# Accelerate Probabilistic Marching Cubes By Deep Learning For Time-Varying Scalar Ensembles

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# Background: Probabilistic Marching Cube [Pöthkow et al. 2011]

## Position Uncertainty of Level-Set

- Uncertainty of ensemble has been extensively studied via analyzing positional uncertainty of level-set visualizations

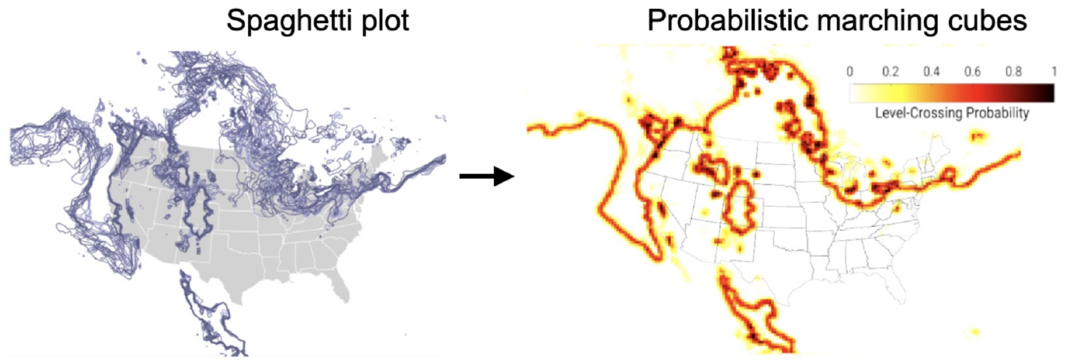



Figure 2: Spaghetti plot vs. probabilistic marching cubes for uncertainty visualization of level sets.

## Probabilistic Marching Cube

- Monte Carlo sampling of multivariate Gaussian distributions [25]
- Nonparametric distributions [24] for uncertainty quantification

‼Computational Challenging due to the expensive Monte Carlo sampling

# Our Contributions

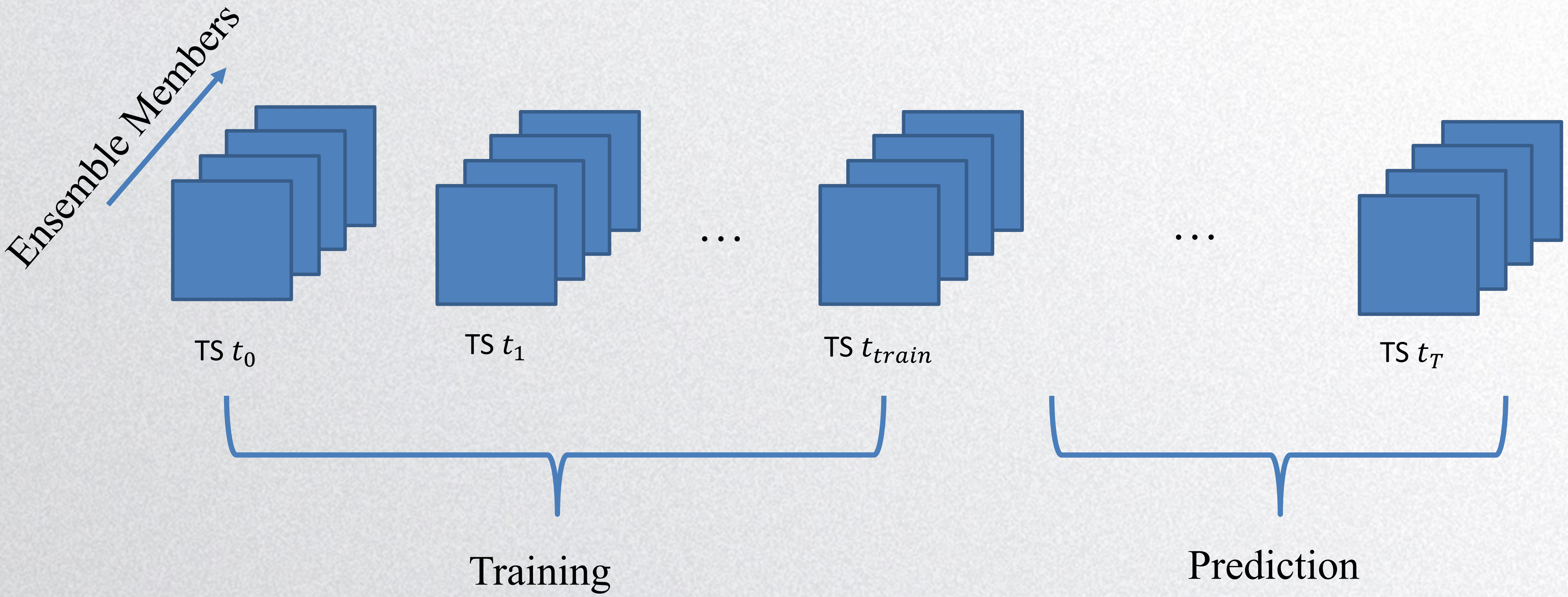
## First Deploy Deep Learning Techniques to Uncertainty Visualization

