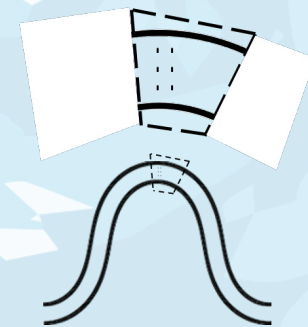
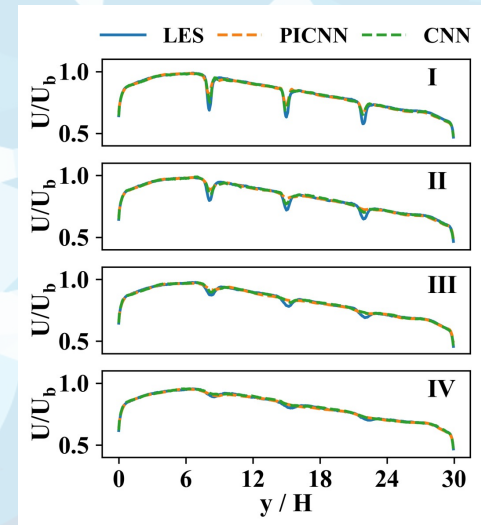
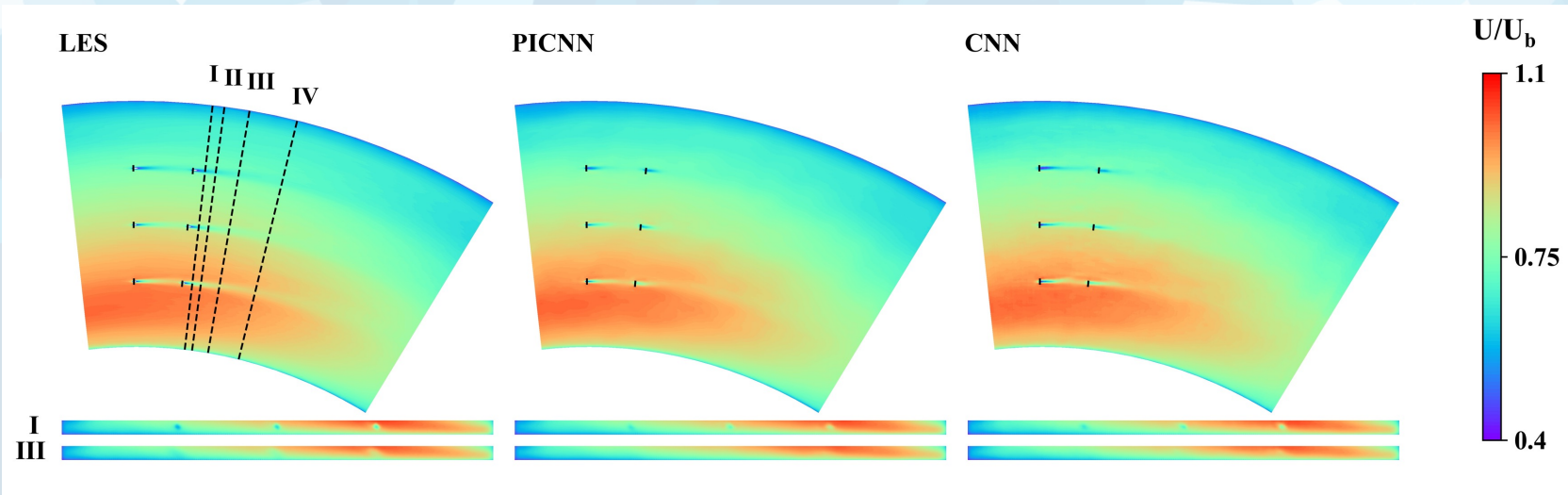


$\|\Delta M\|_2$:
PICNN: 0.0066
CNN: 0.0184

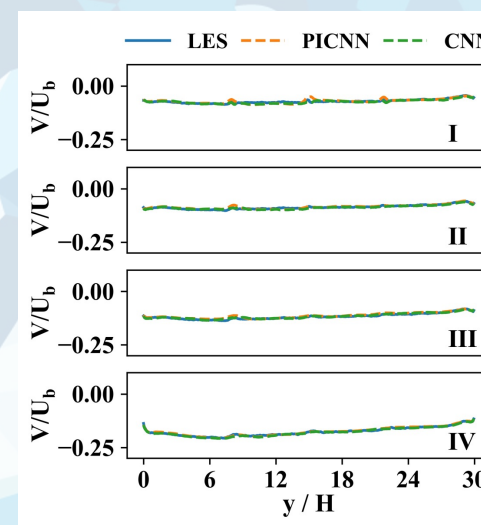
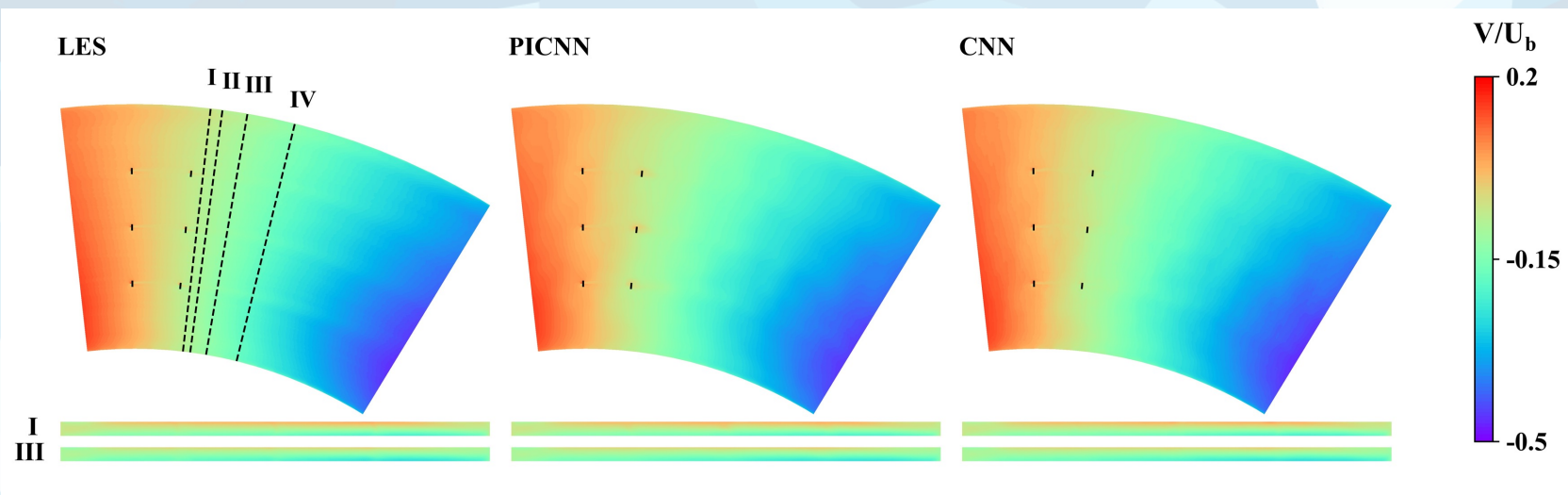


Results- validation case I

$$\text{Percentage error} = \frac{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)} - \psi_{i(AI)}|}{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)}|}$$



Percentage error:
 PICNN: 0.71%
 CNN: 0.72%

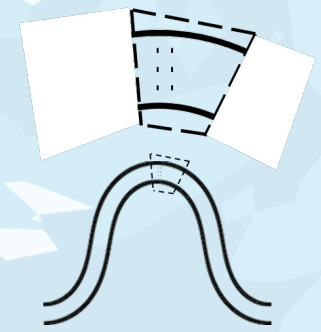
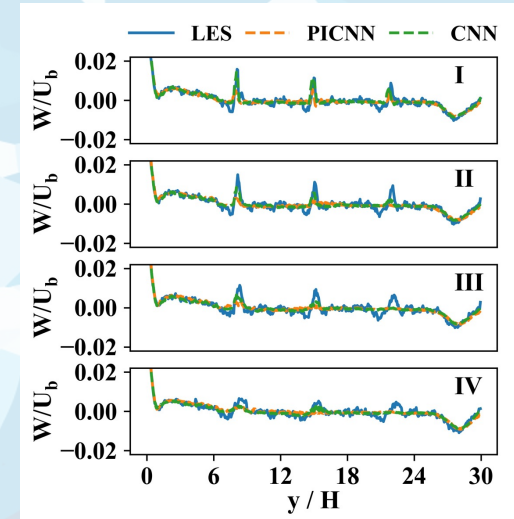
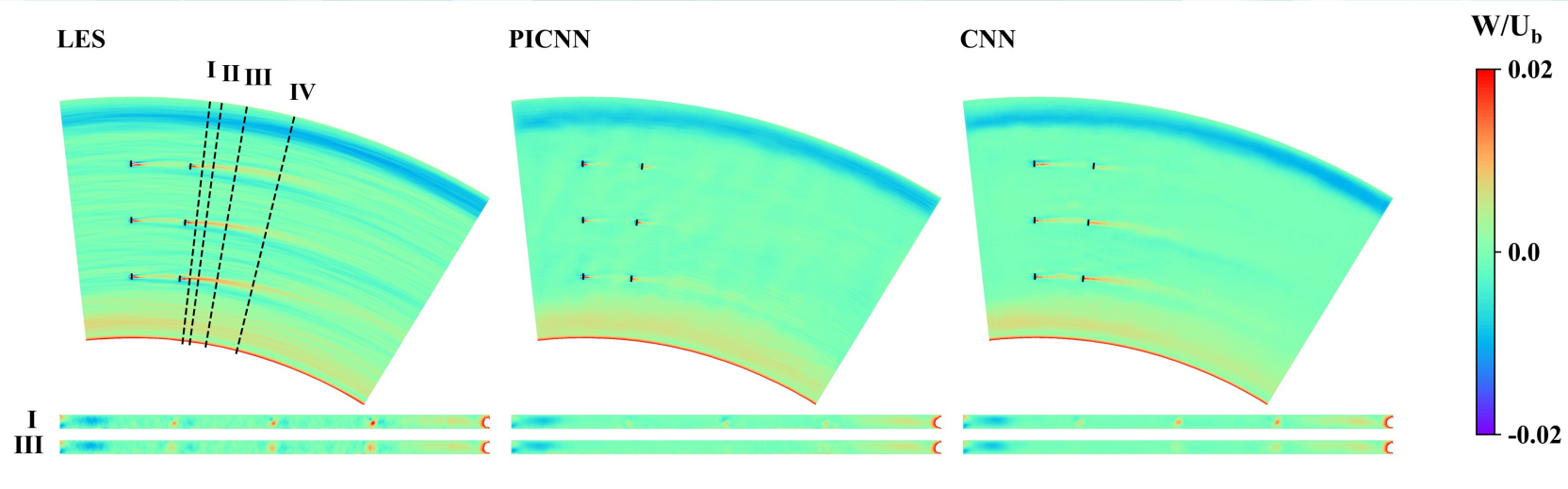


