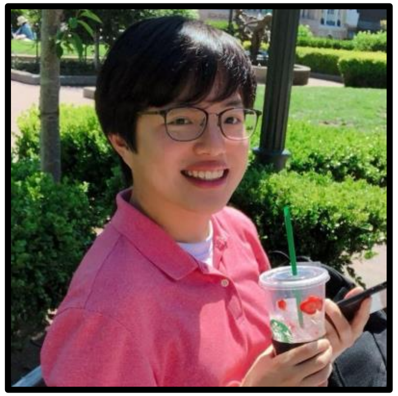
KAIST AI
Kim Jaechul Graduate School

Deep-Learning-Based Precipitation Nowcasting with Ground Weather Station Data and Radar Data


Jihoon Ko*


Kyuhan Lee*


Hyunjin Hwang


Kijung Shin

Precipitation Prediction

- Precipitation is important in our daily life
  - may cause human damage and economic loss
  - improving the accuracy of precipitation prediction is critical

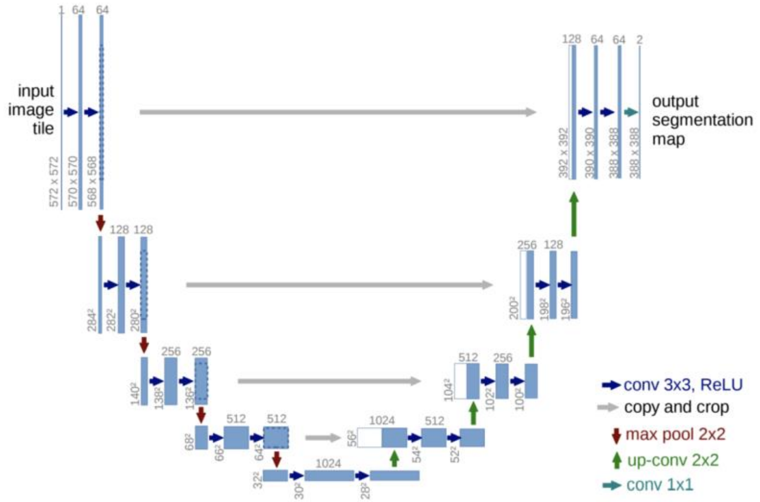
- Widely known conventional techniques for precipitation prediction
  - Numerical Weather Prediction (NWP) models, Optical Flow (Bowler et al., 2004)
  - require enormous computational resources

Image by brgfx on Freepik

Deep Learning Models for Precipitation Nowcasting

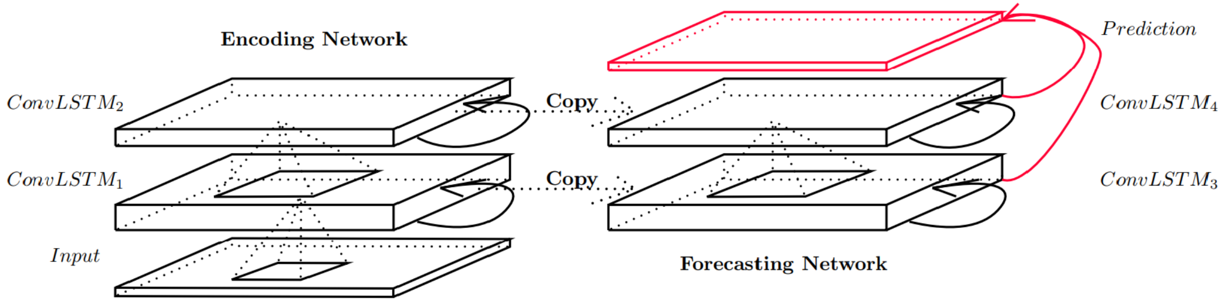
- Deep-learning techniques have been applied to precipitation nowcasting
  - outperform state-of-the-art NWP models, at lead times up to 12 hours

- U-Net (Ronneberger et al., 2015)



- (Agrawal et al., 2019)
- (Lebedev et al., 2019)
- DeepRaNE (Ko et al., 2022)

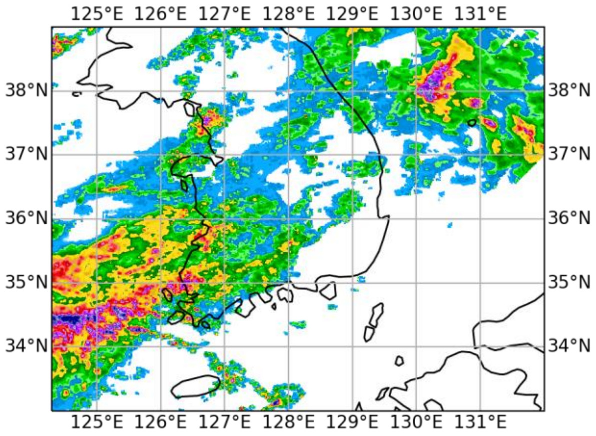
- ConvLSTM (Shi et al., 2015)



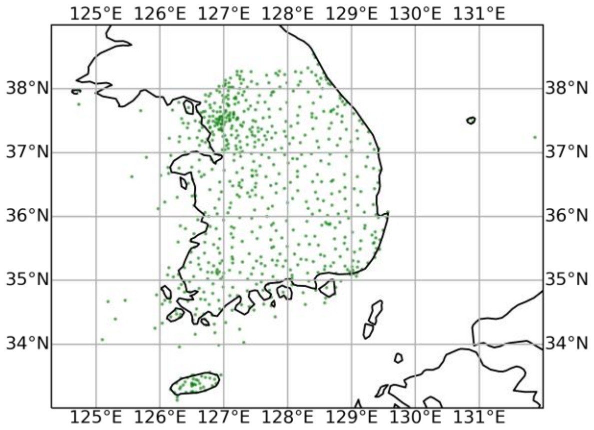
- ConvLSTM (Shi et al., 2015)
- TrajGRU (Shi et al., 2017)
- MetNet-2 (Espeholt et al., 2022)

How about Ground Weather Station Data?

- However, deep learning methods have underutilized meteorological observations from ground weather stations
  - They are not naturally represented in a grid format since ground weather stations are sparsely located



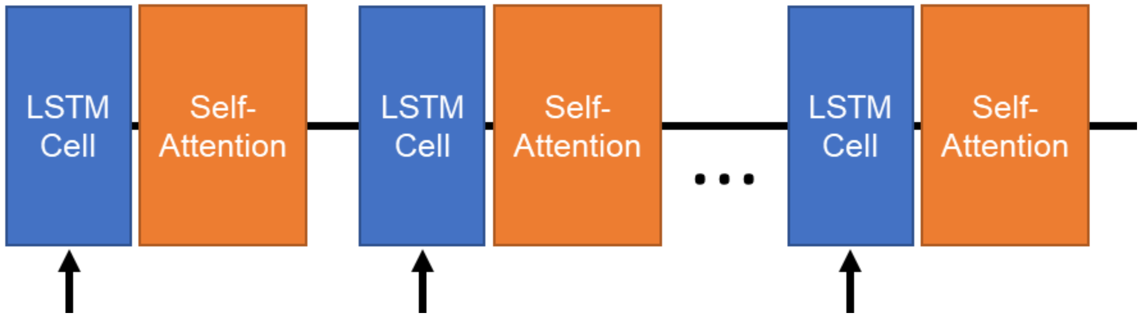
Radar Images
(Grid Format)



Ground Weather Stations
(Sparsely Located)

How about Ground Weather Station Data? (Cont.)