- First research deploys deep learning techniques to uncertainty visualization to predict the positional uncertainty of level sets for uncertain time-varying scalar ensemble data

## Accurate and Fast

- Predict the level-crossing probabilities **accurately**
- Up to **170X** faster than the original probabilistic marching cube algorithm with serial computations
- Up to **10X** faster than the parallel computations

# Our Method: Training Data Generation



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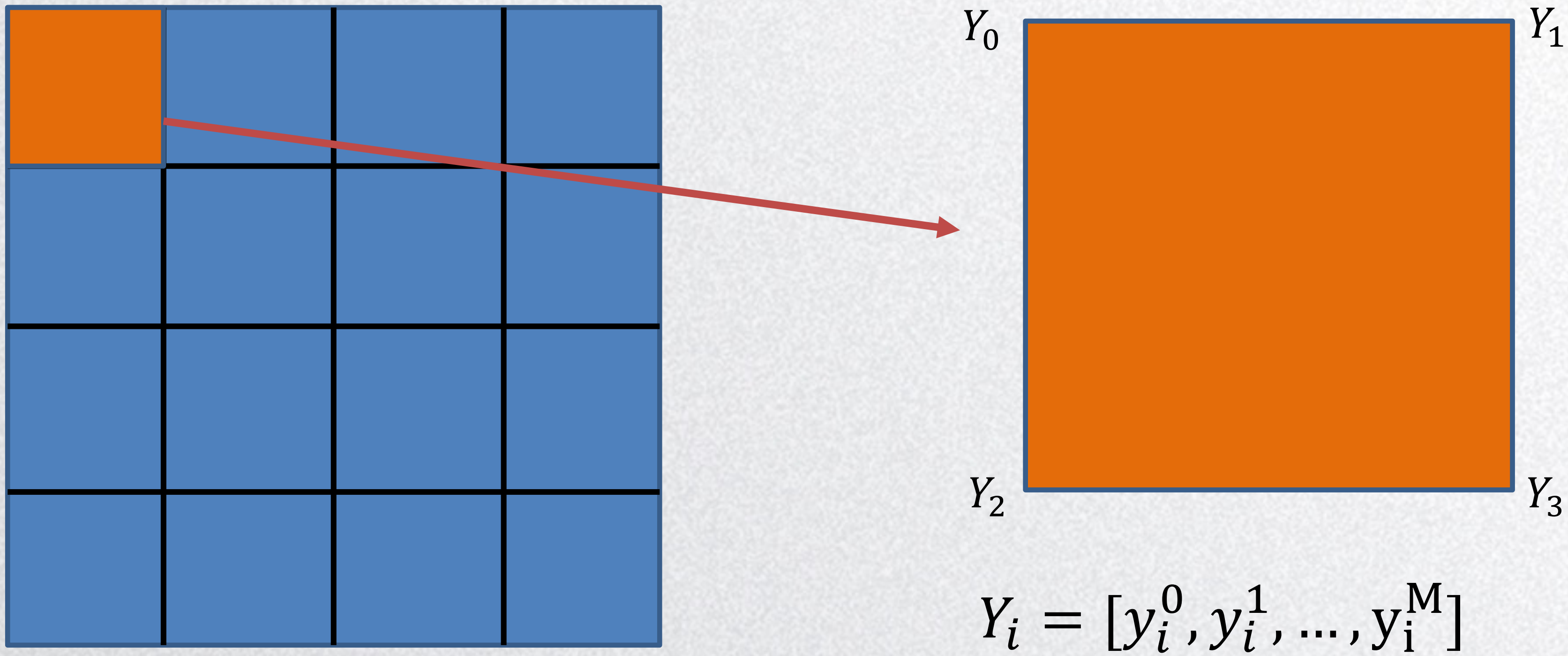


