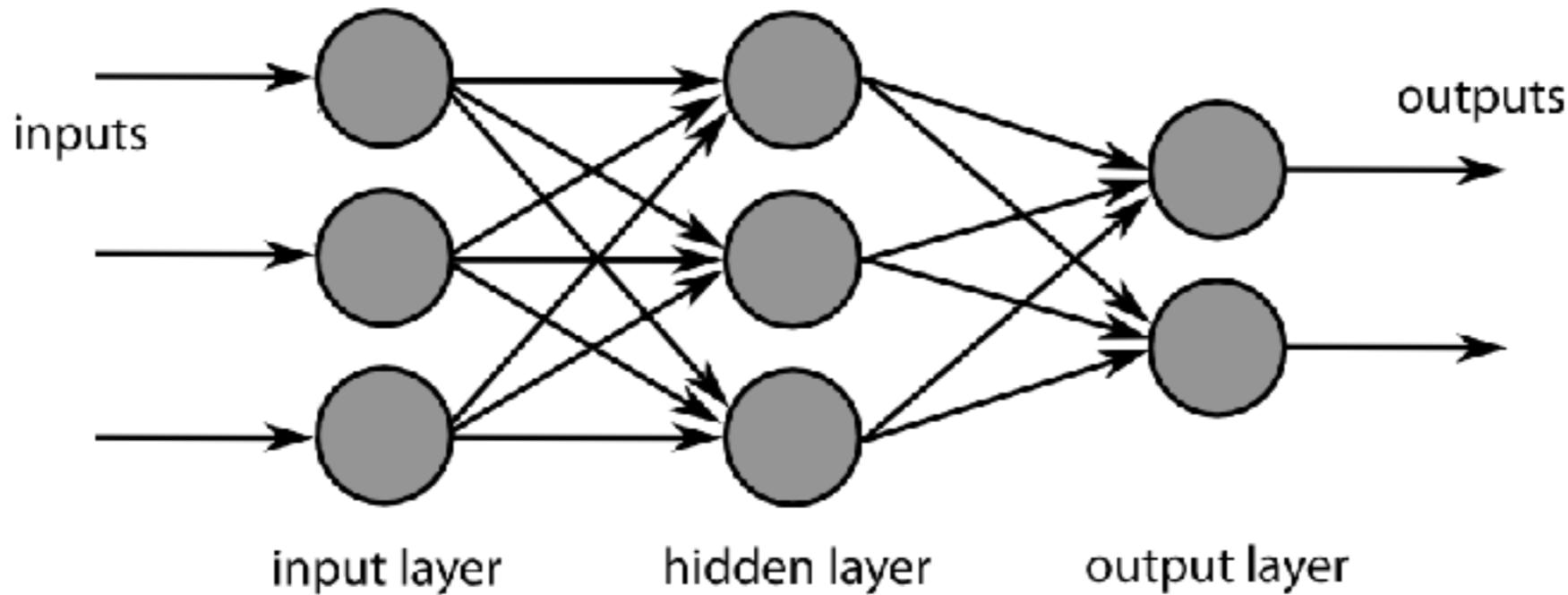


# Forecasting Chaos with Machine Learning

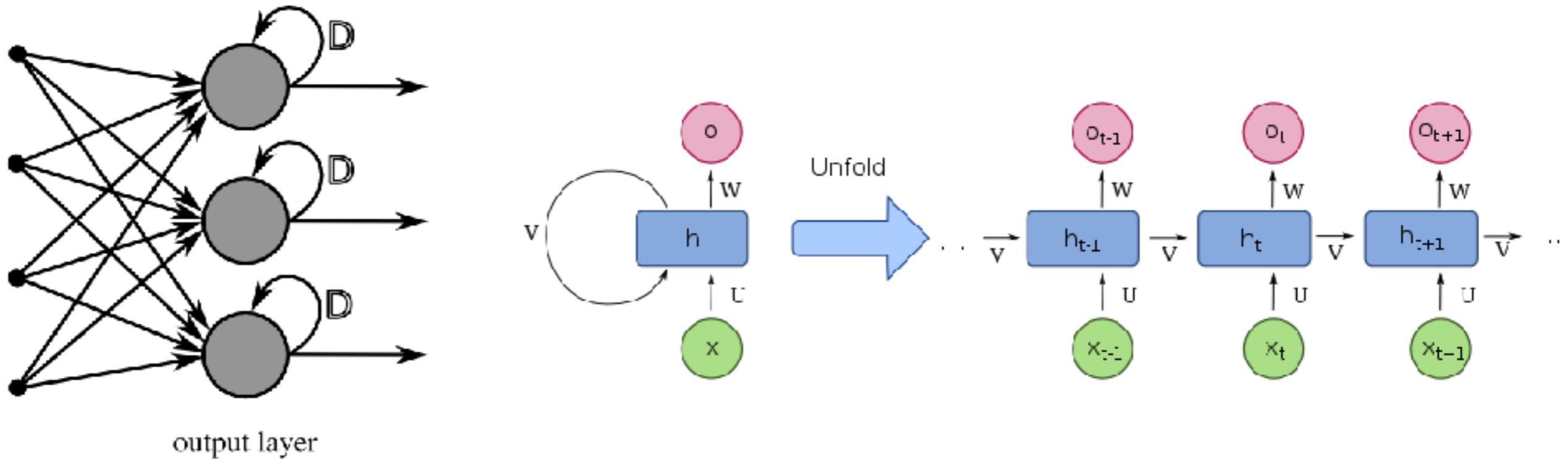
Ryan Abernathy

# Feed Forward Network



- Connections between neurons point only in one direction (directed acyclic graph)
- Used for standard machine learning algorithms
- Network has no “state” (other than weights): activation determined completely by input vector

# Recurrent Network

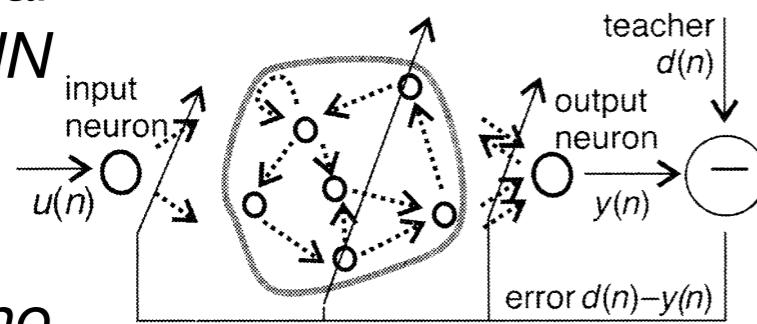


- Internal state of network persists and is fed back to input layers (along with the actual inputs)
- Allows network to have memory
- Used in time-dependent problems (speech recognition, games, etc.)