- How can we utilize meteorological observations from ground weather stations?
  - Interpolation techniques (e.g., Inverse Distance Weighting and Kriging) may be used
  - but expensive both in time and memory, especially to obtain high-resolution data
- **Our solution:** **A**ttentive **S**parse **O**bservation **C**ombiner (**ASOC**)
  - to capture temporal dynamics of the observations from the stations
  - to capture contextual relationships between the observations



Outline

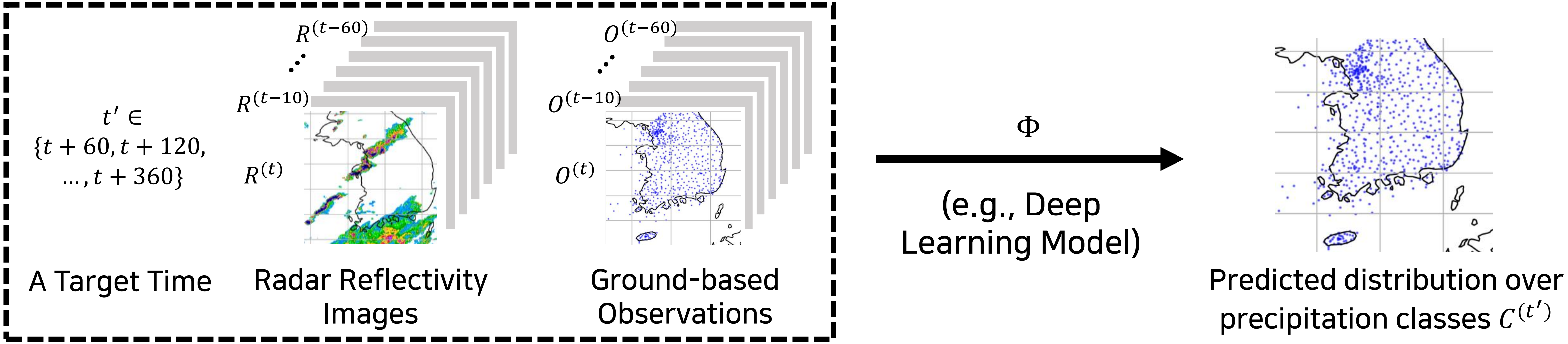
- **Problem Definition**
- Proposed Method: ASOC and ASOC+
- Experimental Results
- Conclusions

Problem Definition

- We formulate the problem as a location-wise classification problem
- We consider three precipitation classes:
  - HEAVY for precipitation at least 10mm/h
  - LIGHT for precipitation at least 1mm/h but less than 10 mm/h
  - OTHERS for precipitation less than 1 mm/h
- We consider lead times from 1 to 6 hours

Problem Definition

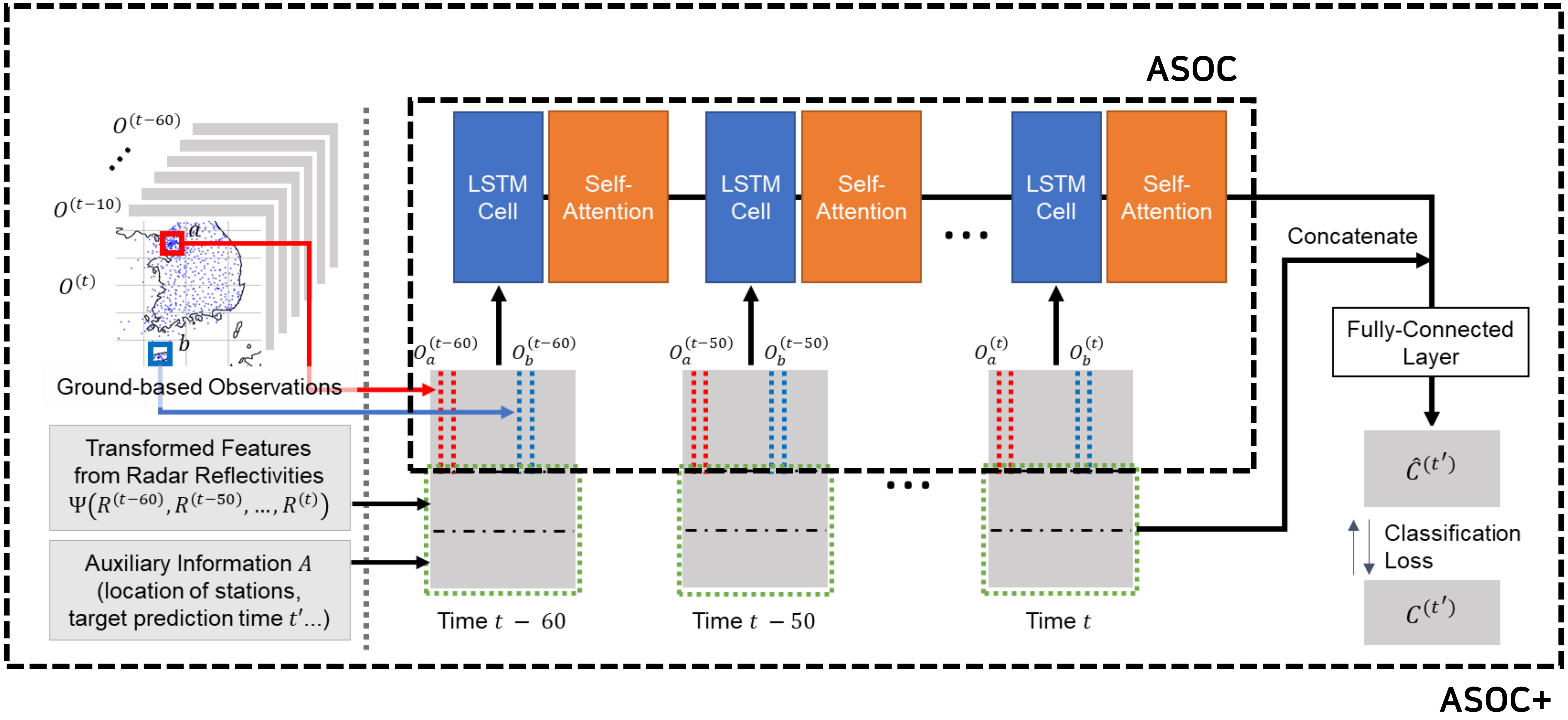
- **Given:**
  a. a target time (in minutes) $t' \in \{t+60, t+120, t+180, \dots, t+360\}$
  b. Radar reflectivity images $R^{(t-60)}, R^{(t-50)}, \dots, R^{(t)}$
  c. Ground-based observations $O^{(t-60)}, O^{(t-50)}, \dots, O^{(t)}$
- **Find:** a prediction function Φ
- **To Maximize:** classification performance