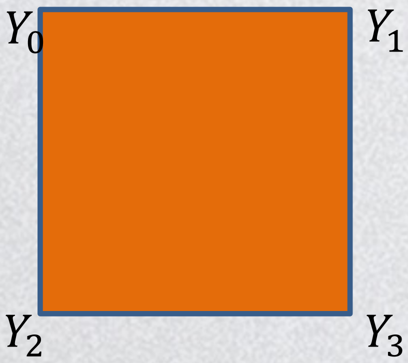

Time step t

$Y_i = [y_i^0, y_i^1, \ldots, y_i^M]$

where $i = 0, 1, 2, 3$

M is the number of ensemble members

# Our Method: Training Data Generation




$Y_i = [y_i^0, y_i^1, \ldots, y_i^M]$

**Means:**

$$\mu = [\mu_0, \mu_1, \mu_2, \mu_3]$$

**Covariance Matrix:**

$$Cov_{i,j} = \frac{1}{M-1}\sum_{m=1}^{M}(y_i^m - \mu_i)(y_j^m - \mu_j)$$

where $i, j = 0, 1, 2, 3$

M is the number of ensemble members

**Drawing r samples from multivariate Gaussian distribution**

LCP $p = \frac{k}{r}$ if a level set passes through k samples

# Our Method: Training Data Generation

One training sample represents one grid cell with a one-dimensional vector of size 16

$$[\mu_0, \mu_1, \mu_2, \mu_3, \sigma_0^2, \sigma_1^2, \sigma_2^2, \sigma_3^2, Cov_{0,1}, Cov_{0,2}, Cov_{0,3}, Cov_{1,2}, Cov_{1,3}, Cov_{2,3}, s, {\color{red}p}]$$

