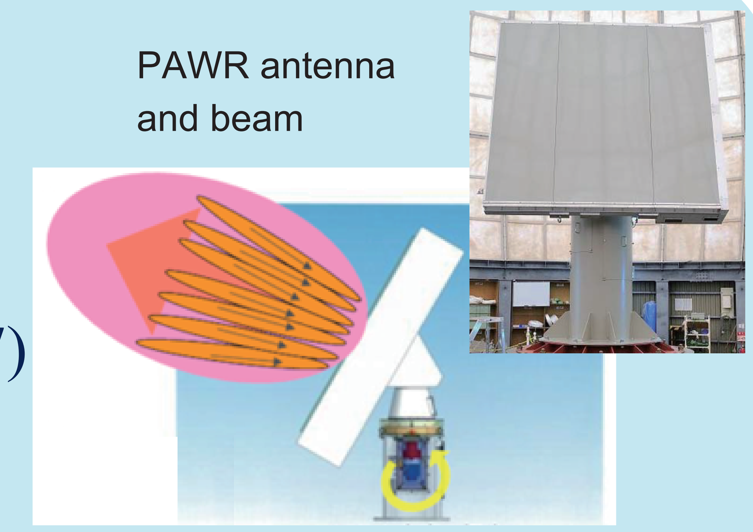
Toward an integrated NWP-DA-AI system for 30-second-update precipitation prediction

Shigenori Otsuka (RIKEN), Yasumitsu Maejima (RIKEN),
Pierre Tandeo (IMT Atlantique), and Takemasa Miyoshi (RIKEN)

Data Assimilation Team

1. Introduction

- Phased-Array Weather Radar (PAWR) at NICT Kobe
  - Every 30 seconds, 60-km-range, 100-m range resolution, 300 azimuth, 110 elevation
- A high-resolution regional NWP system (SCALE-LETKF, Miyoshi et al., 2016a,b, Lien et al., 2017)
- 3D optical flow nowcast: https://weather.riken.jp/ (Otsuka et al. 2016, *WAF*)
- A deep-learning-based system to merge observations and forecasts is newly developed.



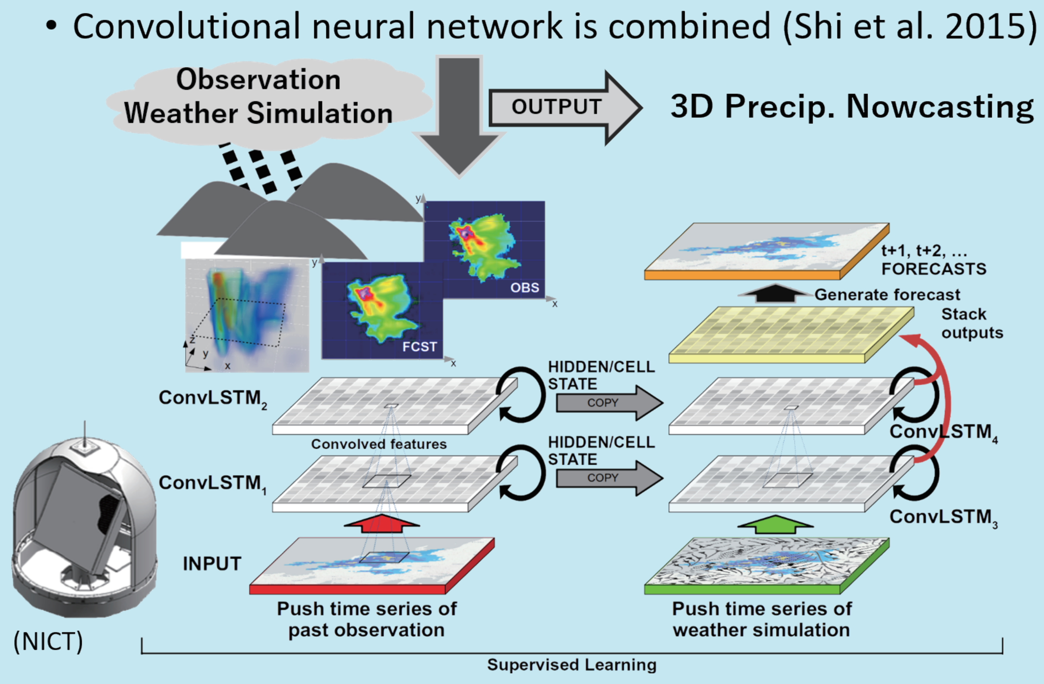
(NICT/Osaka U./TOSHIBA)