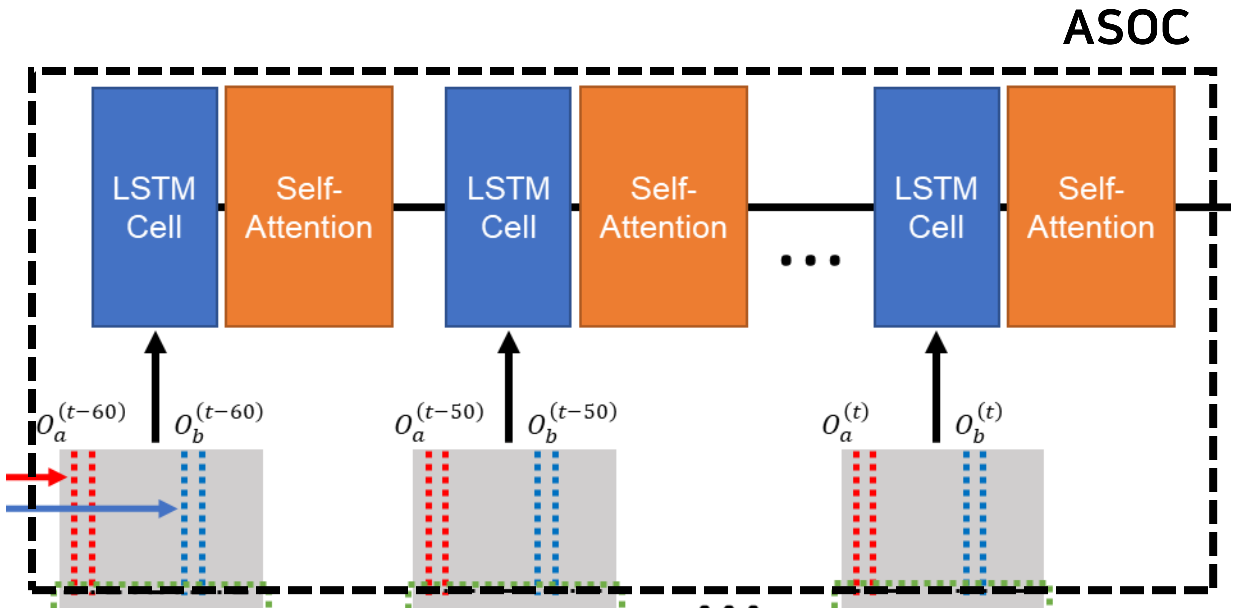
Outline

- Problem Definition
- **Proposed Methods: ASOC and ASOC+**
- Experimental Results
- Conclusions

Overview of ASOC and ASOC+



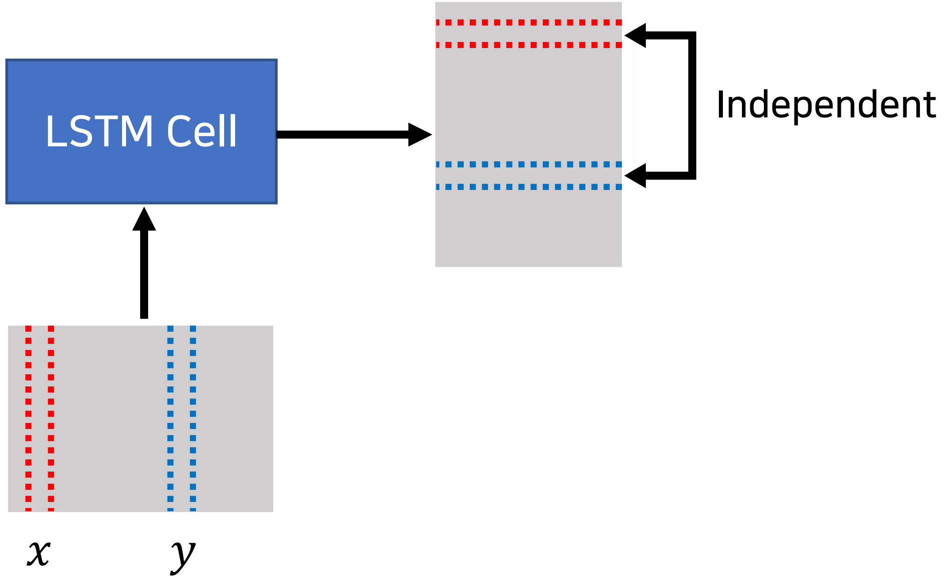
Overview of ASOC (Cont.)



- Temporal dynamics of observations: A sequence of ground-based observations over time are given as inputs
- Contextual relationships between observations: Ground-based observations collected from different weather stations are related to each other
  - Contexts: lead times, overall weather conditions, distance between the stations, etc.

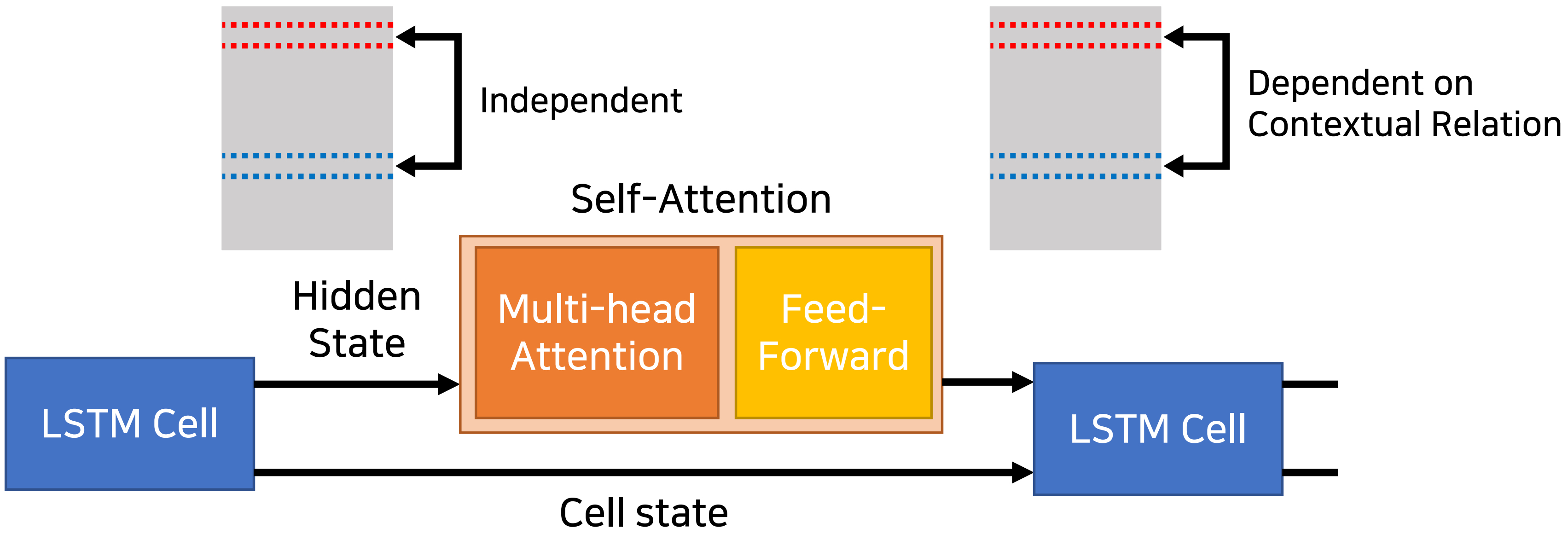
Exploiting Temporal Dynamics

- We use a recurrent architecture, especially **LSTM**, for parameterization and feed the inputs sequentially into the model
- Each LSTM cell processes inputs for one weather station at a time
  - observations from one station do not directly affect the outputs for the other stations