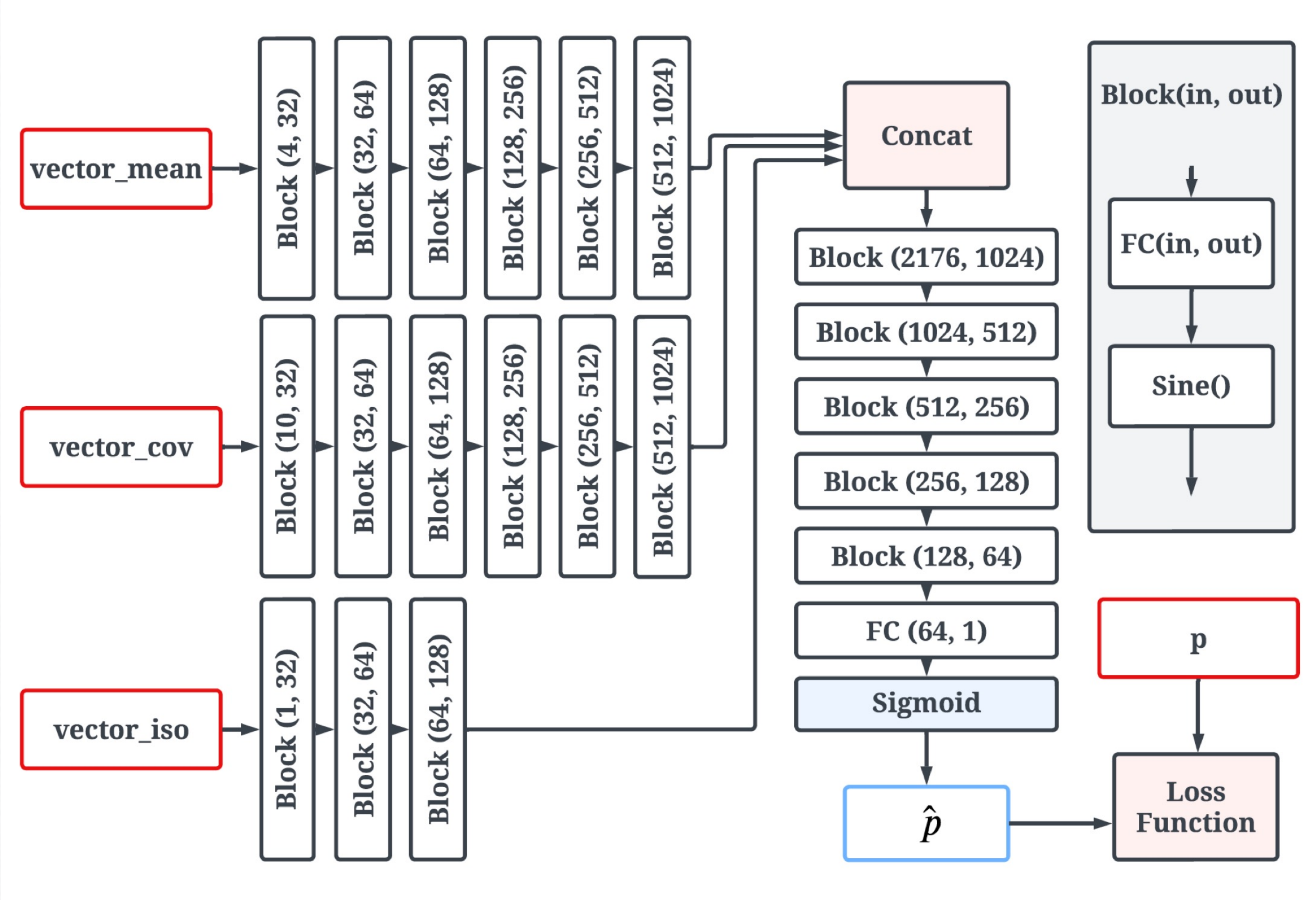
Means
(vector_mean)

Variances and Covariance
(vector_cov)