2. Deep-learning-based system

- Based on Conv-LSTM (Shi et al. 2015, *NIPS*)
  - Long Short Term Memory (Hochreiter & Schmidhuber 1997, *Neural Comp.*)
    - Suitable for time series
  - Convolution: taking account of spatial pattern
  - Weights: copied from the encoder to the forecaster
  - Conv-LSTM outperforms CNN for two-dimensional precipitation nowcasting
- Extended to three-dimensional data
- Future data are used in the decoder network

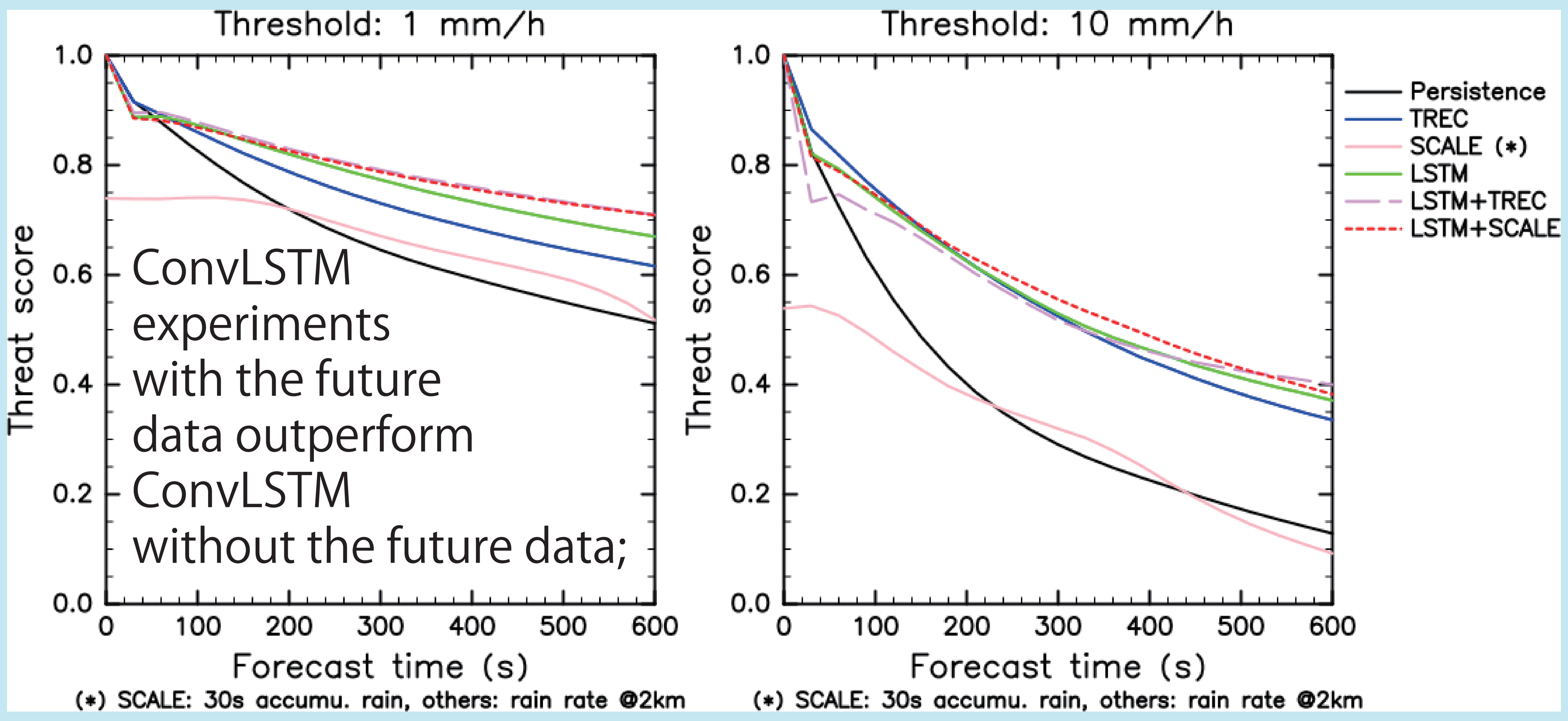
Machine learning with 3D Conv-LSTM

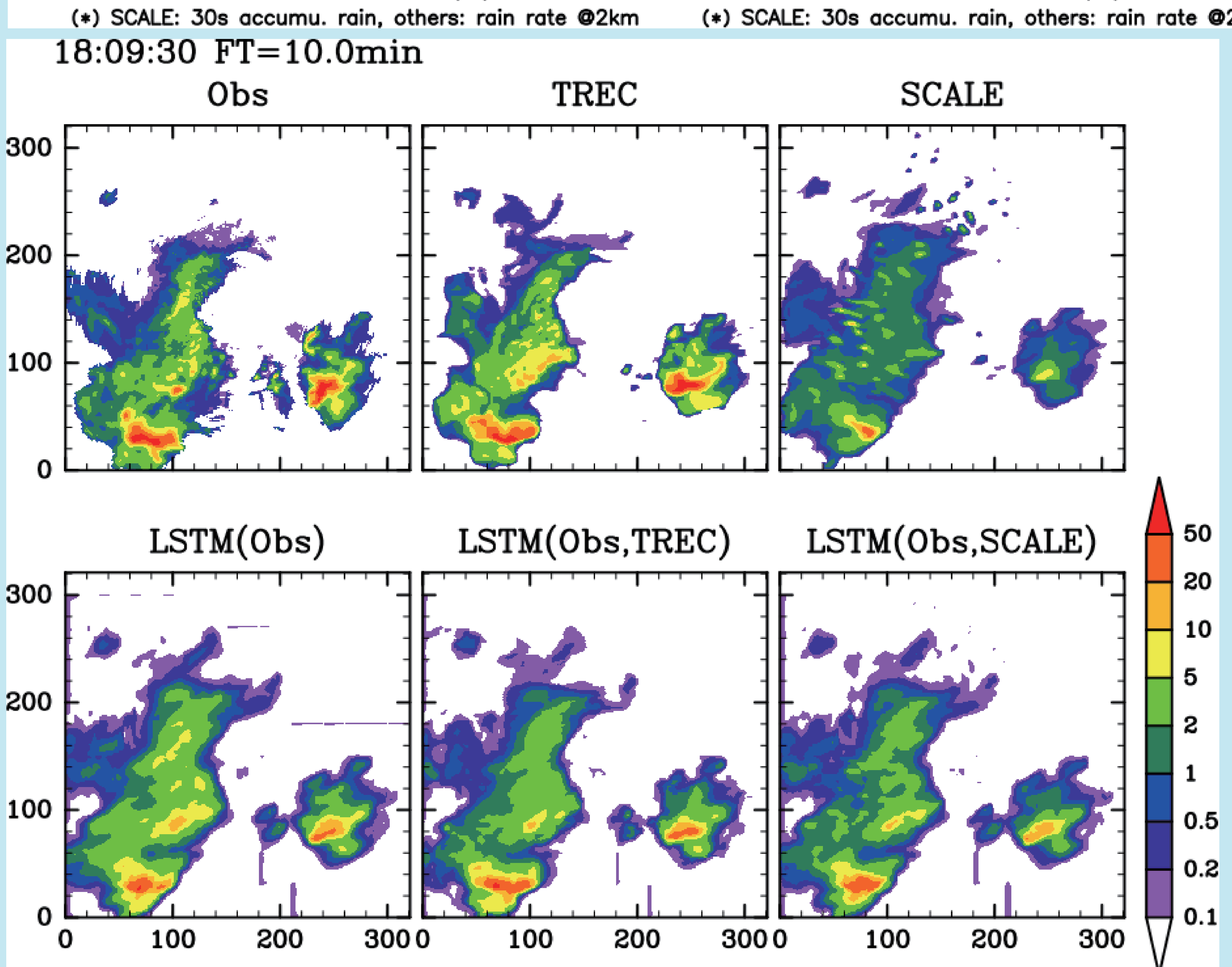
- Long Short-Term Memory is suitable for sequence data (Hochreiter & Schmidhuber 1997)
- Convolutional neural network is combined (Shi et al. 2015)



3. Test case

- Observation data: Kobe PAWR observations, 250-m mesh, 321x321x57 pixels
- Future data:
  - Optical flow-based 3D nowcast (TREC)
  - Surface precipitation forecast by SCALE-LETKF
- Training period: 15:10:00-17:29:30 UTC, 10 June 2019
- Verification period: 17:40:00-17:59:30 UTC, 10 June 2019
- 6 steps for the past data (encoder), 20 steps for the future data (decoder)
  - Subregions of 61 x 61 x 9 pixels (z = 1.5-3.5 km) with rain echoes are extracted from the original data, and are used for training and inference.
- Optimizer: Adam
- Loss function: Balanced mean square error
- Convolution kernel size: 3
- ConvLSTM1: 24 channels, ConvLSTM2: 3 channels





LSTM experiments reproduced the observed rain well. At a later forecast time, intense rain areas tend to be underestimated.

Adopted from Otsuka et al. (2020, in prep.)

5. Summary

- The Conv-LSTM is extended to 3D. A real-time 3D Conv-LSTM system is implemented with the Kobe PAWR.
- The 3D Conv-LSTM captured the evolution of convective cores.
- Conv-LSTM with forecast data outperformed that without forecast data.
- Future perspective: Training with PAWR data in different seasons / training with other model variables such as winds, humidity
- The machine learning architechture will be updated to improve the prediction accuracy.