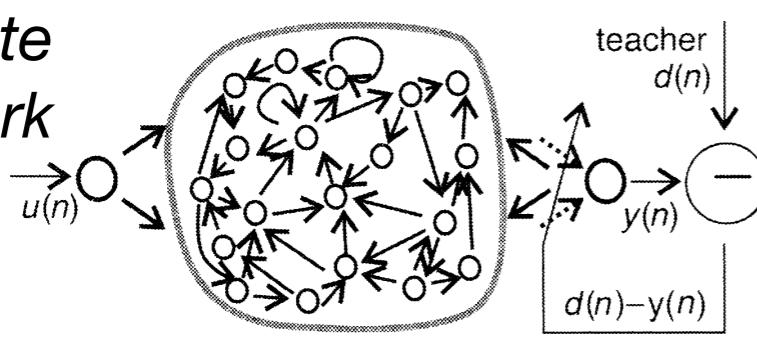
# Reservoir Computing

Traditional

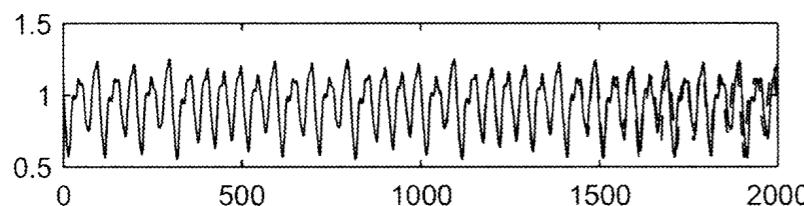
RNN



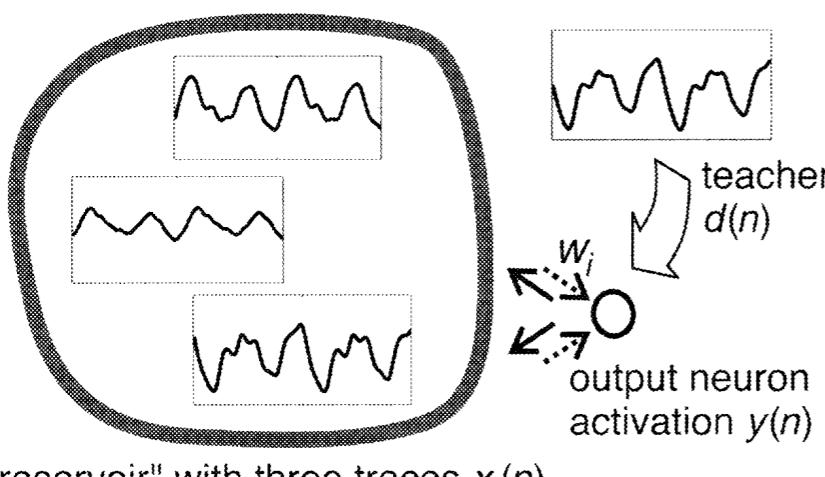
Echo  
State  
Network



A



B



"reservoir" with three traces  $x_i(n)$

## Harnessing Nonlinearity: Predicting Chaotic Systems and Saving Energy in Wireless Communication

BY HERBERT JAEGER, HARALD HAAS  
SCIENCE APR 2004 : 78-80

- Large RNNs ( $> 30$  neurons) are very expensive and unstable to train
- “Reservoir” is a large RNN (1000s of neurons) with feedback loops in connections (often a randomly generated network)
- Reservoir maintains activation even without inputs
- Only the input and output weights are learned; the internal network is fixed
- Skilled at forecasting low-D chaotic systems

# Spatio-temporal chaos: Kuramoto-Sivashinsky equation

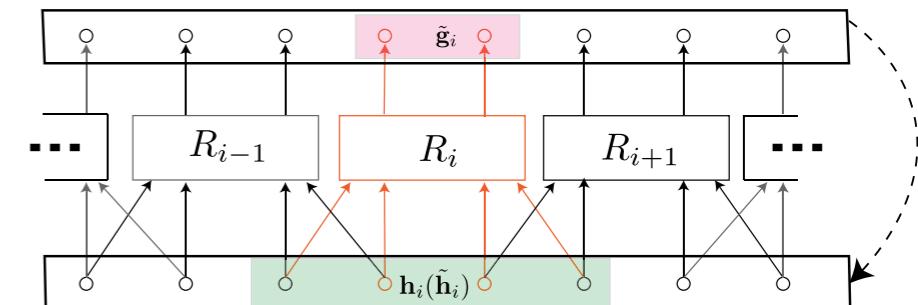
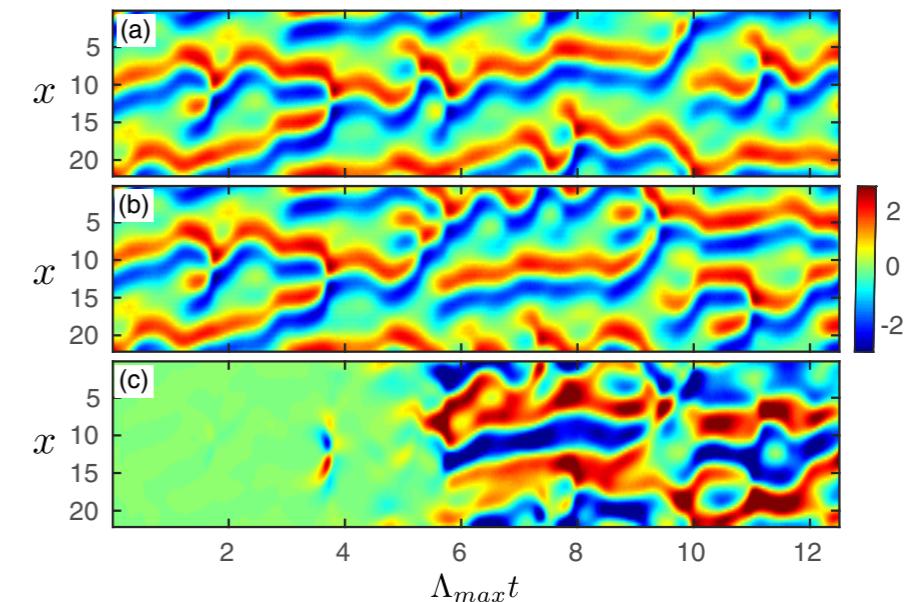
$$y_t = -yy_x - y_{xx} - y_{xxxx} + \mu \cos\left(\frac{2\pi x}{\lambda}\right)$$