Percentage error:
 PICNN: 1.92%
 CNN: 2.06%

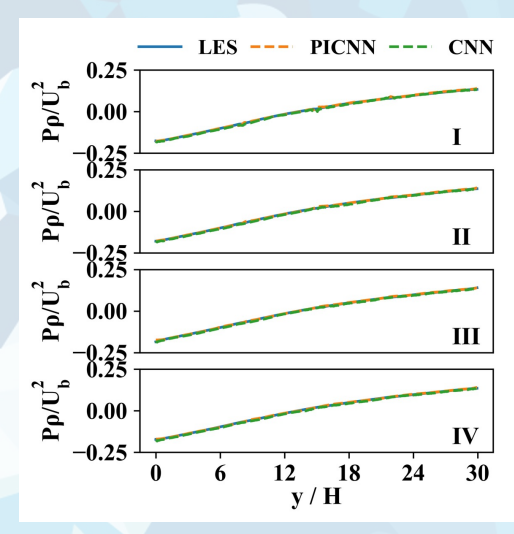
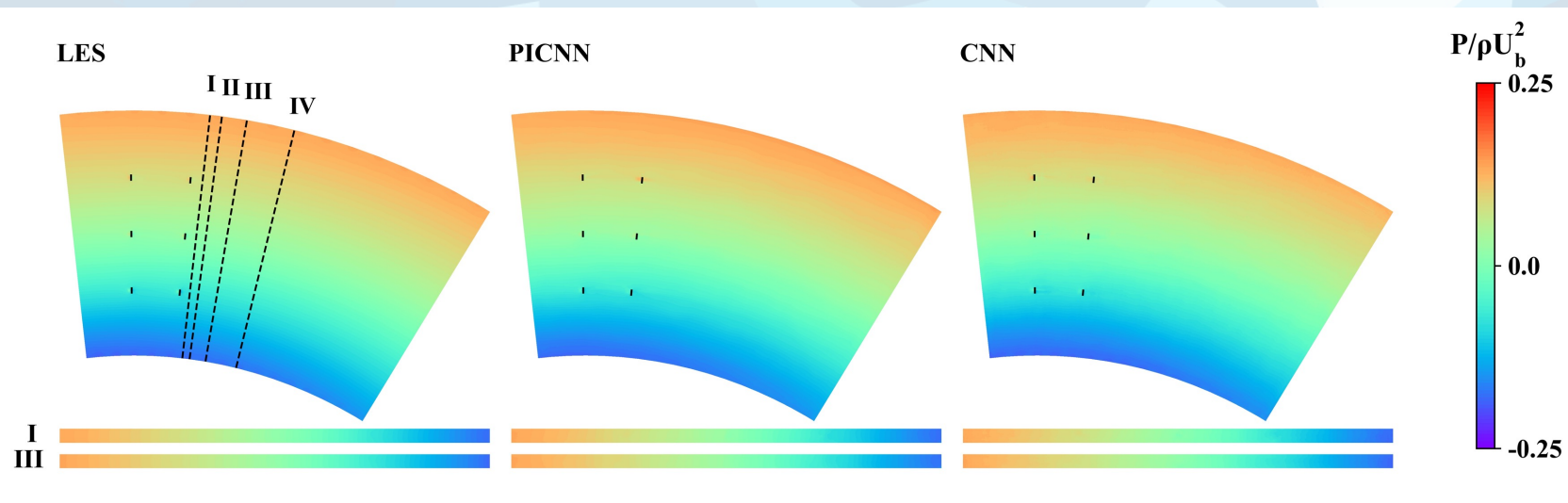


Results- validation case I

$$\text{Percentage error} = \frac{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)} - \psi_{i(AI)}|}{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)}|}$$



Percentage error:
PICNN: 30.80%
CNN: 44.77%

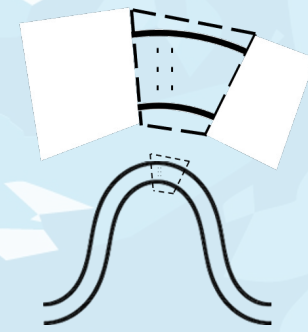
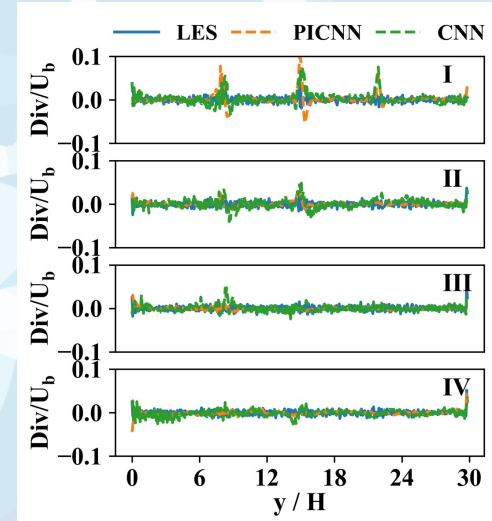
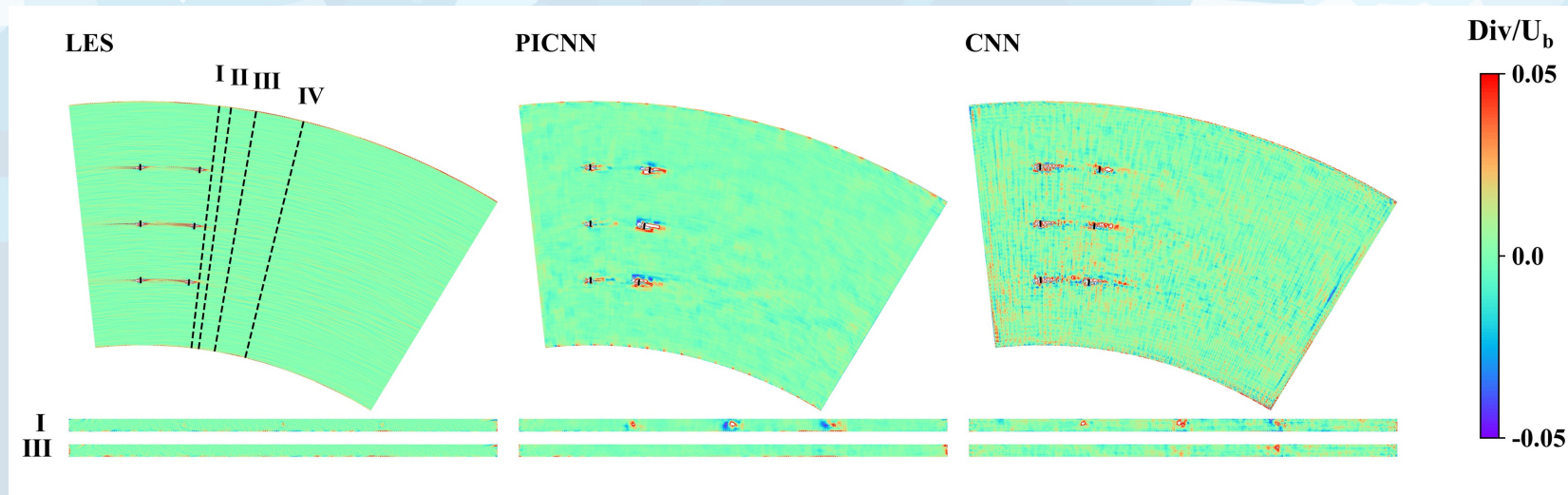


Percentage error:
PICNN: 2.12%
CNN: 5.38%

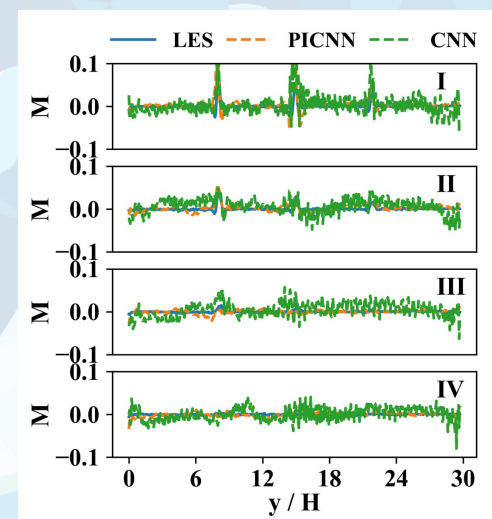
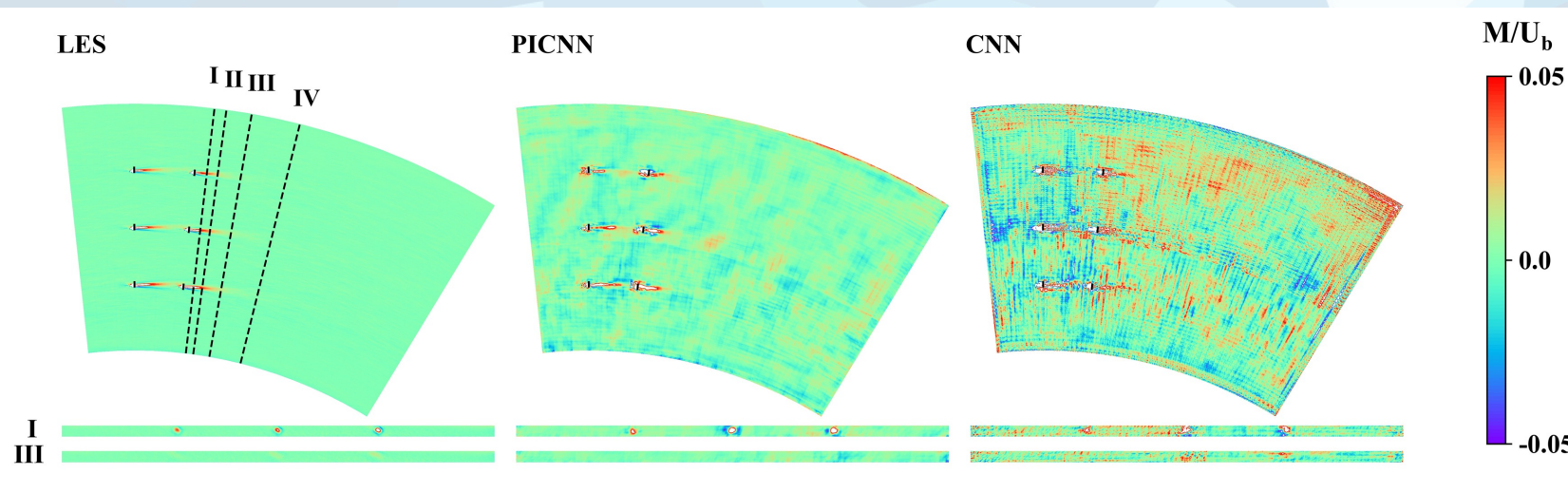


Results- validation case I

$$\|\Delta\psi\|_2 = \sqrt{\frac{1}{N} \sum_{i=1}^N (\psi_{i(LES)} - \psi_{i(AI)})^2}$$