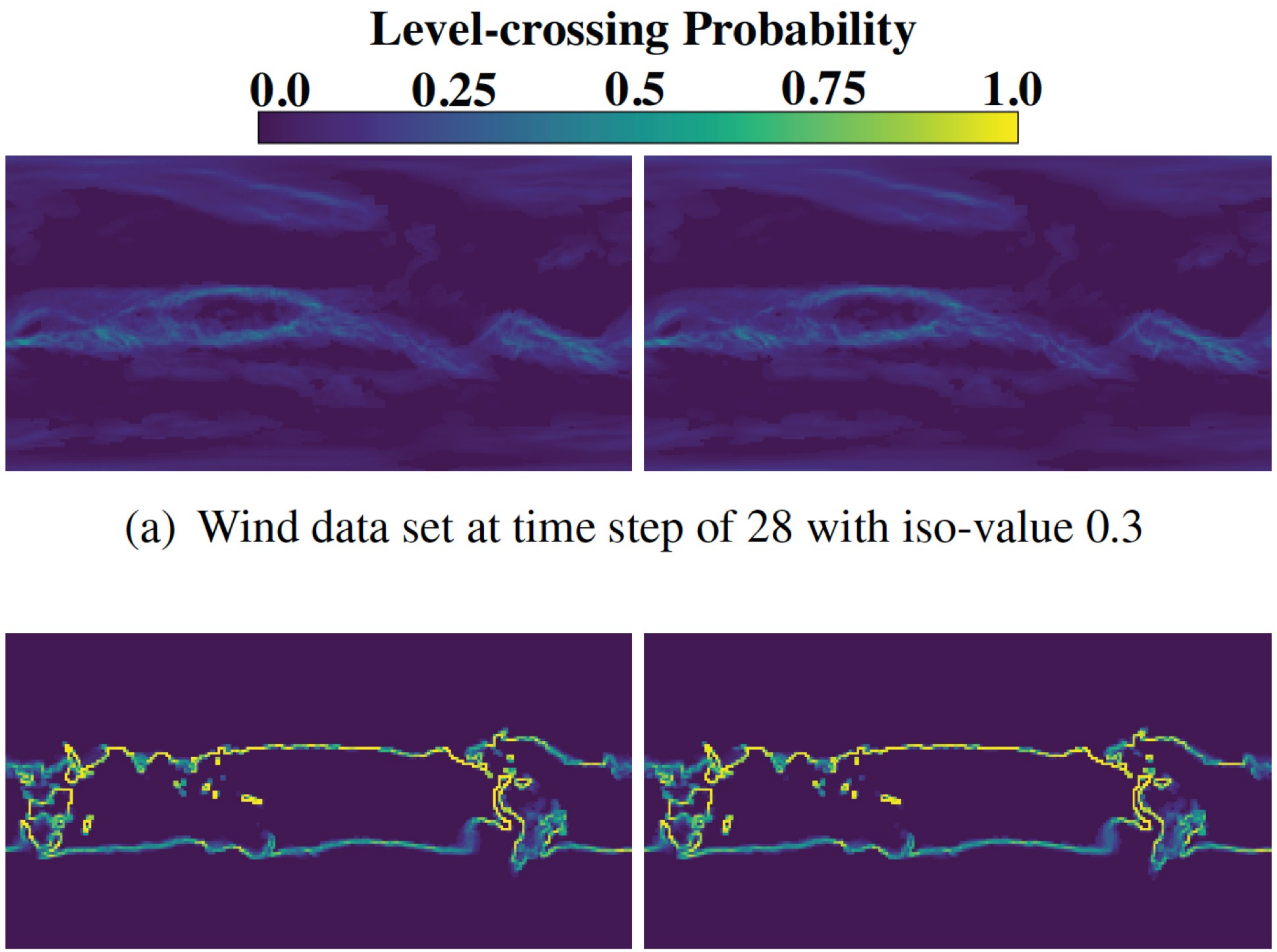
isovalue
(vector_iso)

LCP
($\hat{p}$)