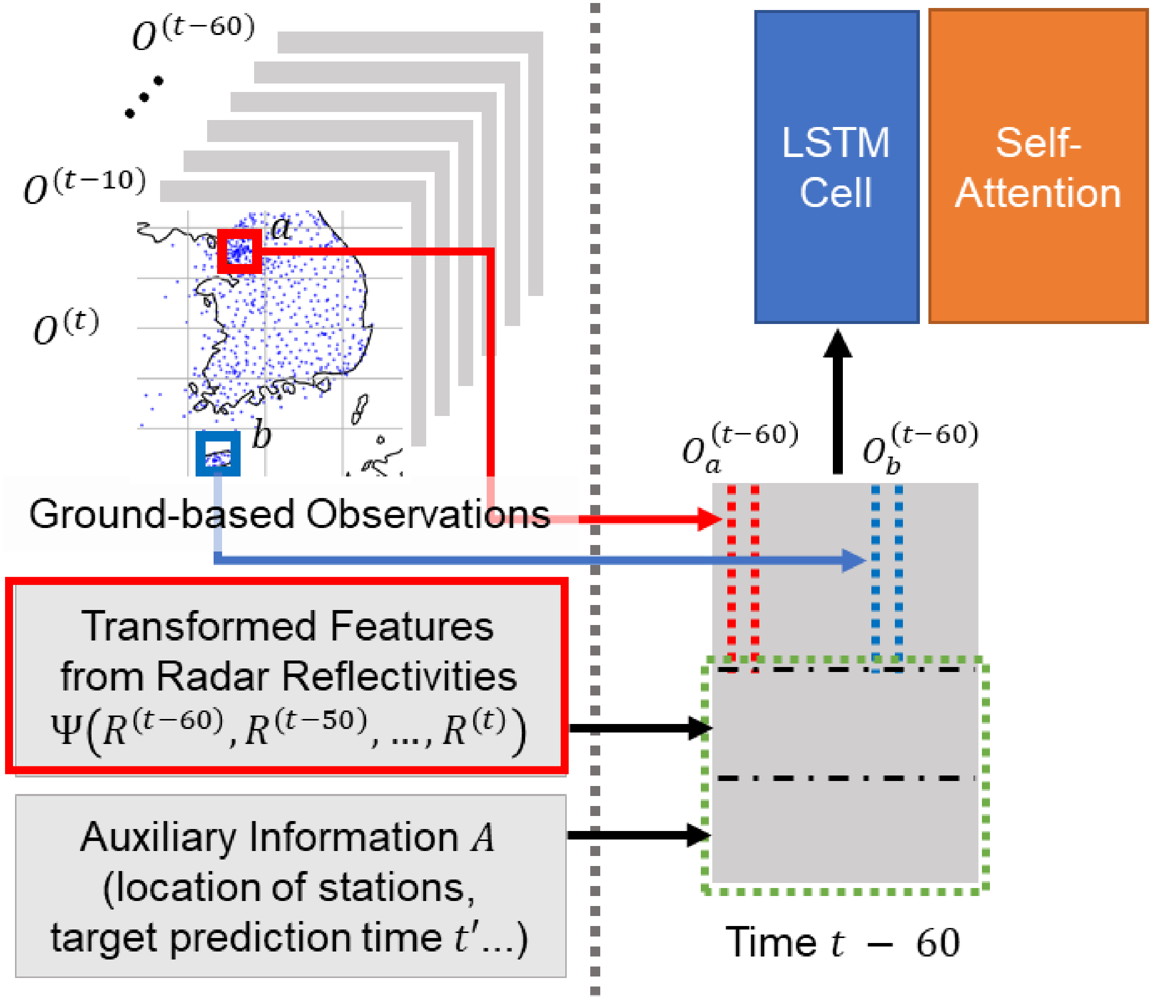
Exploiting Contextual Relationship

- We used self-attention, a state-of-the-art method for learning contextual relationship
- We used an encoder layer of Transformer (Vaswani et al., 2017)
  - consists of a multi-head attention layer and a feed-forward network



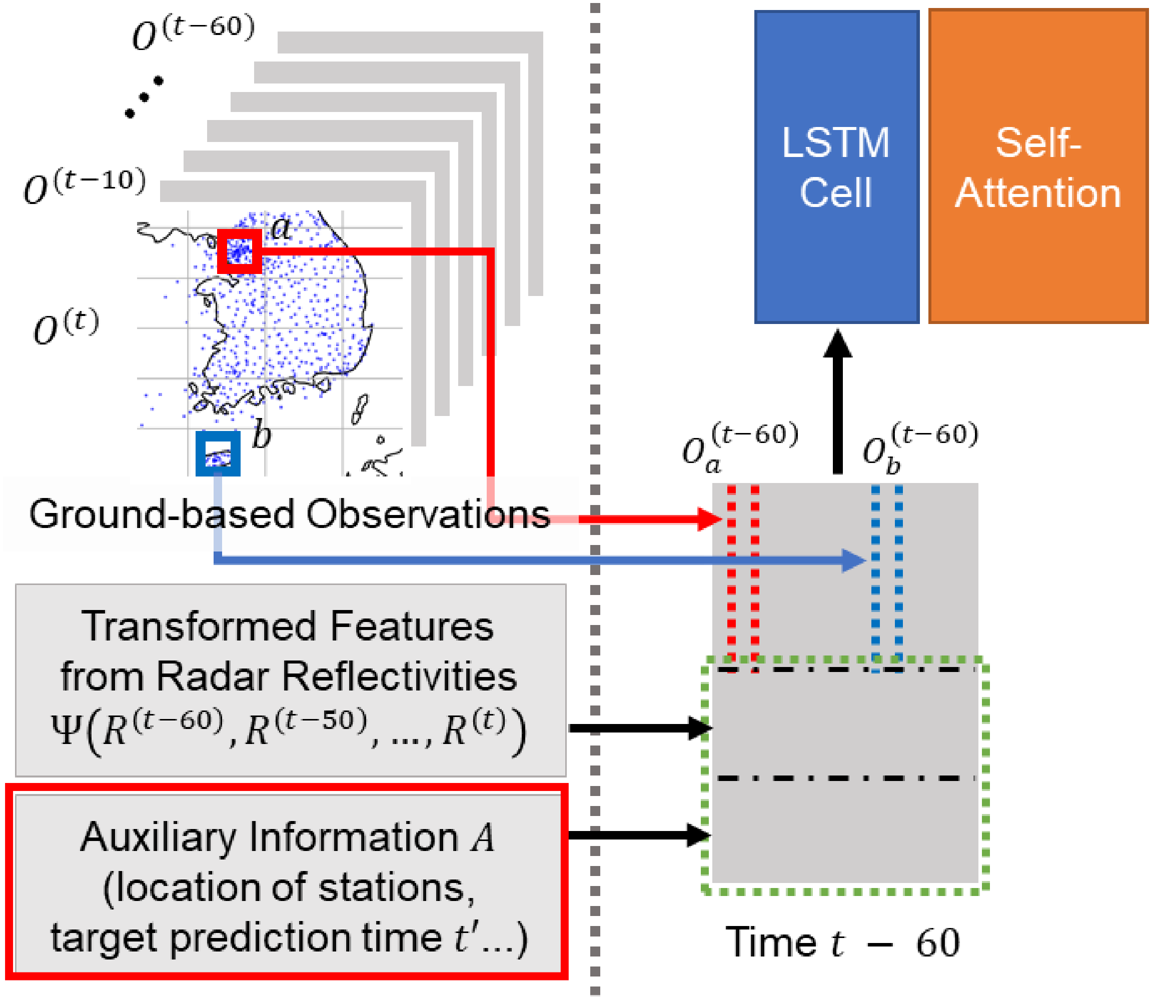
Integration to Image-based Models

- Output pixel embeddings of image-based precipitation nowcasting models can also be used as an additional input
  - We chose DeepRANE (Ko et al., 2022)
  - The combined model is called ASOC+