$\|\Delta Div\|_2$:
PICNN: 0.0105
CNN: 0.0144

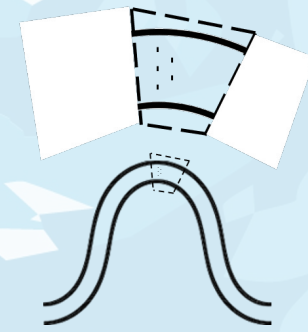
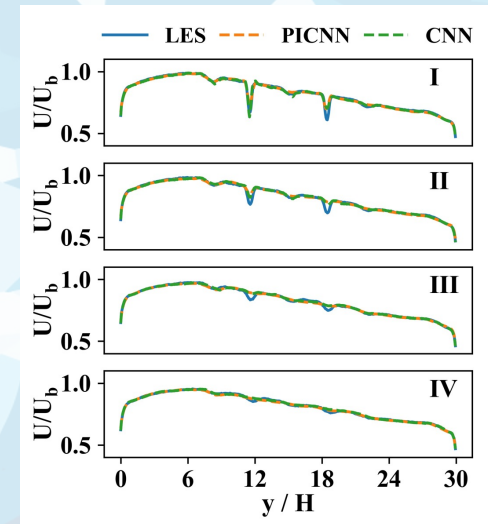
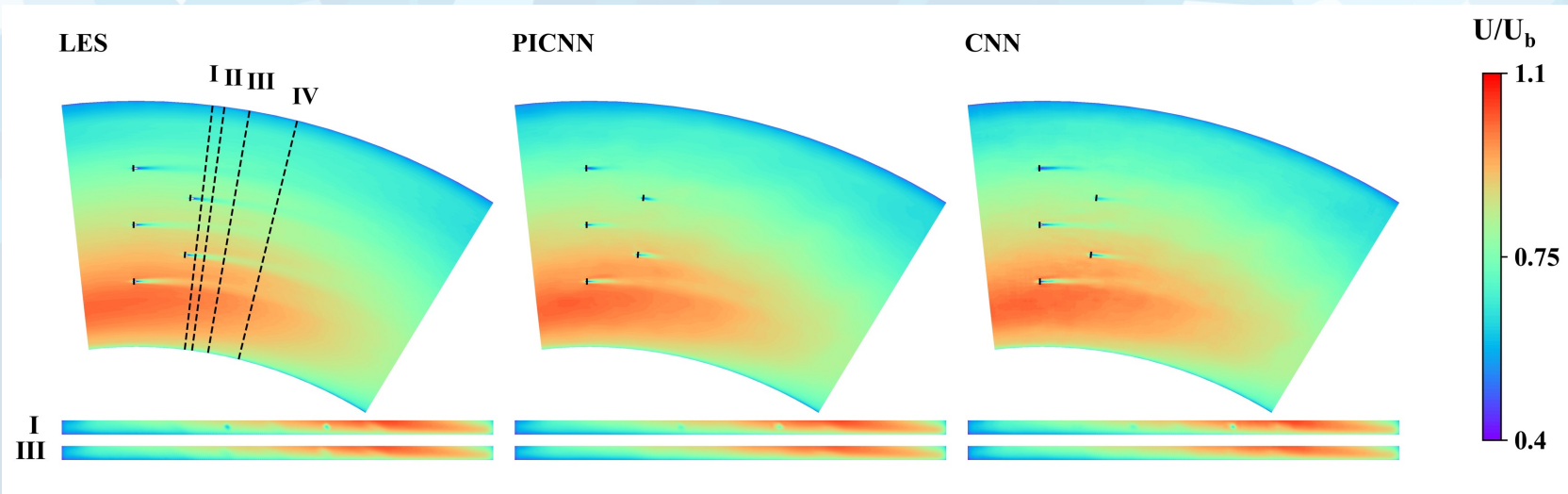


$\|\Delta M\|_2$:
PICNN: 0.0090
CNN: 0.0199

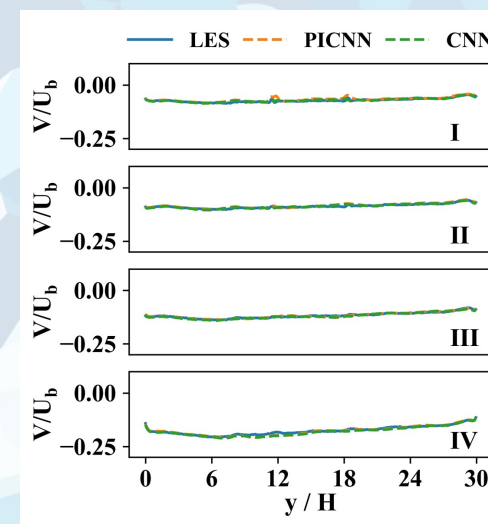
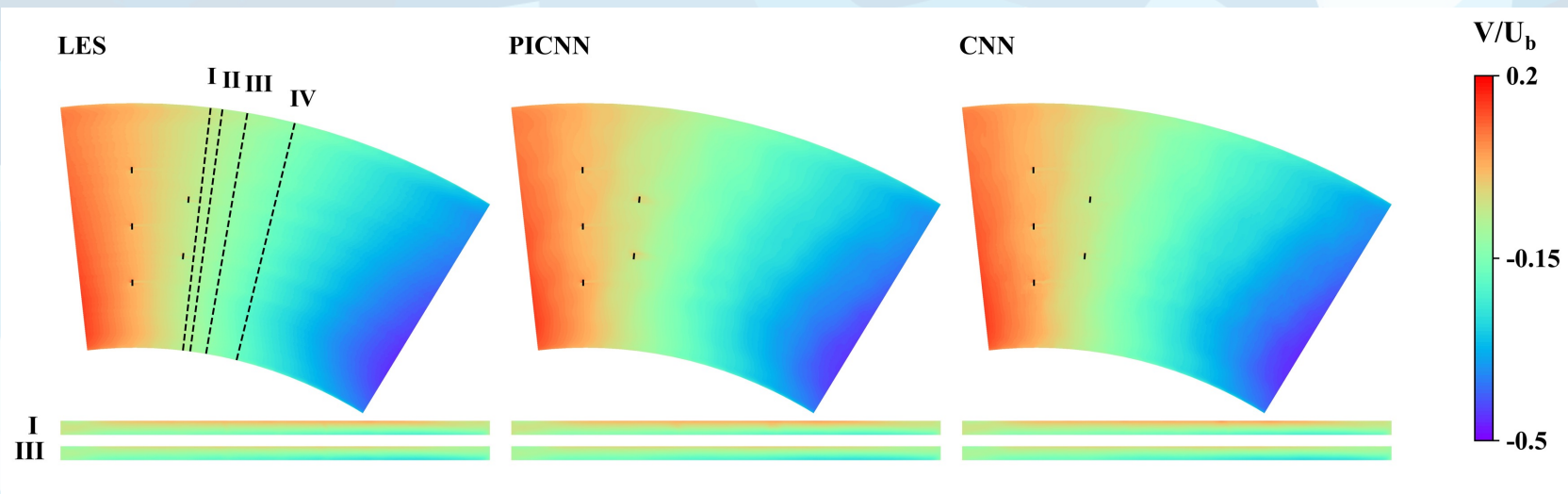


Results- validation case II

$$\text{Percentage error} = \frac{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)} - \psi_{i(AI)}|}{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)}|}$$



Percentage error:
PICNN: 0.69%
CNN: 0.72%

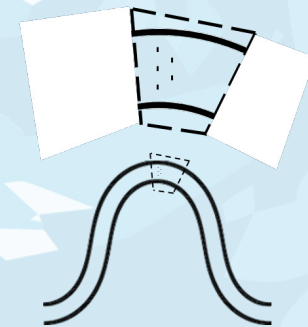
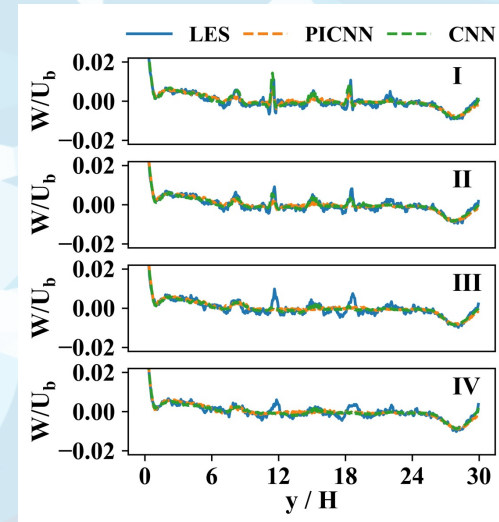
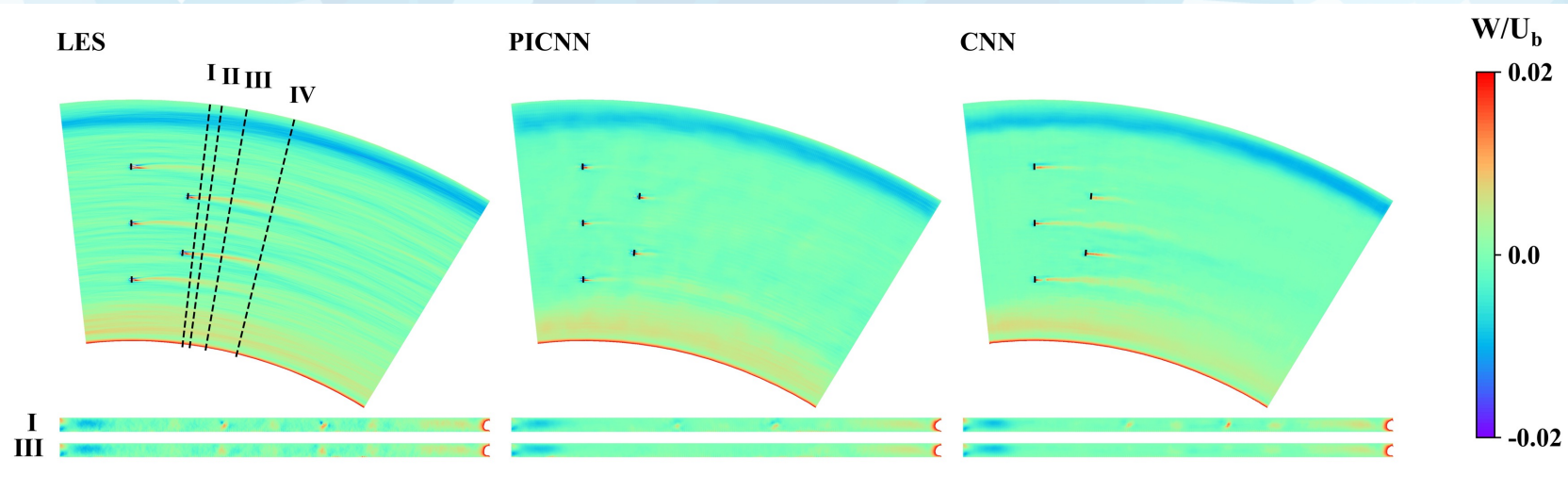


Percentage error:
PICNN: 1.94%
CNN: 2.05%

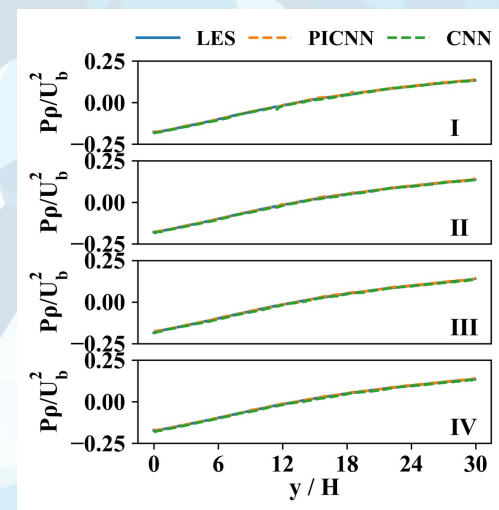
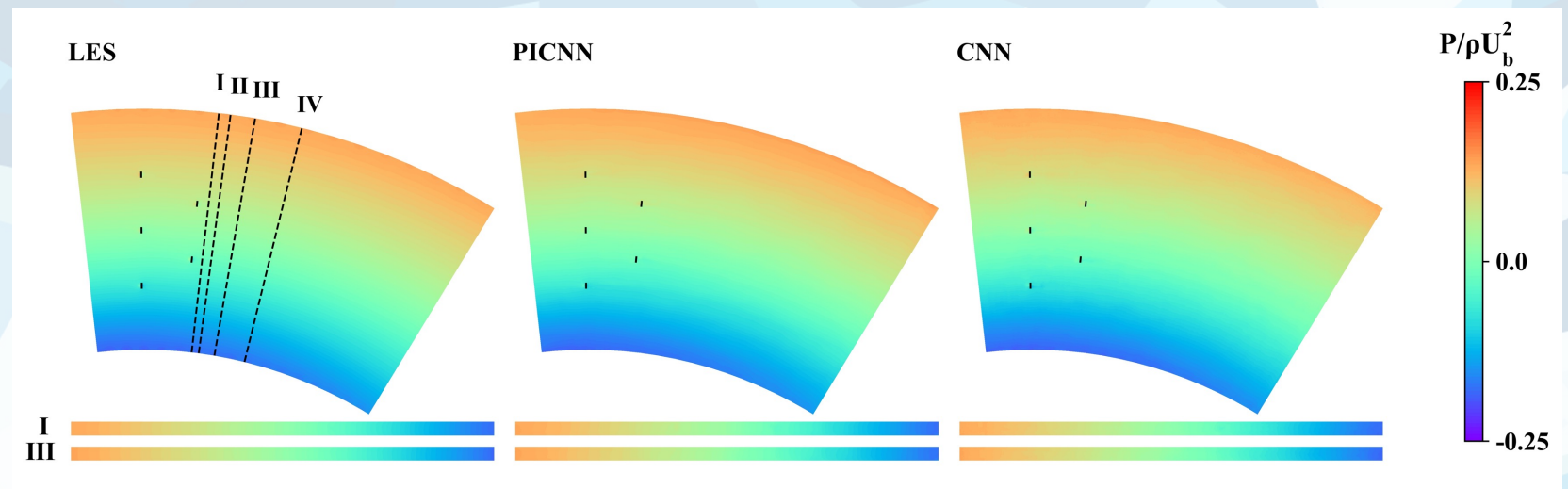