# Our Method: Network Architecture



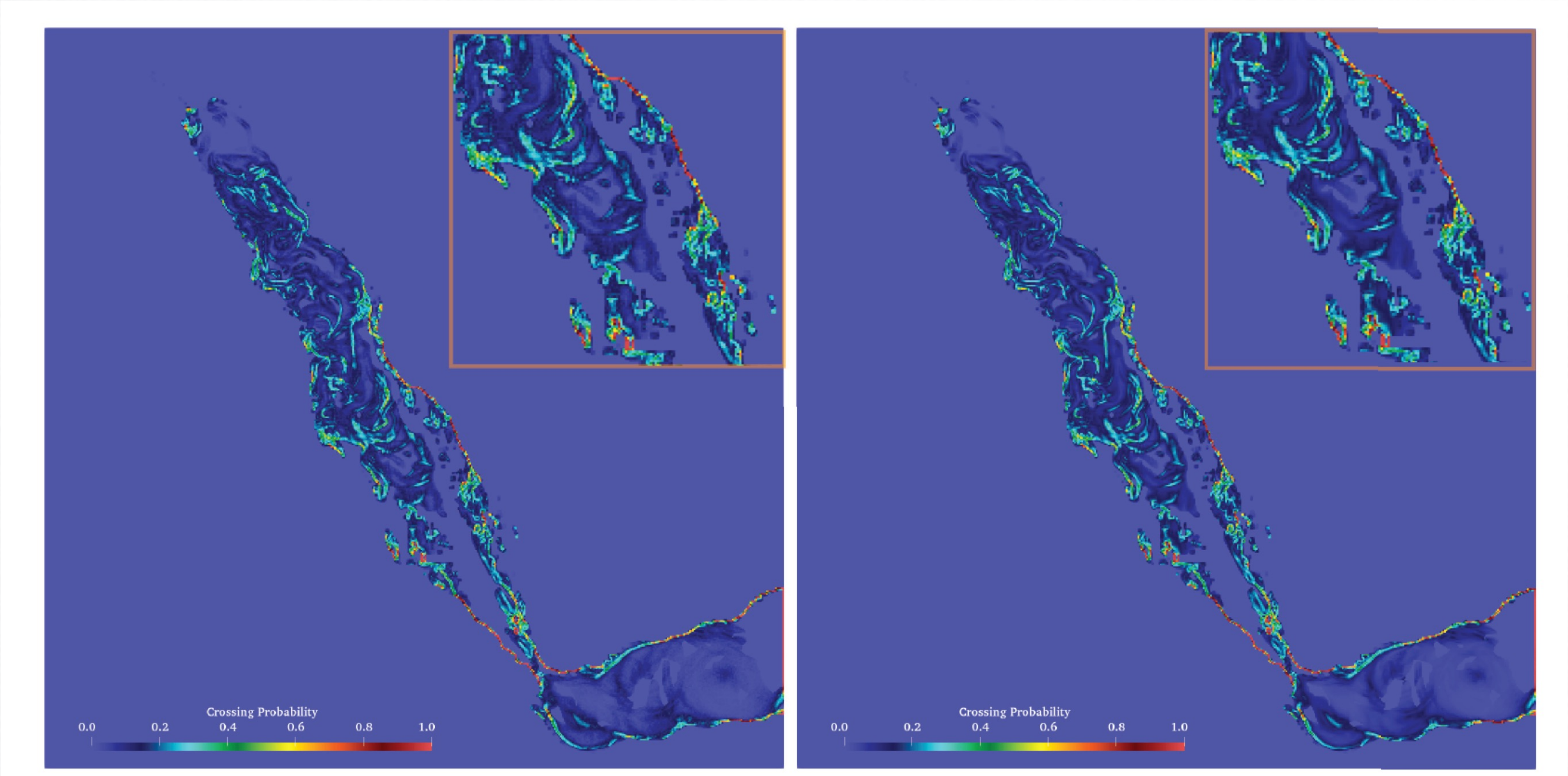
# **Results:** predicted LCP are indistinguishable from the ground truth