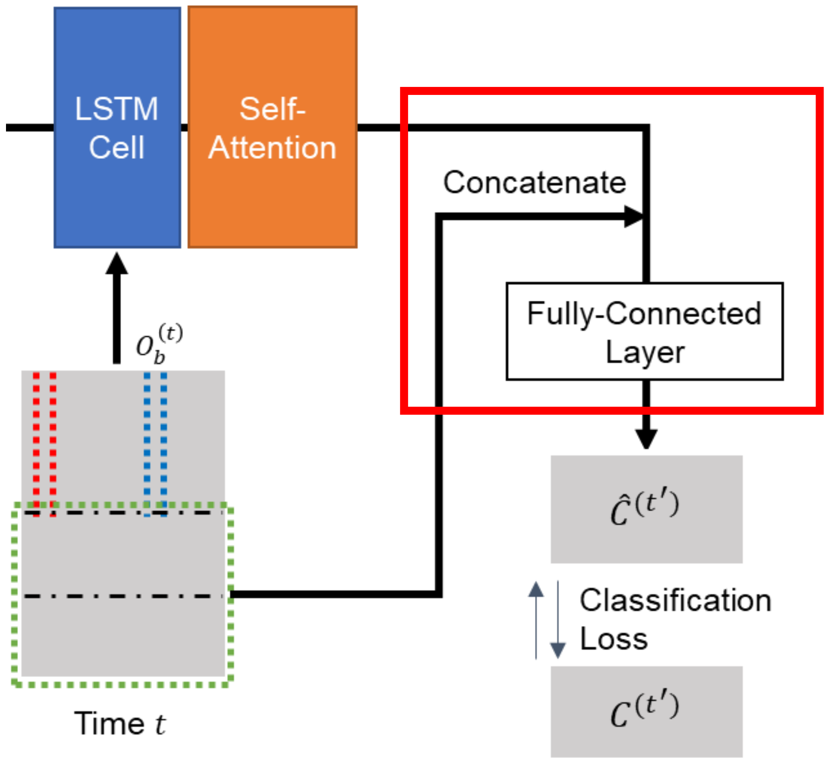
Integration to Image-based Models (Cont.)

- Output pixel embeddings of image-based precipitation nowcasting models can also be used as an additional input
  - We chose DeepRANE (Ko et al., 2022)
  - The combined model is called ASOC+
- We additionally used 12-dimensional vector containing auxiliary information
  a. The location of each region (2D vector)
  b. The observation date (2D vector)
  c. The observation time (2D vector)
  d. The lead time information (6D one-hot vector)



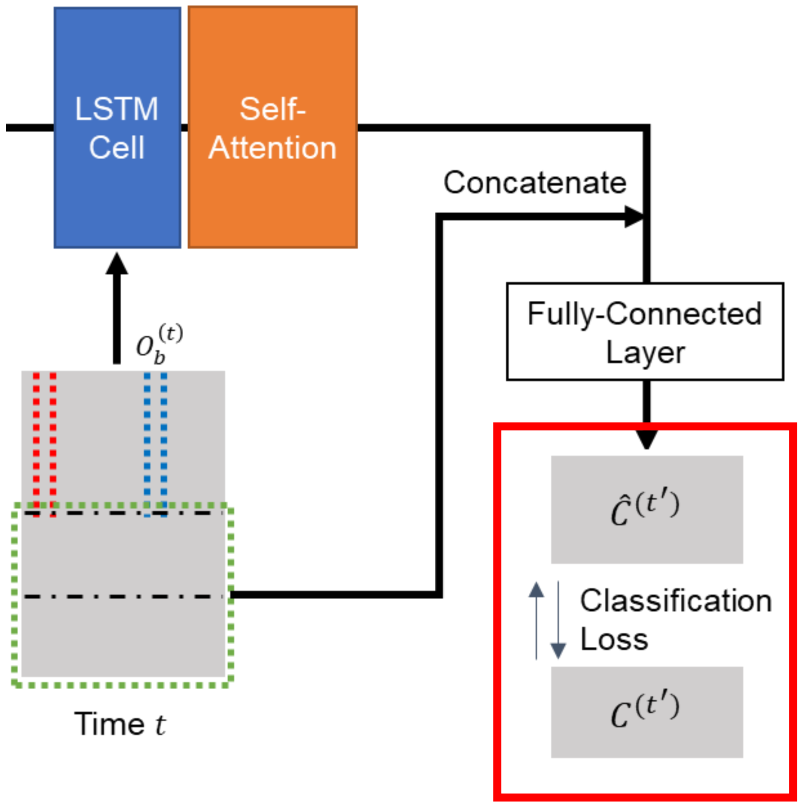
Computing the Final Outputs

- ASOC obtains the final output probability distribution for each region through an additional fully-connected layer from
  - The output of the LSTM part
  - The final input vector of the LSTM part



Computing the Final Outputs (Cont.)

- ASOC obtains the final output probability distribution for each region through an additional fully-connected layer from
  - The output of the LSTM part
  - The final input vector of the LSTM part
- We used a loss function designed for classification under class-imbalance
  - DeepRaNE (Ko et al., 2022)

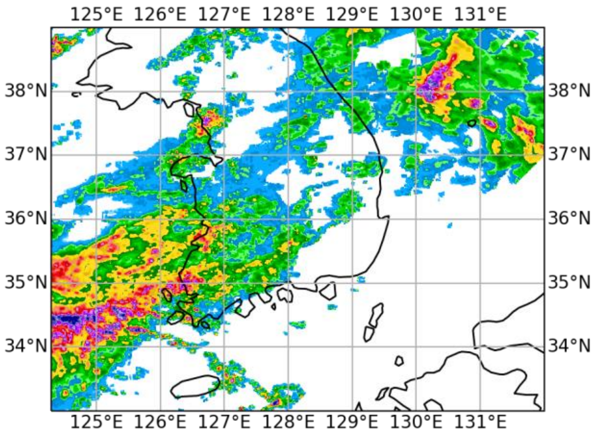


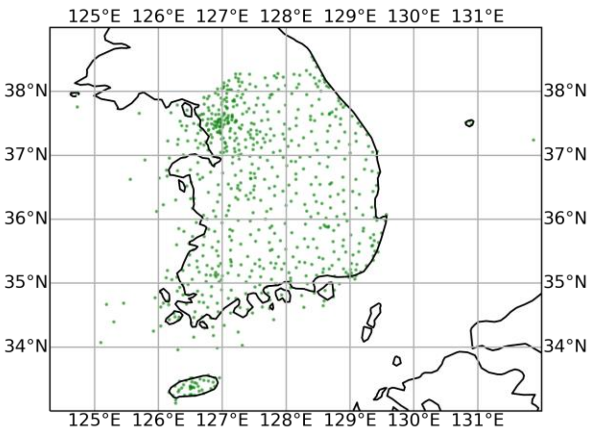
Outline

- Problem Definition
- Proposed Method: ASOC and ASOC+
- **Experimental Results**
- Conclusions

Experimental Settings

- **Datasets:**
  - Radar reflectivity images around South Korea
    - measured every ten minutes from 2014 to 2020
    - 1468 x 1468 in size and has a 1km x 1km resolution
  - Ground observations from Automated Weather Stations (AWS) in South Korea
    - collected from 714 weather stations every ten minutes from 2014 to 2020
    - containing wind direction and speed, temperature, cumulative precipitation, humidity, and barometric pressure





Experimental Settings (Cont.)

- **Baseline Approaches:**
  - Radar Images Only
    - DeepRaNE
  - Ground-based Observations Only
    - LSTM
    - Persistence Model: use the current precipitation class in each region as prediction
  - Ground-based Observations and Radar Images
    - DeepRaNE+Kriging: interpolate ground observations using Kriging to be used as extra input channels

Experimental Settings (Cont.)