Results- validation case II

$$\text{Percentage error} = \frac{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)} - \psi_{i(AI)}|}{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)}|}$$



Percentage error:
PICNN: 29.05%
CNN: 43.25%

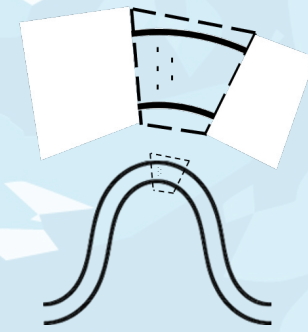
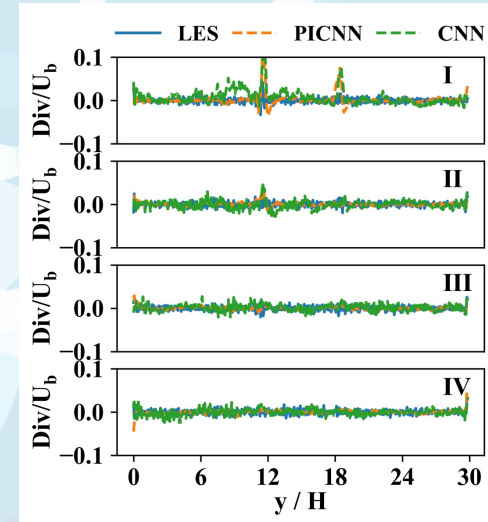
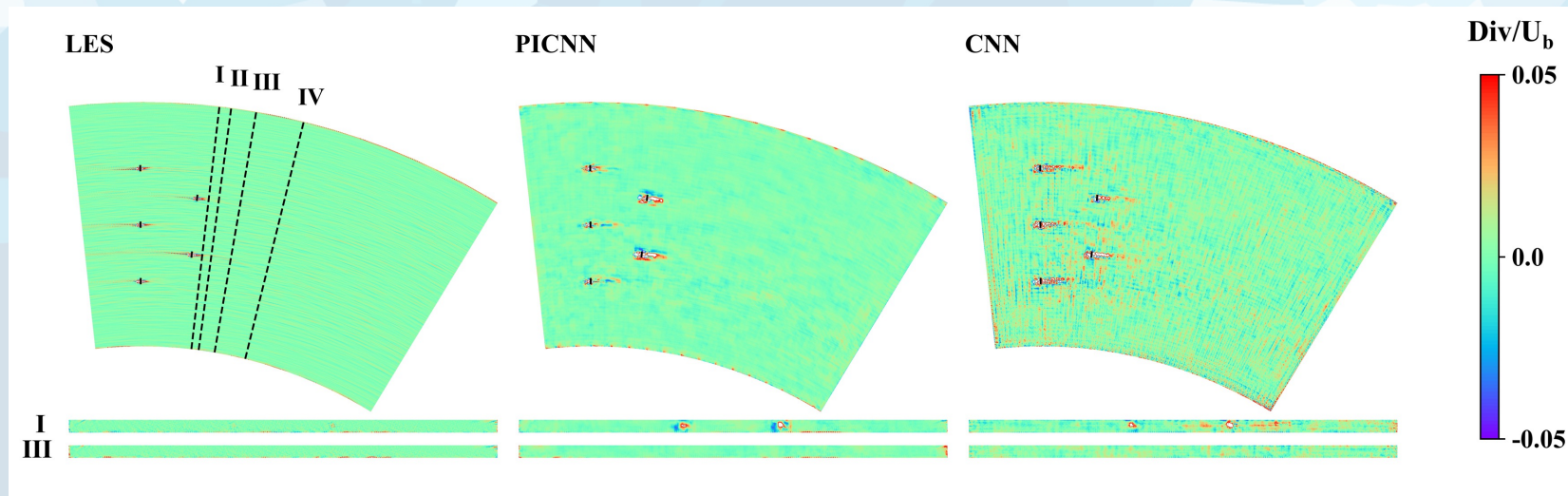


Percentage error:
PICNN: 2.14%
CNN: 5.23%

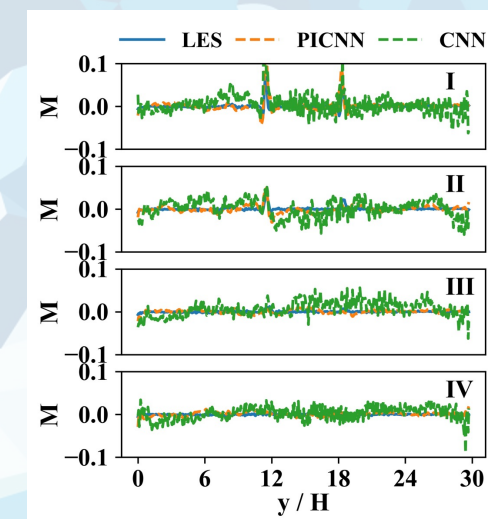
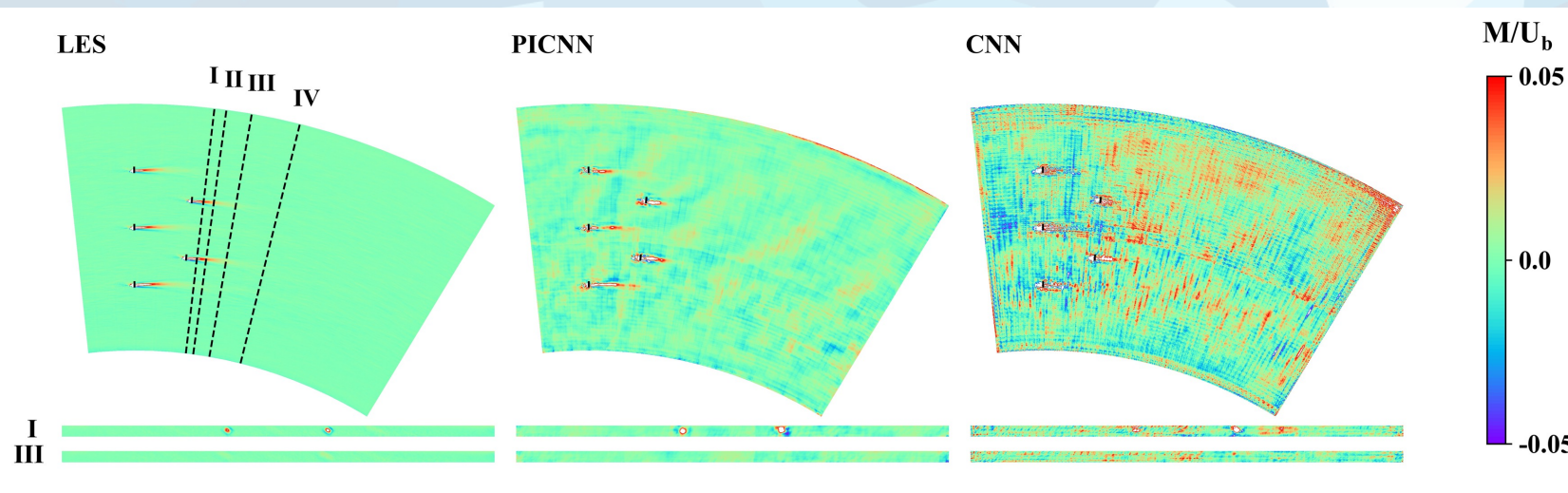


Results- validation case II

$$\|\Delta\psi\|_2 = \sqrt{\frac{1}{N} \sum_{i=1}^N (\psi_{i(LES)} - \psi_{i(AI)})^2}$$



$\|\Delta Div\|_2$:
PICNN: 0.0104
CNN: 0.0142



$\|\Delta M\|_2$:
PICNN: 0.0086
CNN: 0.0196

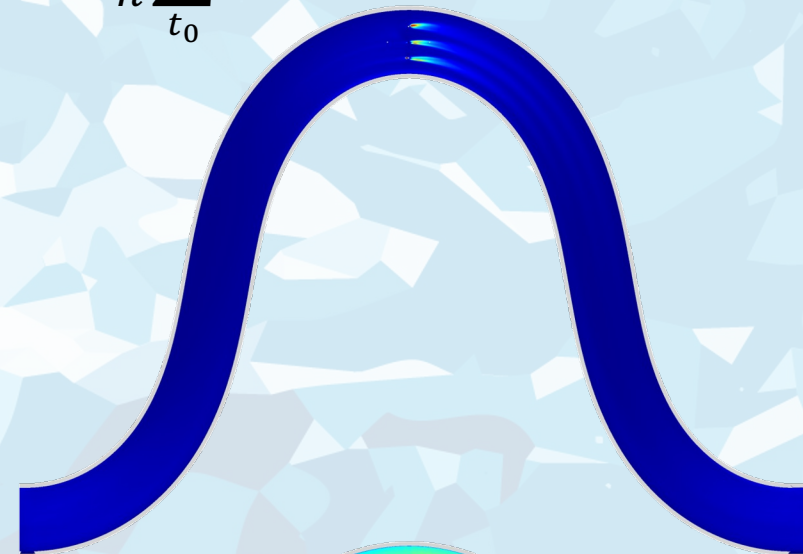
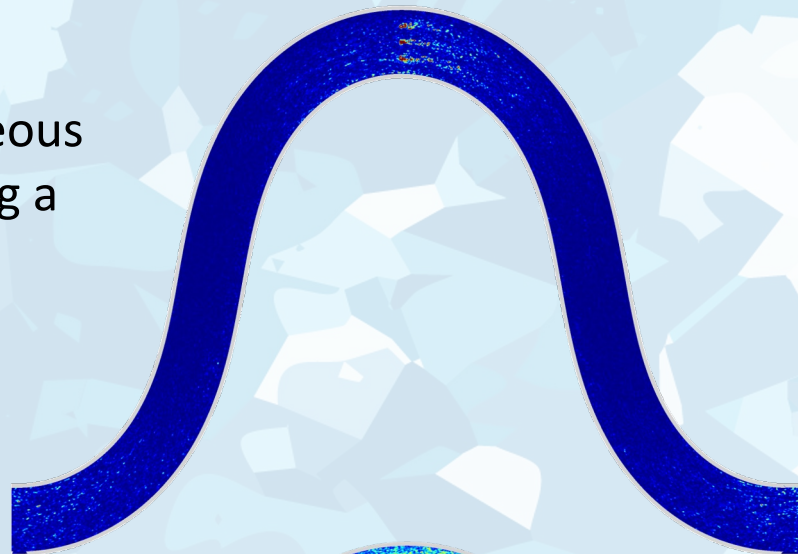