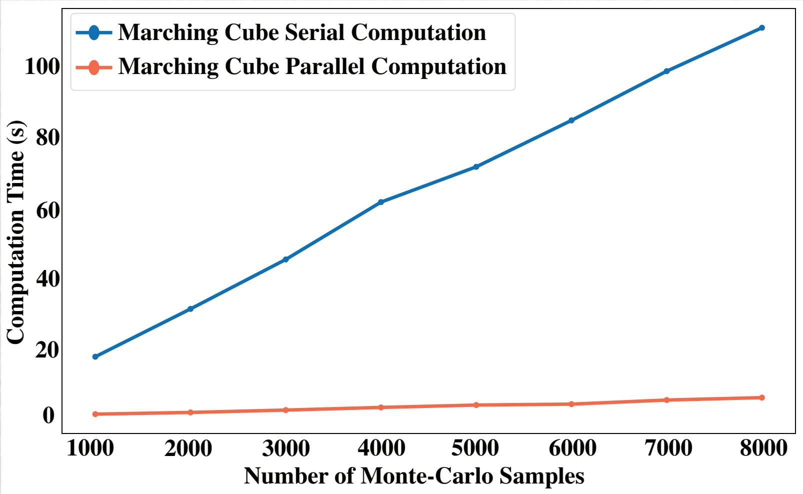

(a) Wind data set at time step of 28 with iso-value 0.3

(b) Temperature data set at time step 22 with iso-value 0.8

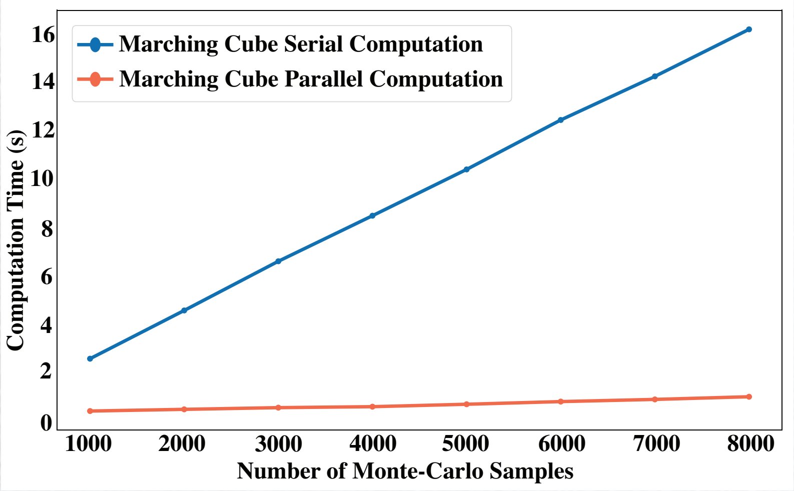
# **Results:** predicted LCP are indistinguishable from the ground truth



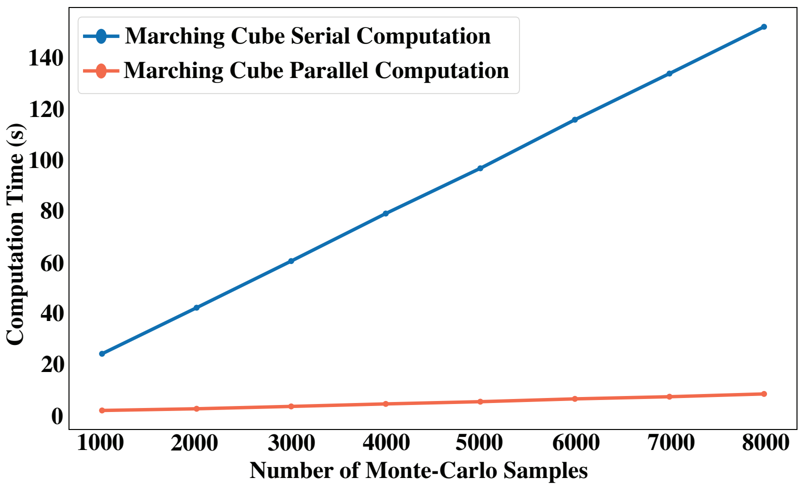
# Results: Faster than the Original Probabilistic Marching Cubes