- Nonlinear 1D dynamical system
- Commonly used model
- <https://www.youtube.com/watch?v=MdHk52m-5BY>

## Model-Free Prediction of Large Spatiotemporally Chaotic Systems from Data: A Reservoir Computing Approach

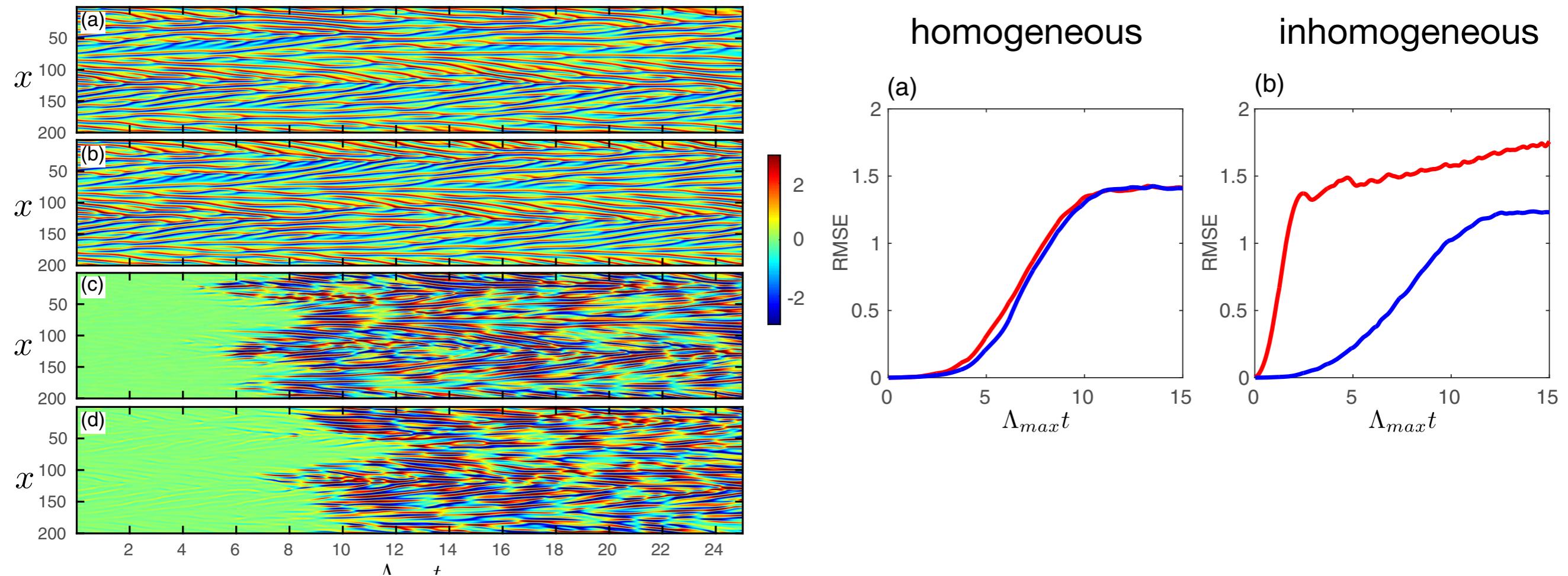
Jaideep Pathak,<sup>1,2,\*</sup> Brian Hunt,<sup>3,4</sup> Michelle Girvan,<sup>1,3,2</sup> Zhixin Lu,<sup>1,3</sup> and Edward Ott<sup>1,2,5</sup>