Training- Reynolds stress

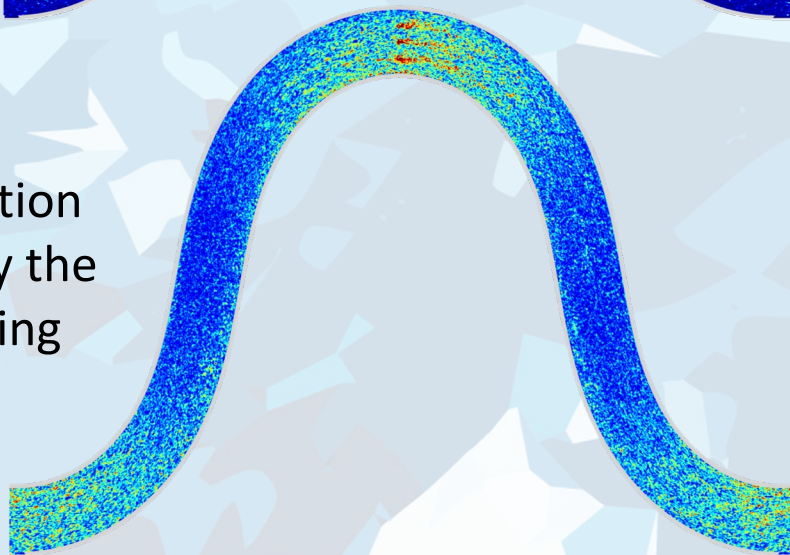
$$u'u'_{input} = (u_{LES} - \bar{u}_{CNN})(u_{LES} - \bar{u}_{CNN})$$

$$\overline{u'u'}_{output} = \frac{1}{n} \sum_{t_0}^{t_n} (u_{LES} - \bar{u}_{LES})(u_{LES} - \bar{u}_{LES})$$

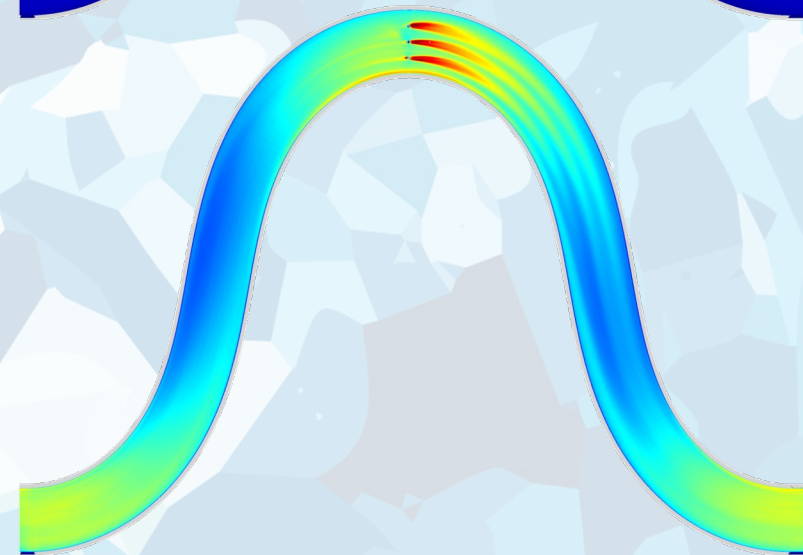
Input is the instantaneous Reynolds stress, having a highly heterogeneous distribution



Rendering the distribution more homogeneous by the cubic root pre-processing



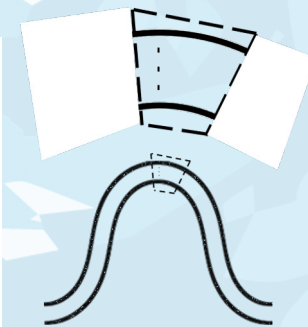
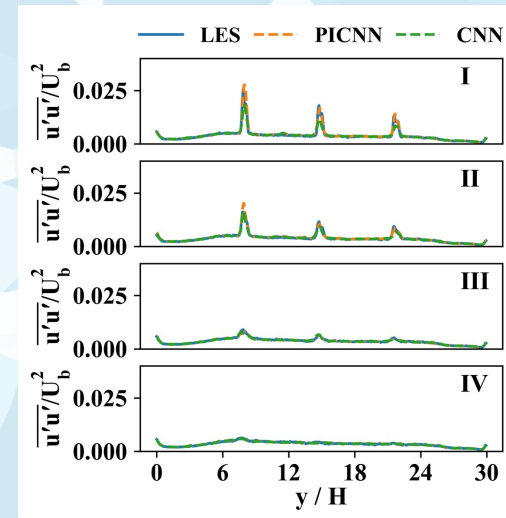
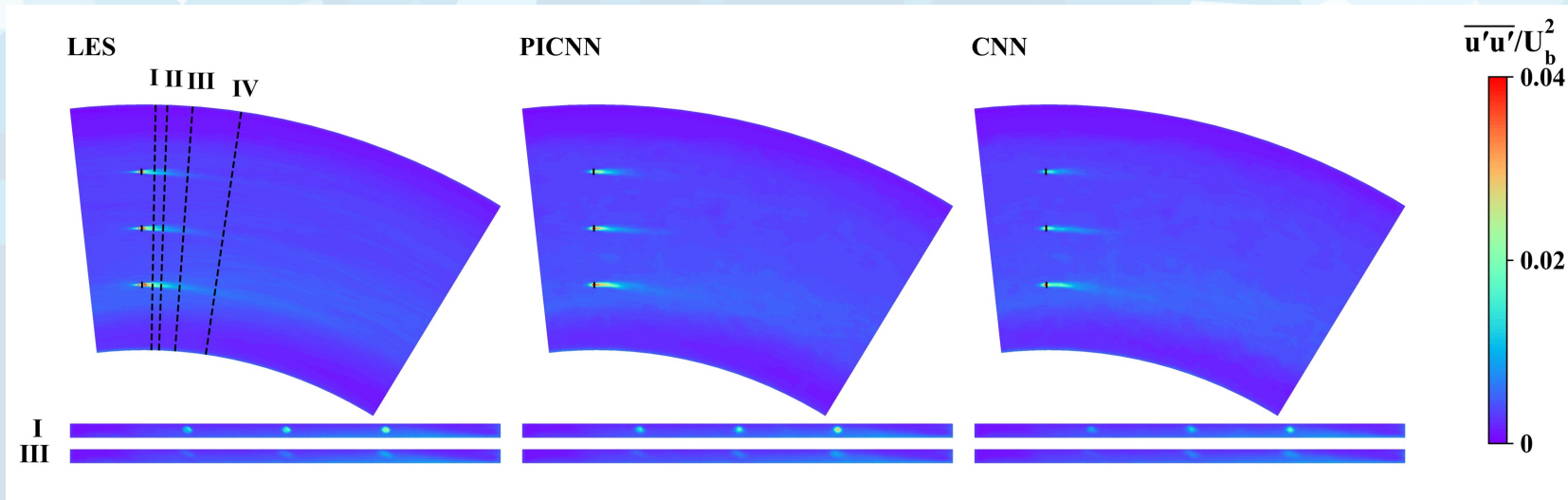
CNN
→



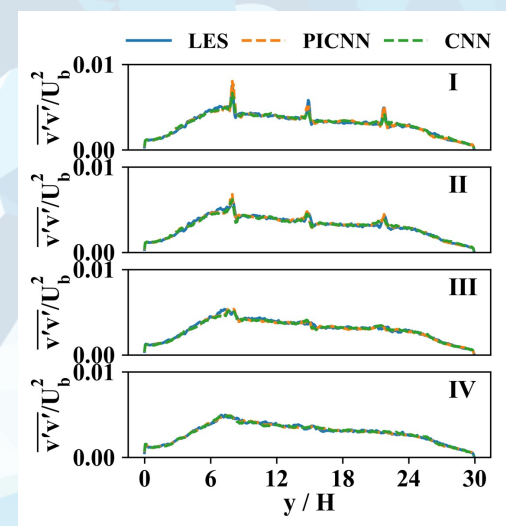
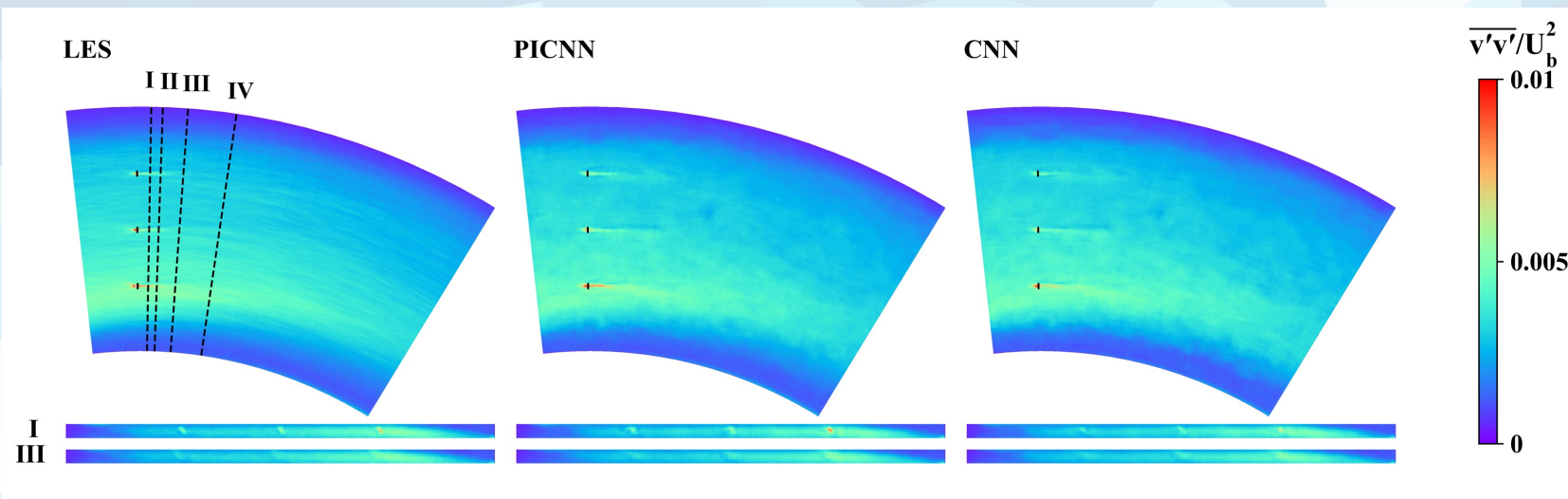


Results- training case

$$\text{Percentage error} = \frac{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)} - \psi_{i(AI)}|}{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)}|}$$