**Wind**. Time step = 33, isovalue = 0.2




**Temperature**. Time step = 22, isovalue = 0.8




**Red Sea**. Time step = 53, isovalue = 0.1

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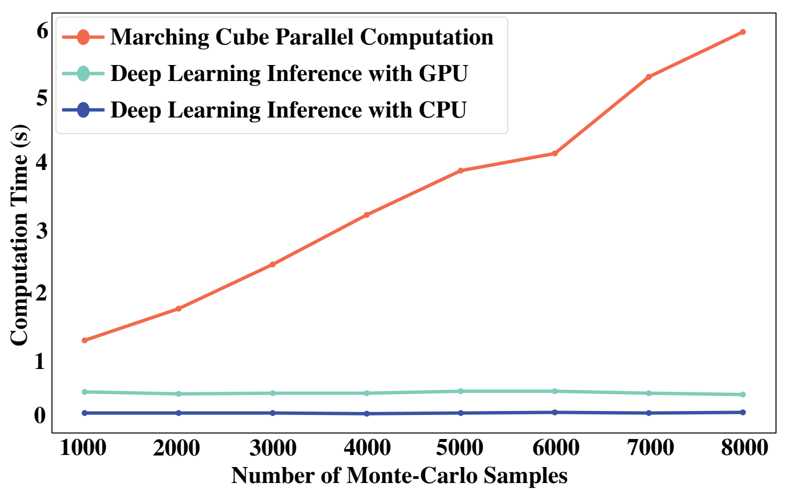


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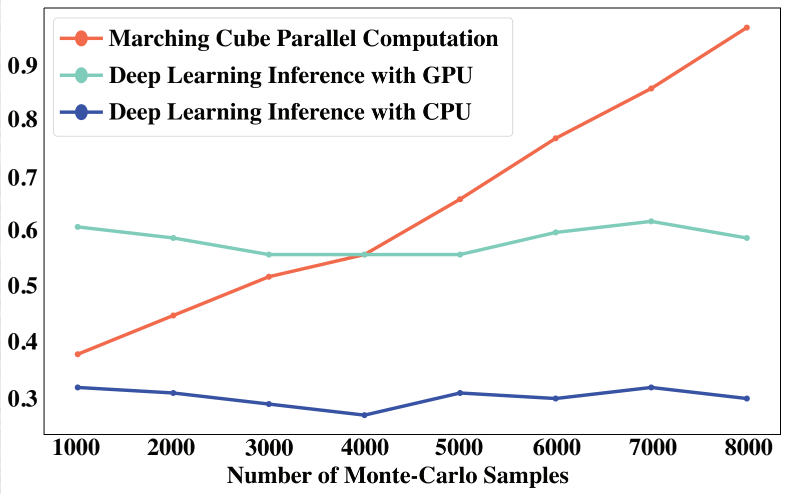


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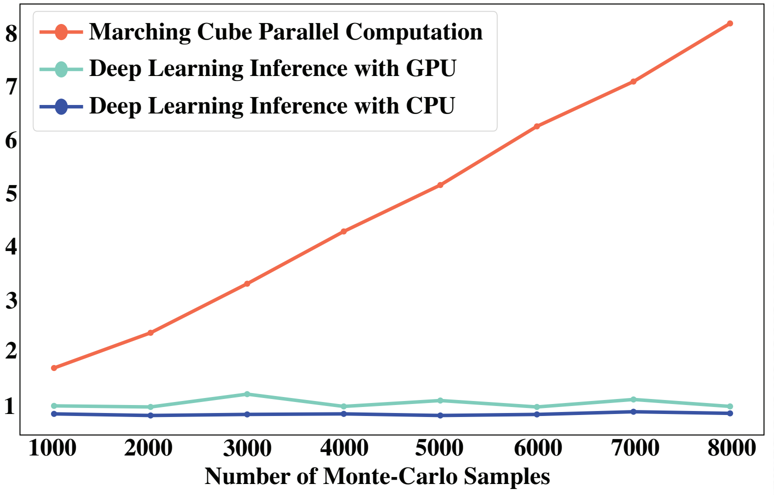


**Red Sea**. Time step = 53, isovalue = 0.1

# Conclusions

- **First assessment of DL to uncertainty:** We propose the first assessment of DL to uncertainty visualization to predict the positional uncertainty of level sets for uncertain time-varying scalar ensemble data
- **Accurate:** Our method can predict the level-crossing probabilities accurately
- **Fast:** Our method is up to **170X** faster than the original probabilistic marching cubes technique with serial computations and up to **10X** faster compared to the parallel version

# Future Work

- **3D:** Extend our method to 3D
- **Flexibility:** Enhance the flexibility of prediction for varying isovalues
- **Generalization:** Investigate more generalized DL method across varying datasets

# THANK YOU

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