- **Evaluation Metrics:**
  - CSI and F1 scores for two precipitation classes at each lead time from 1 to 6 hours
    - HEAVY for precipitation at least 10mm/h
    - RAIN for precipitation at least 1mm/h (= HEAVY + LIGHT)

		Predicted	
	precipitation $\geq c$	Positive	Negative
Actual	Positive	TP_c	FN_c
	Negative	FP_c	TN_c

$$\mathrm{CSI}_c = \frac{\mathrm{TP}_c}{\mathrm{TP}_c + \mathrm{FP}_c + \mathrm{FN}_c},$$

$$\mathrm{F1}_c = \frac{2 \cdot \mathrm{TP}_c}{2 \cdot \mathrm{TP}_c + \mathrm{FP}_c + \mathrm{FN}_c},$$

Results: Effectiveness of ASOC+ and ASOC

- Among the approaches that use only ground-based observations as the input, ASOC performed significantly better than the others
- Among all approaches, ASOC+ performed best overall, achieving the 5.7% better CSI scores on average than the others

Input Data		Ground-based Observations Only						Ground-based Observations and Radar Images					
Precipitation level	Lead time	ASOC CSI	ASOC F1	LSTM CSI	LSTM F1	Persistence CSI	Persistence F1	ASOC+ CSI	ASOC+ F1	DeepRaNE + Kriging CSI	DeepRaNE + Kriging F1	DeepRaNE only CSI	DeepRaNE only F1
HEAVY (≥10mm/h)	60 minutes	0.262	0.415	**0.296**	**0.457**	0.259	0.412	**0.444**	**0.615**	0.316	0.480	0.390	0.562
	120 minutes	0.156	0.270	**0.178**	**0.302**	0.152	0.264	**0.309**	**0.472**	0.200	0.333	0.280	0.438
	180 minutes	0.120	0.215	**0.127**	**0.225**	0.102	0.185	**0.218**	**0.357**	0.158	0.273	0.210	0.348
	240 minutes	**0.094**	**0.173**	0.090	0.166	0.073	0.136	0.169	0.289	0.128	0.226	**0.170**	**0.291**
	300 minutes	**0.079**	**0.147**	0.064	0.121	0.057	0.108	**0.141**	**0.247**	0.108	0.195	0.135	0.238
	360 minutes	**0.070**	**0.132**	0.048	0.091	0.046	0.087	0.096	0.176	0.092	0.168	**0.116**	**0.207**
RAIN (≥1mm/h)	60 minutes	**0.532**	**0.695**	0.527	0.690	0.518	0.683	**0.671**	**0.803**	0.483	0.652	0.609	0.757
	120 minutes	**0.430**	**0.602**	0.408	0.580	0.396	0.568	**0.548**	**0.708**	0.409	0.581	0.501	0.667
	180 minutes	**0.376**	**0.546**	0.347	0.515	0.331	0.498	**0.468**	**0.638**	0.375	0.546	0.449	0.620
	240 minutes	**0.334**	**0.501**	0.306	0.468	0.288	0.447	**0.428**	**0.599**	0.339	0.507	0.411	0.583
	300 minutes	**0.299**	**0.460**	0.275	0.432	0.256	0.408	**0.394**	**0.565**	0.315	0.479	0.381	0.552
	360 minutes	**0.270**	**0.425**	0.250	0.401	0.231	0.375	**0.359**	**0.529**	0.294	0.454	0.354	0.523
Average		**0.252**	**0.382**	0.243	0.371	0.226	0.348	**0.354**	**0.500**	0.268	0.408	0.334	0.482

Results: Ablation Study (Cont.)

- For HEAVY, ASOC+ achieved the best CSI and F1 scores on average
  - followed by ASOC-A (without self-attention blocks) and ASOC-P (uses only cumulative precipitation related features among the ground-based features)
- The ground-based features for cumulative precipitation contributed most to the performance of ASOC+

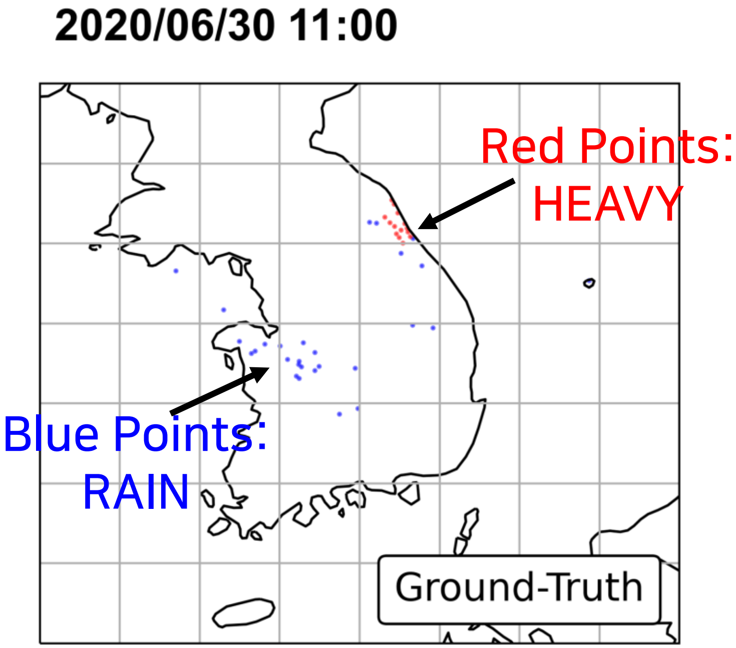
w/o self-attention

with specific features only

Precipitation level	Lead time	ASOC+ CSI	ASOC+ F1	ASOC-A CSI	ASOC-A F1	ASOC-P CSI	ASOC-P F1	ASOC-W CSI	ASOC-W F1	ASOC-T CSI	ASOC-T F1	ASOC-D CSI	ASOC-D F1	ASOC-H CSI	ASOC-H F1	ASOC-B CSI	ASOC-B F1
HEAVY (≥10mm/h)	60 minutes	0.444	0.615	**0.464**	**0.634**	0.399	0.571	0.406	0.578	0.317	0.481	0.297	0.458	0.380	0.550	0.408	0.579
	120 minutes	**0.309**	**0.472**	0.285	0.443	0.292	0.452	0.243	0.392	0.259	0.412	0.240	0.387	0.277	0.434	0.270	0.425
	180 minutes	**0.218**	0.357	**0.218**	**0.358**	0.207	0.343	0.186	0.313	0.205	0.340	0.202	0.336	0.213	0.351	0.196	0.328
	240 minutes	**0.169**	**0.289**	0.154	0.267	0.162	0.279	0.153	0.266	0.160	0.276	0.161	0.277	0.171	0.291	0.131	0.232
	300 minutes	**0.141**	**0.247**	0.125	0.222	0.124	0.221	0.120	0.214	0.131	0.231	0.138	0.242	0.132	0.233	0.136	0.239
	360 minutes	0.096	0.176	0.094	0.172	0.094	0.173	0.109	0.197	0.103	0.187	**0.124**	**0.221**	0.117	0.209	0.115	0.206
RAIN (≥1mm/h)	60 minutes	**0.671**	**0.803**	0.670	0.802	0.657	0.793	0.623	0.768	0.588	0.740	0.645	0.784	0.609	0.757	0.630	0.773
	120 minutes	0.548	0.708	**0.550**	**0.710**	0.549	0.709	0.516	0.681	0.517	0.682	0.520	0.684	0.523	0.687	0.526	0.690
	180 minutes	0.468	0.638	0.477	0.646	**0.488**	**0.656**	0.451	0.622	0.466	0.635	0.460	0.630	0.468	0.637	0.463	0.633
	240 minutes	0.428	0.599	0.425	0.596	**0.440**	**0.611**	0.413	0.585	0.421	0.593	0.414	0.585	0.426	0.598	0.391	0.562
	300 minutes	0.394	0.565	0.390	0.561	**0.404**	**0.576**	0.366	0.535	0.390	0.561	0.380	0.550	0.390	0.561	0.393	0.564
	360 minutes	0.359	0.529	0.365	0.535	**0.371**	**0.541**	0.336	0.503	0.361	0.530	0.356	0.525	0.362	0.531	0.364	0.533
Average		**0.354**	**0.500**	0.351	0.496	0.349	0.494	0.327	0.471	0.326	0.472	0.328	0.473	0.339	0.487	0.335	0.480