Percentage error:
PICNN: 5.33%
CNN: 6.04%

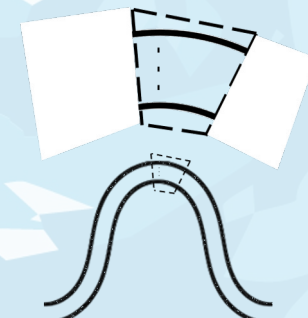
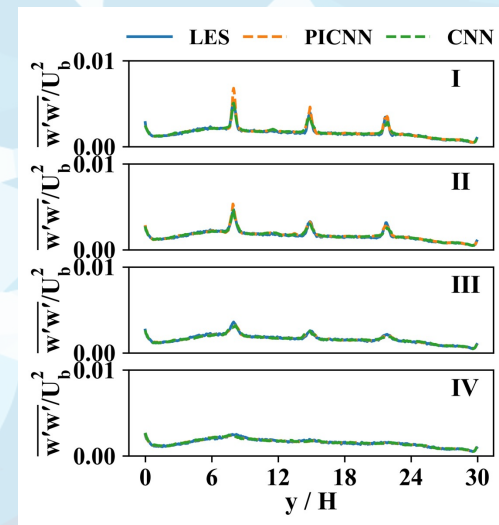
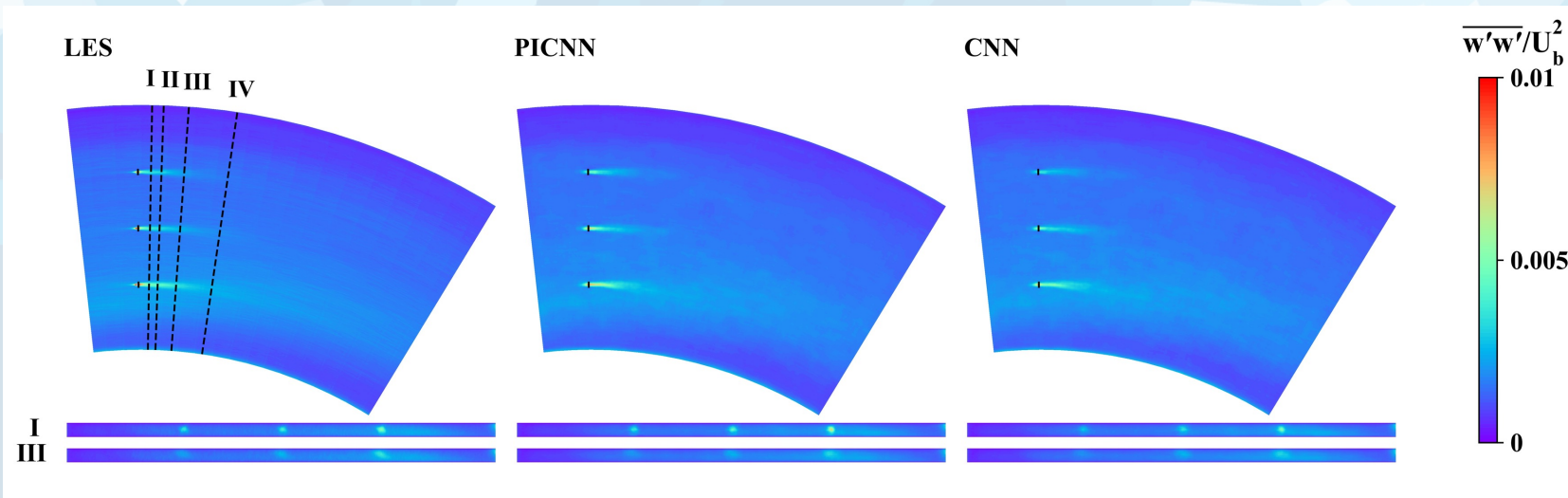


Percentage error:
PICNN: 4.52%
CNN: 5.00%

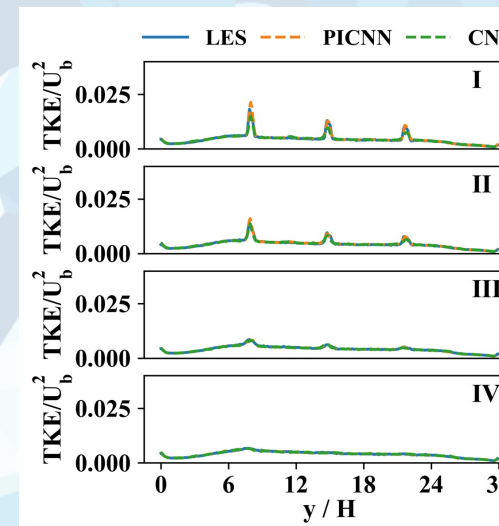
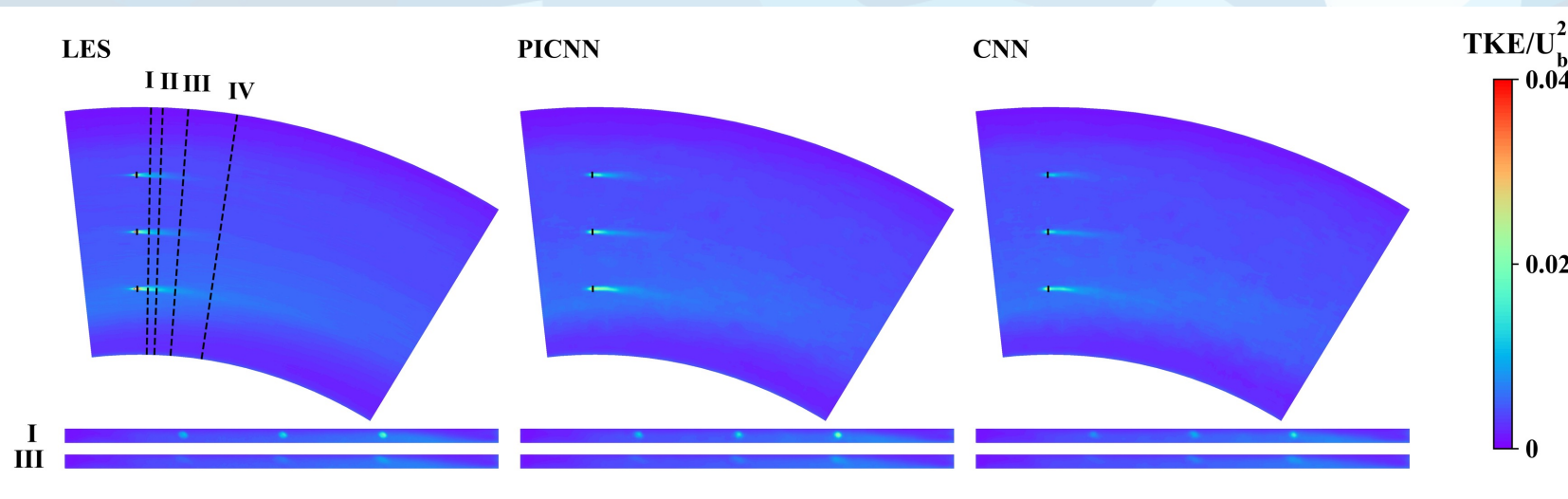


Results- training case

$$\text{Percentage error} = \frac{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)} - \psi_{i(AI)}|}{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)}|}$$



Percentage error:
PICNN: 4.70%
CNN: 5.05%

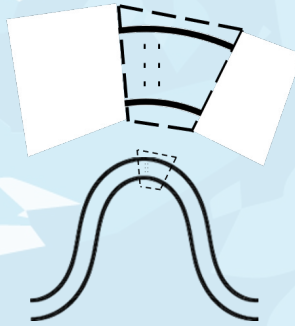
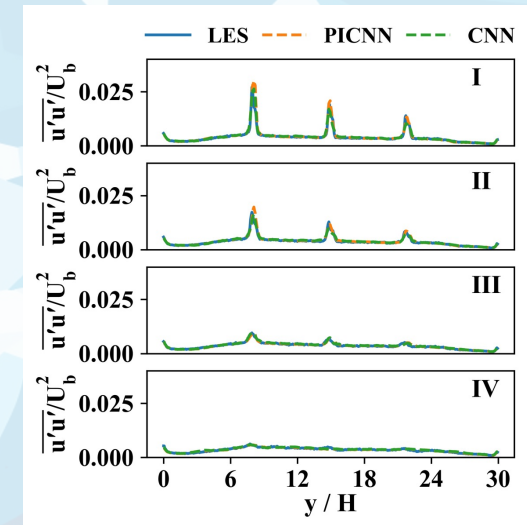
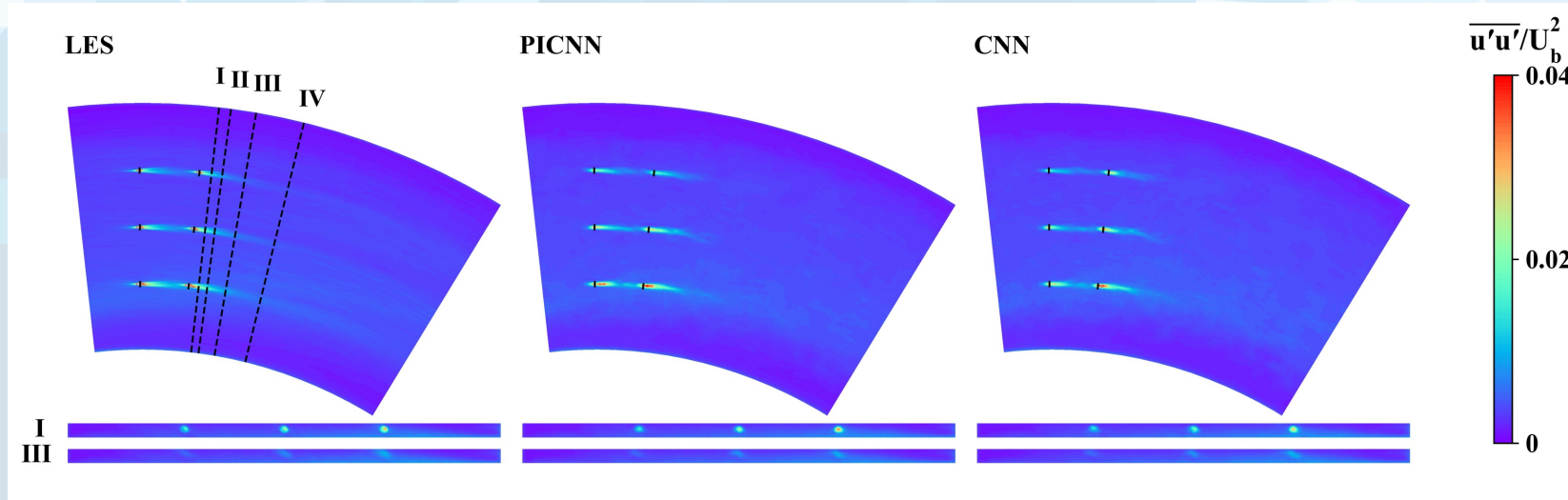


Percentage error:
PICNN: 3.93%
CNN: 4.51%

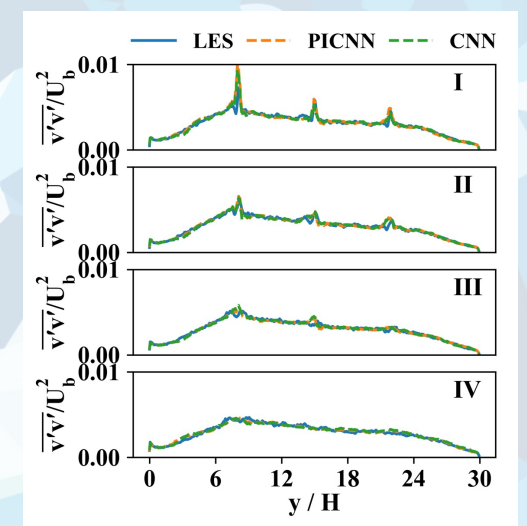
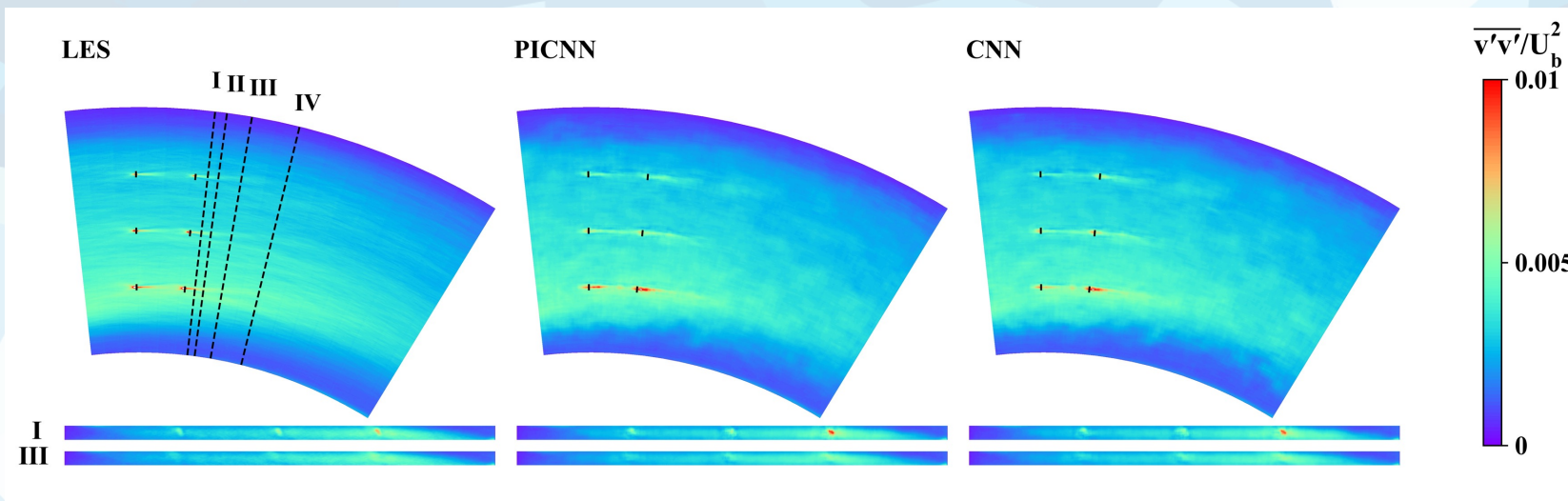