- Single reservoir approach doesn't scale to large domain sizes  $L$
- Analogy to CNN: use multiple reservoirs spread over the spatial domain



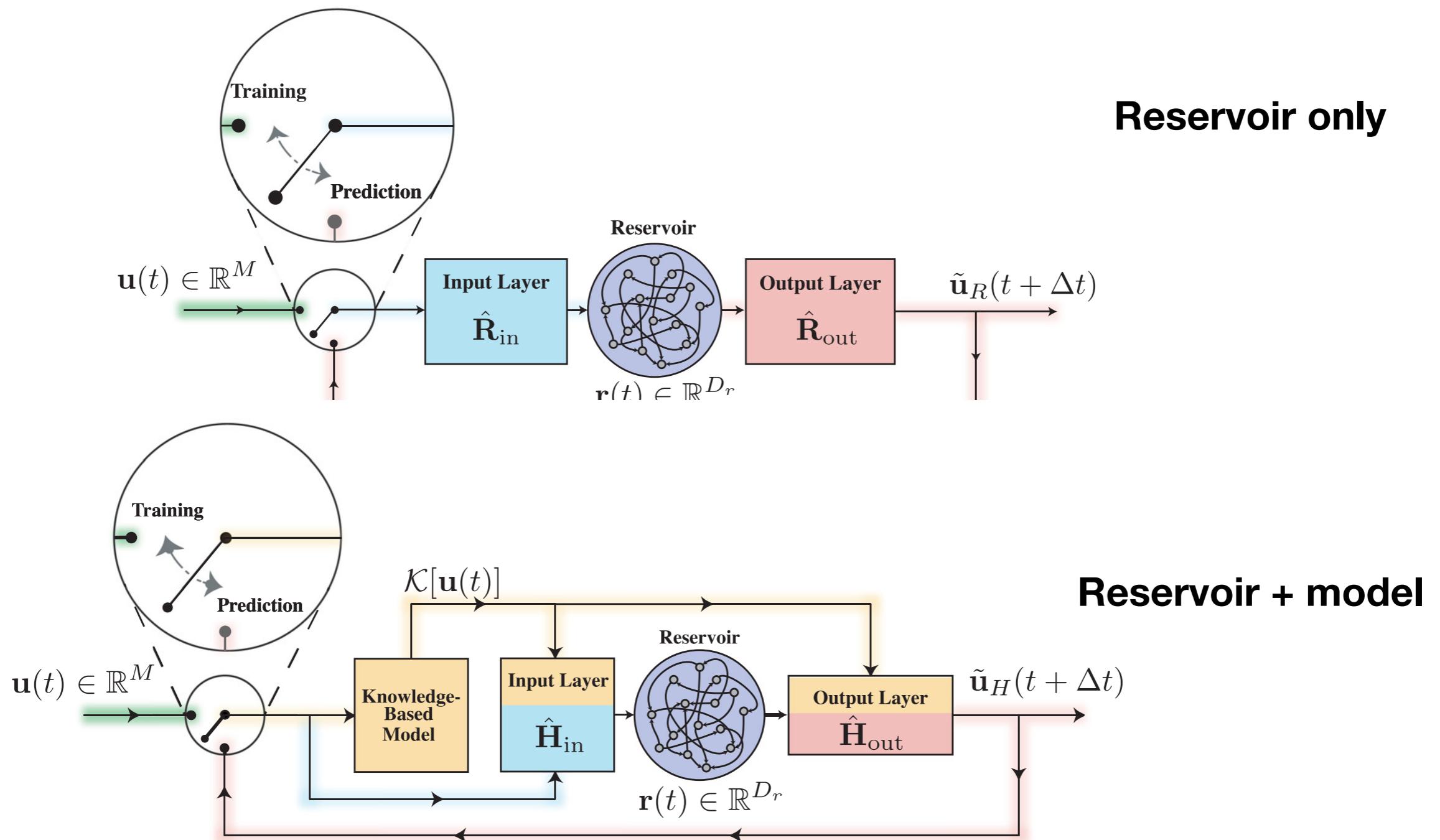
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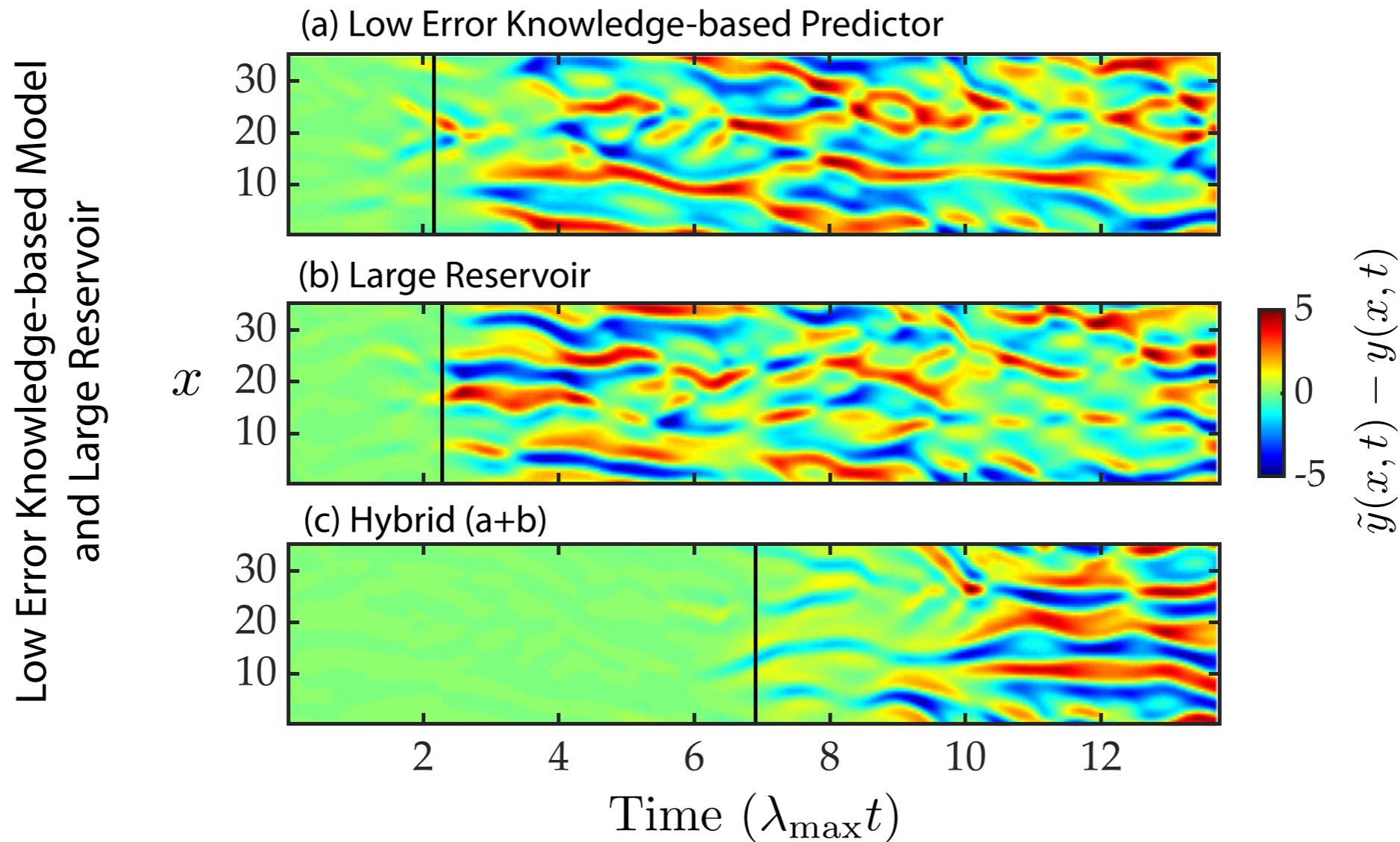
## Hybrid forecasting of chaotic processes: Using machine learning in conjunction with a knowledge-based model

Jaideep Pathak,<sup>1</sup> Alexander Wikner,<sup>2</sup> Rebeckah Fussell,<sup>3</sup> Sarthak Chandra,<sup>1</sup>  
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$$y_t = -yy_x - (1 + \epsilon)y_{xx} - y_{xxxx}$$

**Imperfect model**