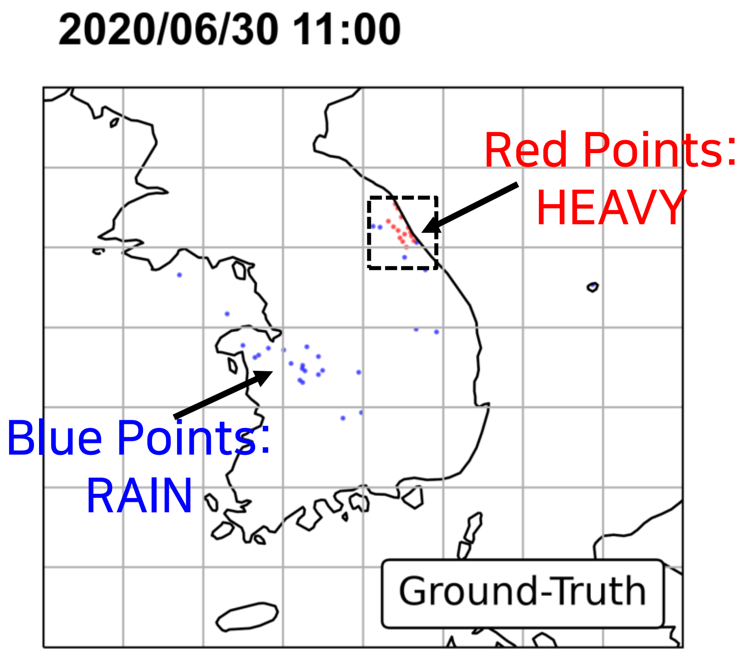
Results: Further Analysis in Heavy Rainfall Cases

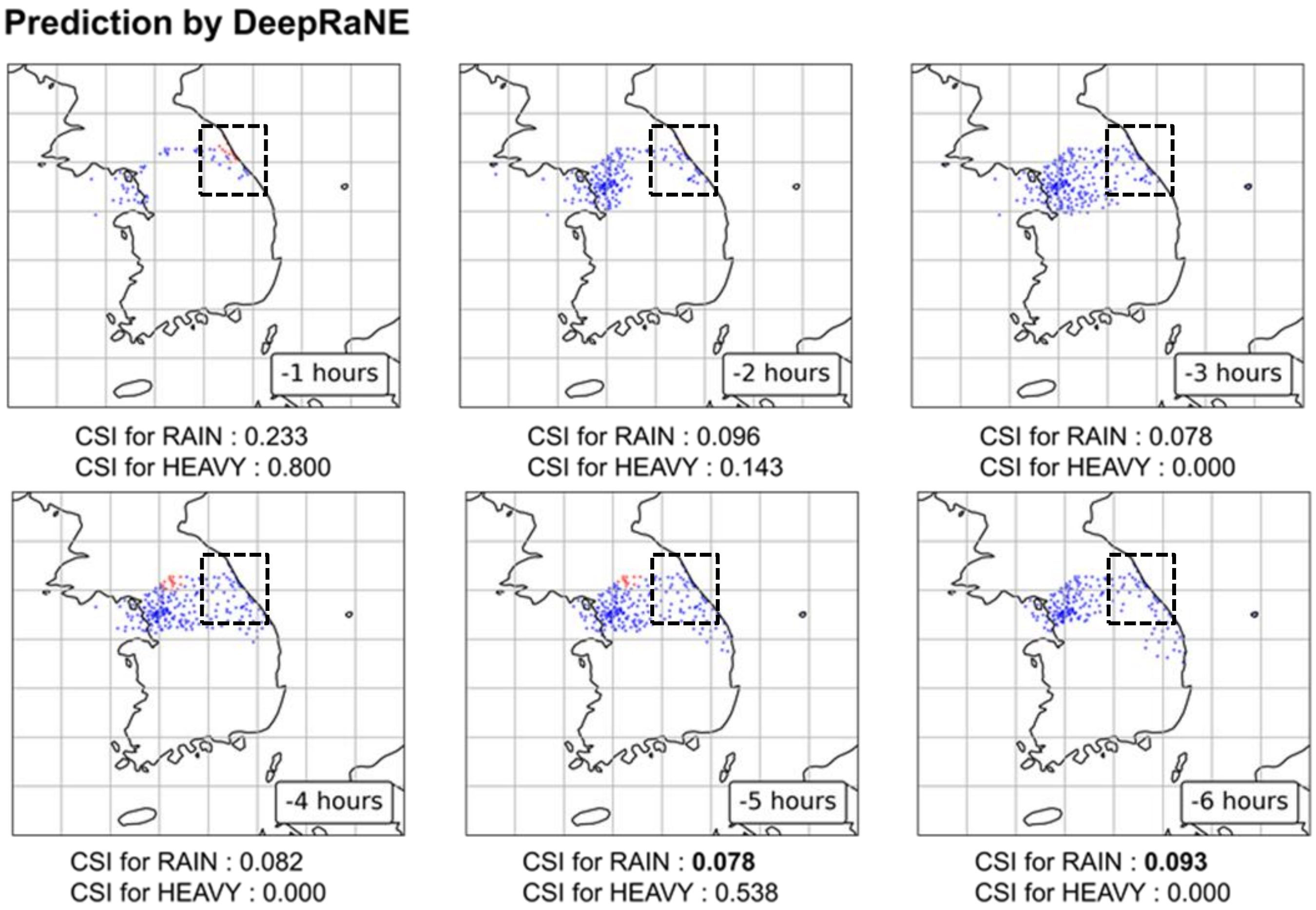
- Focused on 425 cases in the test set where a precipitation intensity rate is 30+ mm/hr at one or more regions
- ASOC+ achieved 18.7% better CSI scores and 19.6% better F1 scores on average for HEAVY than DeepRaNE



Results: Further Analysis in Heavy Rainfall Cases

- DeepRaNE fails to predict the locations of HEAVY cases when the lead time is greater than 2 hours