Results- validation case I

$$\text{Percentage error} = \frac{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)} - \psi_{i(AI)}|}{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)}|}$$



Percentage error:
PICNN: 6.80%
CNN: 7.25%

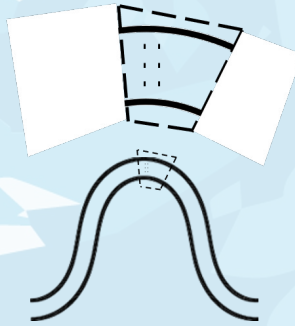
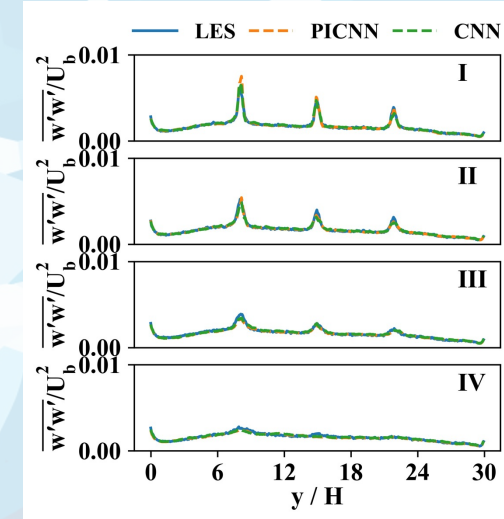
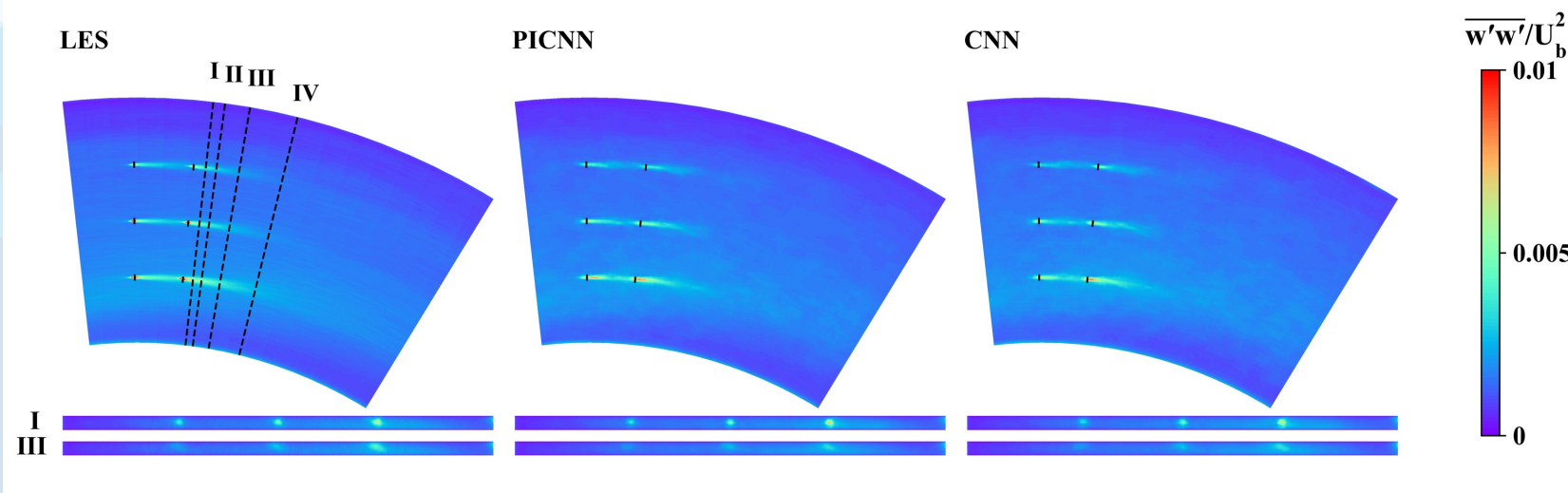


Percentage error:
PICNN: 5.83%
CNN: 5.85%

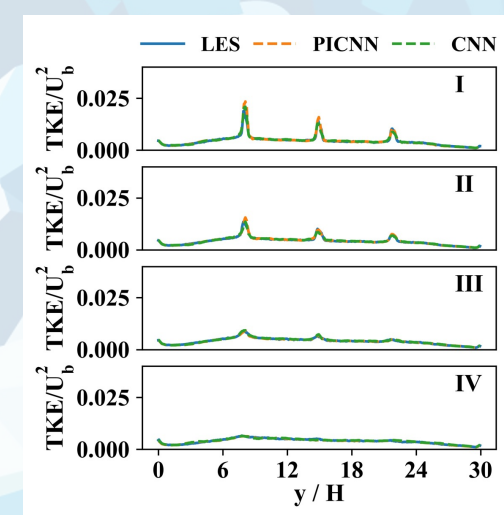
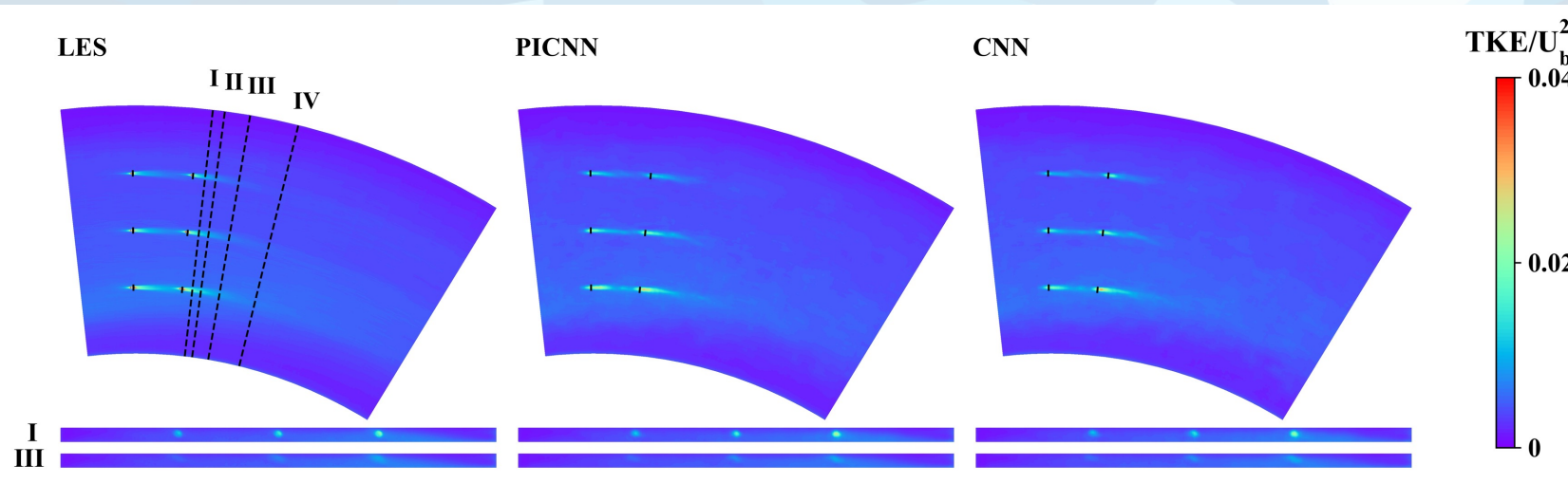


Results- validation case I

$$\text{Percentage error} = \frac{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)} - \psi_{i(AI)}|}{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)}|}$$



Percentage error:
PICNN: 5.66%
CNN: 5.68%

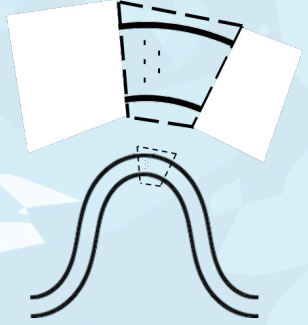
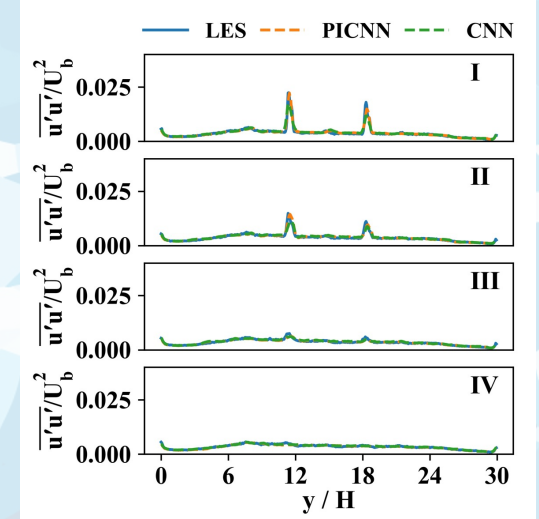
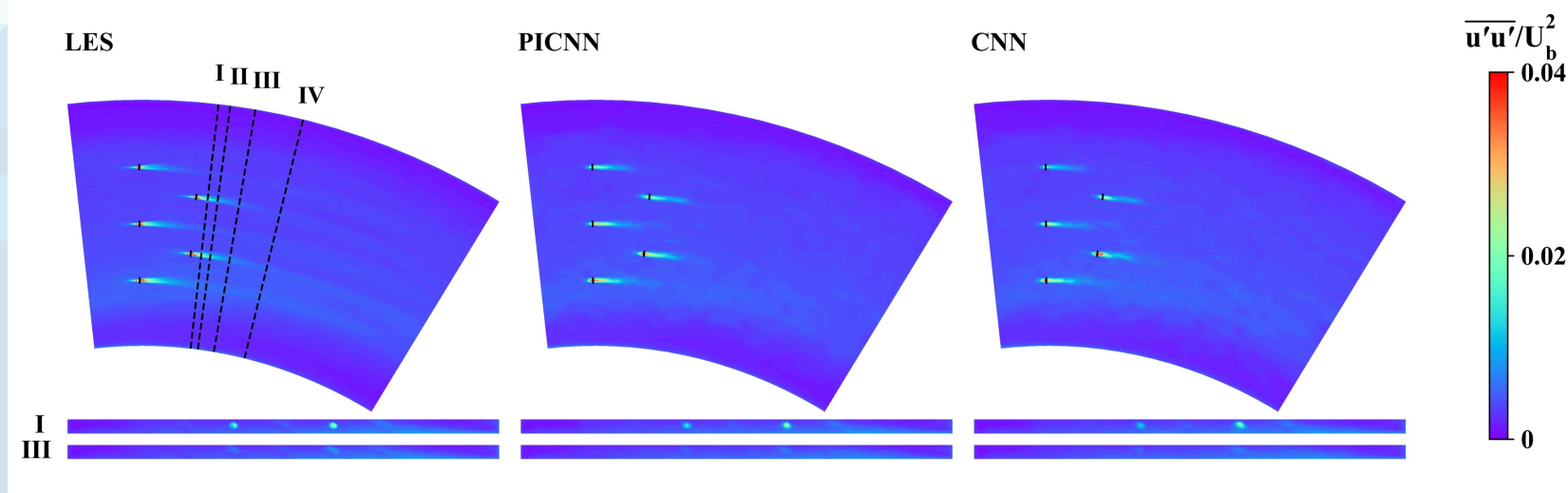


Percentage error:
PICNN: 5.21%
CNN: 5.33%

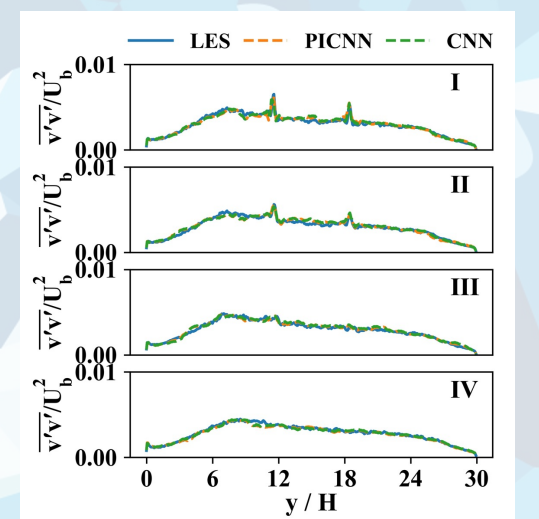
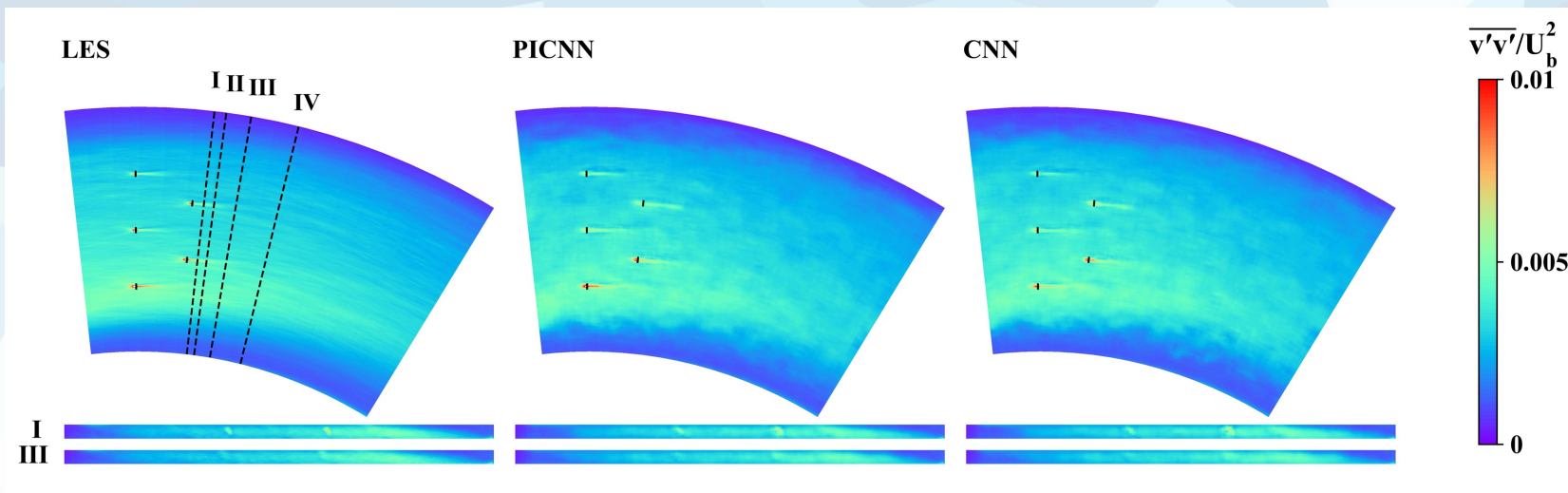


Results- validation case II

$$\text{Percentage error} = \frac{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)} - \psi_{i(AI)}|}{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)}|}$$



Percentage error:
PICNN: 6.61%
CNN: 7.10%

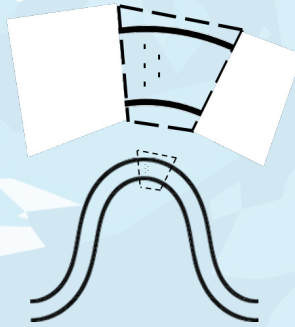
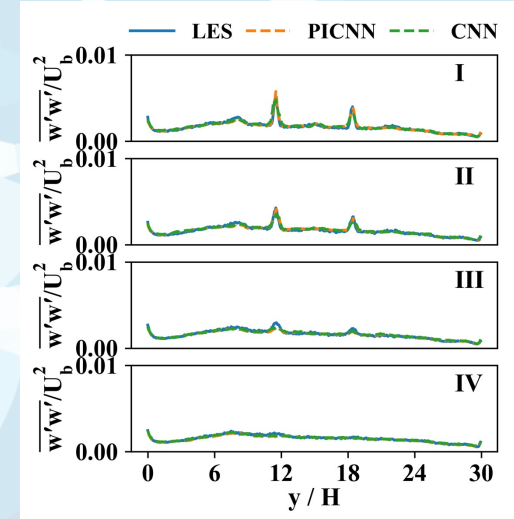
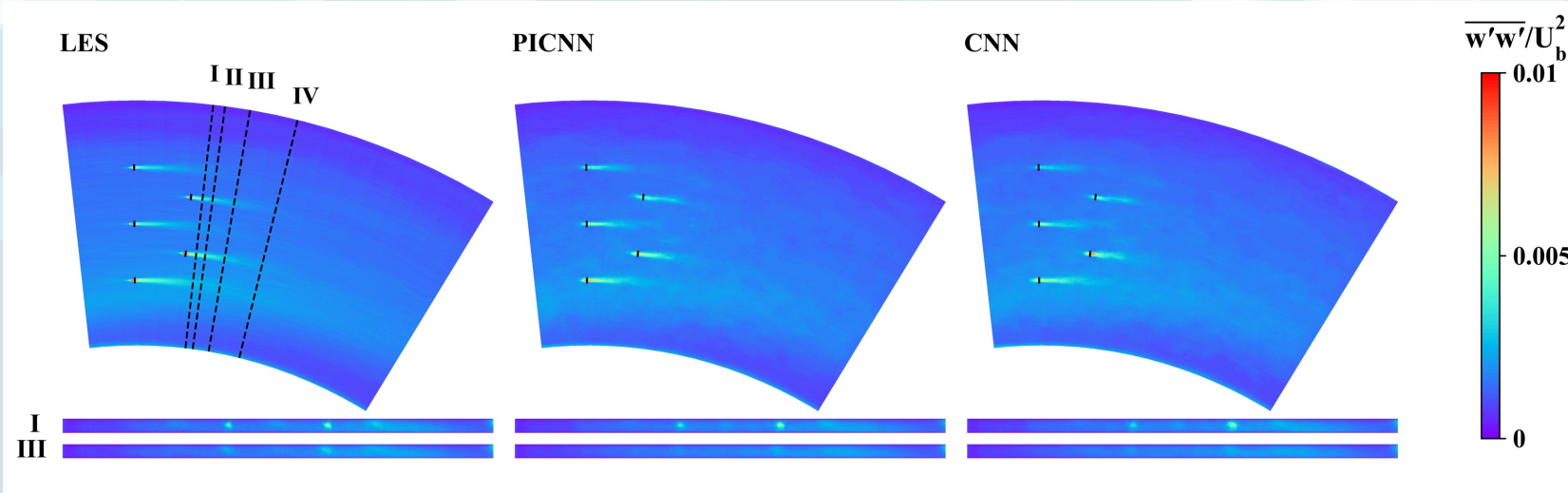


Percentage error:
PICNN: 5.57%
CNN: 5.73%

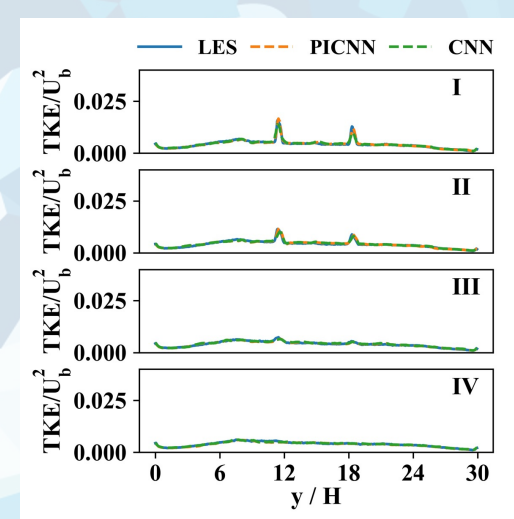
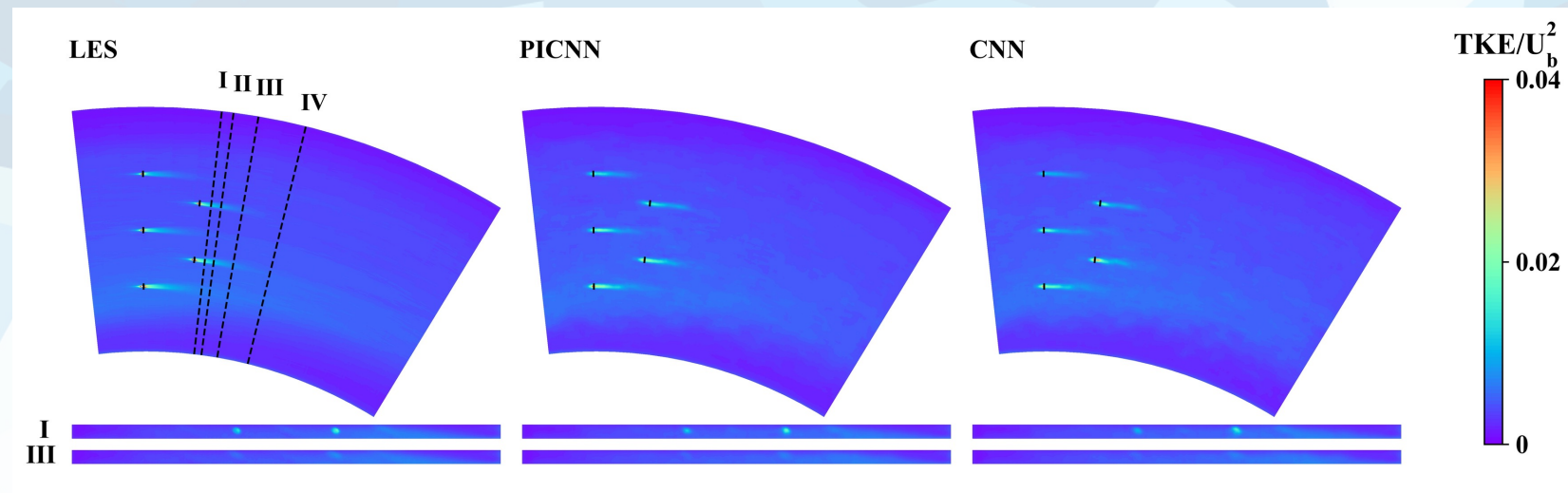


Results- validation case II

$$\text{Percentage error} = \frac{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)} - \psi_{i(AI)}|}{\frac{1}{N} \sum_{i=1}^N |\psi_{i(LES)}|}$$



Percentage error:
PICNN: 5.43%
CNN: 5.65%



Percentage error:
PICNN: 5.03%
CNN: 5.33%



Parting thoughts

- The AI model, with and without physics constraints, can successfully generate 3D realizations of the time-averaged flow field of MHK turbine arrays in large-scale meandering rivers.
- The physics constraints significantly reduce the divergence and momentum indices in the predicted flow field without impacting the computational cost or the accuracy of the predictions.
- The developed AI generates the time-averaged flow field using roughly 2.8% of the LES computational cost.





Questions