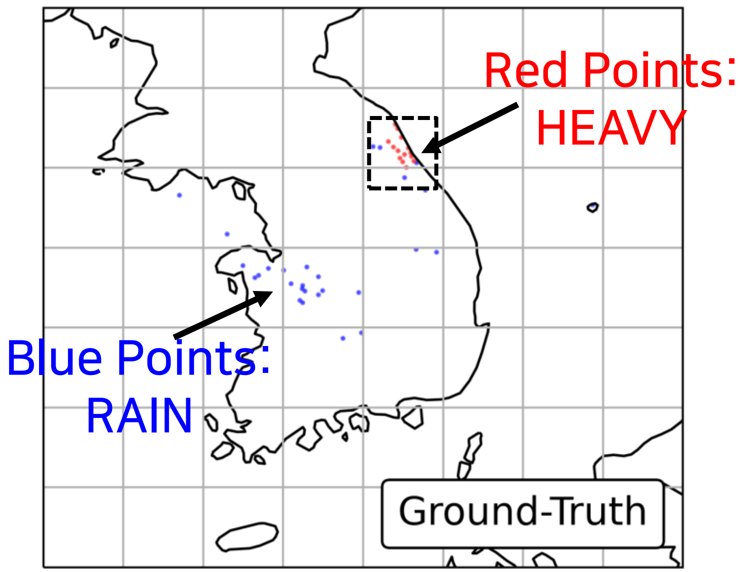




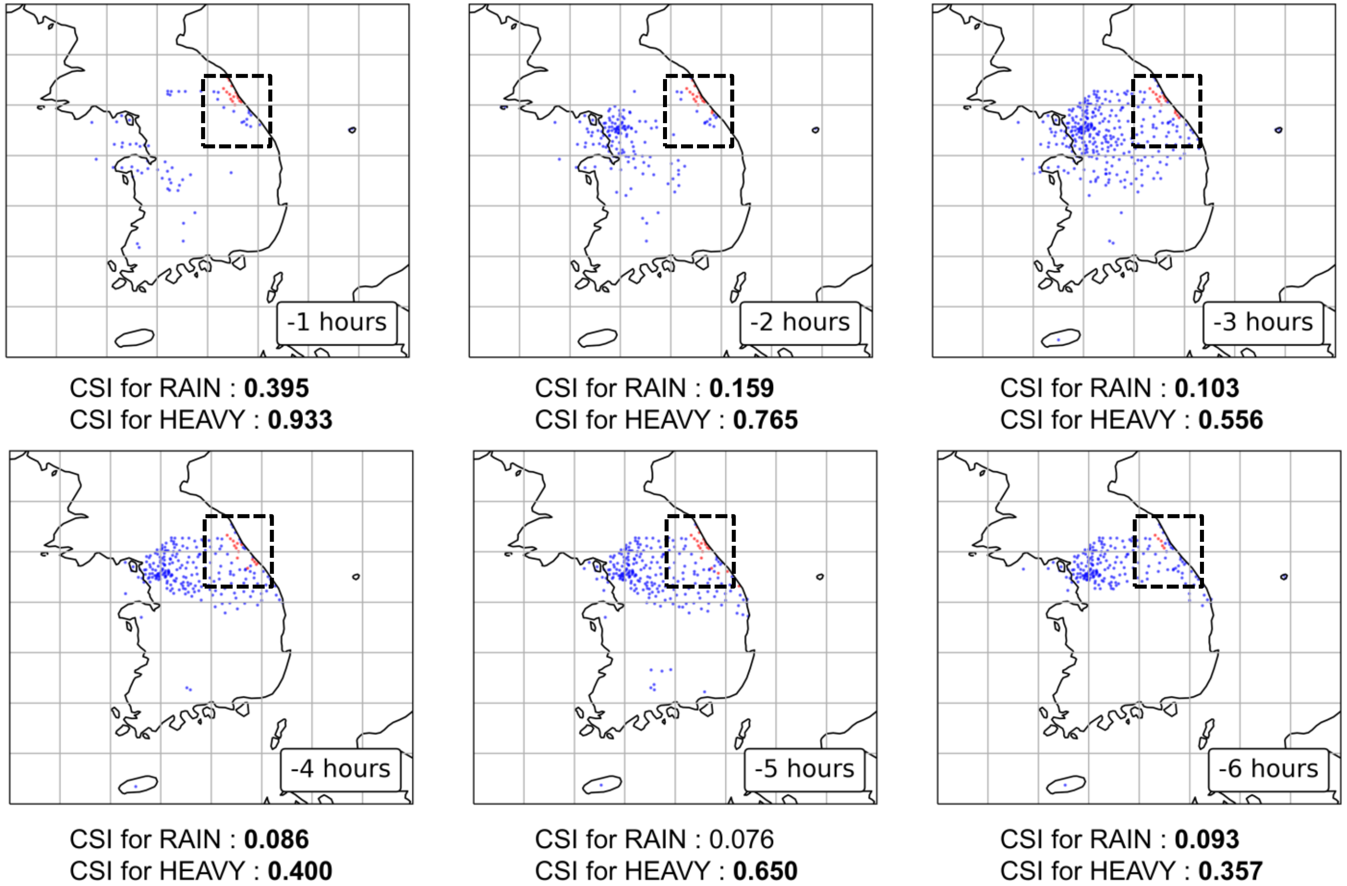
Results: Further Analysis in Heavy Rainfall Cases

- ASOC+ predicts the locations quite accurately even when the lead time is greater than 2 hours

2020/06/30 11:00



Prediction by ASOC+



Outline

- Problem Definition
- Proposed Method: ASOC and ASOC+
- Experimental Results
- **Conclusions**

Conclusions

- We proposed **ASOC**, a novel attentive and recurrent model for precipitation nowcasting using ground-based observations

☑ Effectively utilized meteorological observations by considering temporal dynamics and the attentive relationships

☑ Easily combined with state-of-the-art radar image-based models

☑ improved the CSI score for predicting HEAVY and RAIN at 1-6 hr lead times by 5.7%

The implementation used in the paper are available at
https://github.com/jihoonko/ASOC

Reference

Stanley G Benjamin, Dezsö Dévényi, Stephen S Weygandt, Kevin J Brundage, John M Brown, Georg A Grell, Dongsoo Kim, Barry E Schwartz, Tatiana G Smirnova, Tracy Lorraine Smith, et al. An hourly assimilation–forecast cycle: The ruc. Monthly Weather Review, 132(2):495–518, 2004.

Neill EH Bowler, Clive E Pierce, and Alan Seed. Development of a precipitation nowcasting algorithm based upon optical flow techniques. Journal of Hydrology, 288(1-2):74–91, 2004.

Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In International Conference on Medical image computing and computer-assisted intervention, pages 234–241, 2015.

Xingjian Shi, Zhourong Chen, Hao Wang, Dit-Yan Yeung, Wai-Kin Wong, and Wang-chun Woo. Convolutional lstm network: A machine learning approach for precipitation nowcasting. In NIPS, 2015.

Xingjian Shi, Zhihan Gao, Leonard Lausen, Hao Wang, Dit-Yan Yeung, Wai-Kin Wong, and Wang-chun Woo. Deep learning for precipitation nowcasting: A benchmark and a new model. In NIPS, 2017.

Shreya Agrawal, Luke Barrington, Carla Bromberg, John Burge, Cenk Gazen, and Jason Hickey. Machine learning for precipitation nowcasting from radar images. arXiv preprint arXiv:1912.12132, 2019.

Vadim Lebedev, Vladimir Ivashkin, Irina Rudenko, Alexander Ganshin, Alexander Molchanov, Sergey Ovcharenko, Ruslan Grokhovetskiy, Ivan Bushmarinov, and Dmitry Solomentsev. Precipitation nowcasting with satellite imagery. In KDD, 2019.

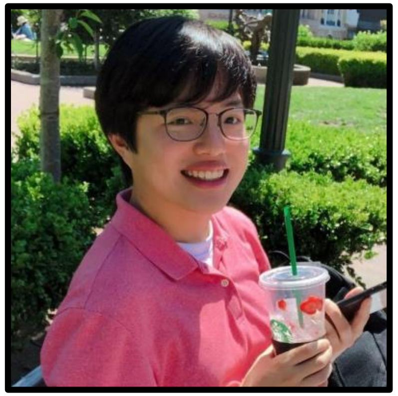
J. Ko, K. Lee, H. Hwang, S.-G. Oh, S.-W. Son, and K. Shin, “Effective training strategies for deep-learning-based precipitation nowcasting and estimation,” Computers & Geosciences, vol. 161, p. 105072, 2022.

L. Espeholt, S. Agrawal, C. Sønderby, M. Kumar, J. Heek, C. Bromberg, C. Gazen, J. Hickey, A. Bell, and N. Kalchbrenner, “Skillful twelve hour precipitation forecasts using large context neural networks,” Nature Communication, 2022.

KAIST AI
Kim Jaechul Graduate School

Deep-Learning-Based Precipitation Nowcasting with Ground Weather Station Data and Radar Data



Jihoon Ko* | Kyuhan Lee* | Hyunjin Hwang | Kijung Shin