KIAPS
KOREA INSTITUTE OF ATMOSPHERIC PREDICTION SYSTEMS

Estimating the Observation Impact based on Attentive 3D-Convolutional RNN

Hyeon-Ju Jeon, Jeon-Ho Kang, In-Hyuk Kwon
Korea Institute of Atmospheric Prediction Systems (KIAPS)

1 Motivation & Objectives

- **(Background) KIM Package for Observation Processing (KPOP) in Data Assimilation (DA) system**
  - ✓ KPOP contributes to enhancing the performance of the DA system by not only adding new observations but also improving the quality of existing observations.
  - ✓ To support the efficient operation of KPOP, evaluating the impact of the assimilated observations on the forecast performance is necessary.
- **(Motivation) Challenging to develop the Forecast Sensitivity and Observation Impacts (FSOI) system due to the high complexity resulting from KIM's non-linearity**
  - ✓ **Ensemble FSO**: using ensembles of analysis states and corresponding forecasts instead of adjoint analysis, **Hybrid FSOI**: combination of the adjoint approach and ensemble approach

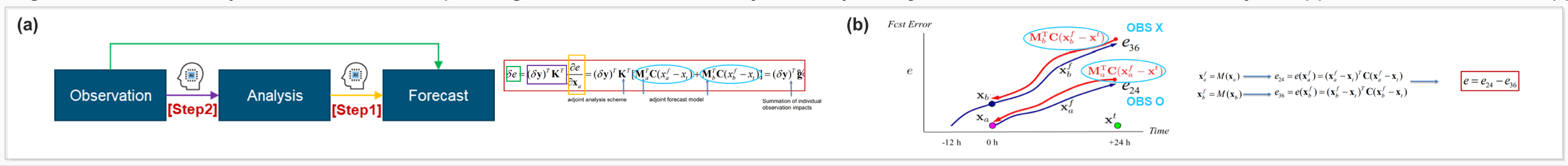


Figure 1. (a) illustrates the structure of the designed 2-steps AI based FSOI system, and (b) depicts the observation impact estimated by the degree of change according to observations.

- **(Objectives1) This study presents a novel approach for estimating forecast sensitivity by comprehensively analyzing diverse meteorological characteristics in an AI manner.**
- **(Objectives2) We discovers the spatiotemporal dependence of atmospheric variables and the multiple characteristics of meteorological phenomena.**

2 Methods

- **For learning the relationship of atmospheric states between adjacent regions, we proposed a CNN-based prediction model called A3D-CRNN to extract spatial patterns of atmospheric phenomena with various properties.**

A3D-CRNN: Attentive 3D-Convolutional RNN

- Spatial distribution
  - ✓ Both vertical convection and horizontal advection
    - ✓ Extending the two-dimensional convolution filter to three dimensions
- Temporal features
  - ✓ Dynamic patterns of atmospheric phenomena over time
    - ✓ Gated recurrent unit (GRU) based model for the robustness of long-term prediction
- Atmospheric phenomena
  - ✓ Multiple scales of the atmospheric phenomena
    - ✓ Using the inception network to reflect the multi-scale of spatial patterns
  - ✓ Various shapes of atmospheric phenomena
    - ✓ Attention module is developed to extract distinguishing features even for regions that exceed the size of the CNN filter

Estimating the Forecast Sensitivity

- Concepts
  - ✓ We compared the prediction accuracy with (x_t) and without (x_t') the analysis field at time t.

$$x_t = < \boldsymbol{anal_t}, A_{t-n} >, x_t' = < \boldsymbol{bkg_t}, A_{t-n} >,$$
$$A_{t-n} = \{anal_{t-n} | n \le N\}.$$
(N indicates the sequence length)

- Formulation
  - ✓ Forecasts sensitivity FS in time t is computed as:

$$FS(x_t, f) = \sum_{x_t, x_t' \in X_t} \left(f(x_t) - f(x_t')\right),$$

where $f(\cdot)$ denotes the function for obtaining the prediction accuracy by A3D-CRNN model.

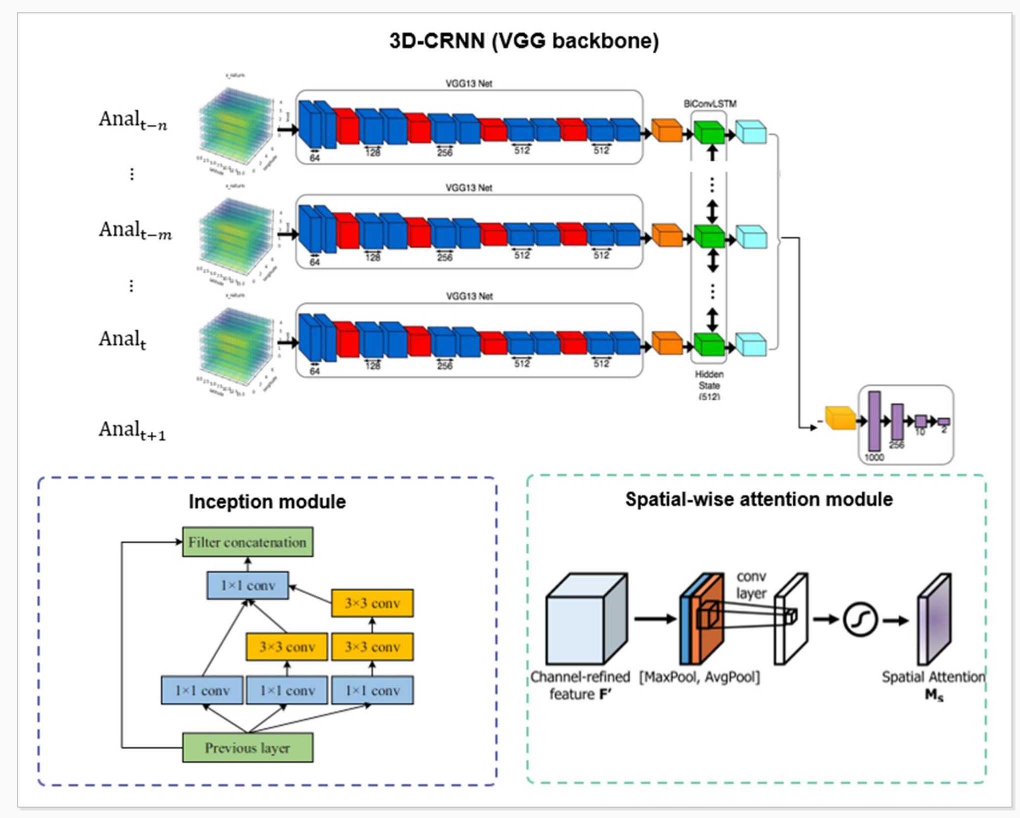
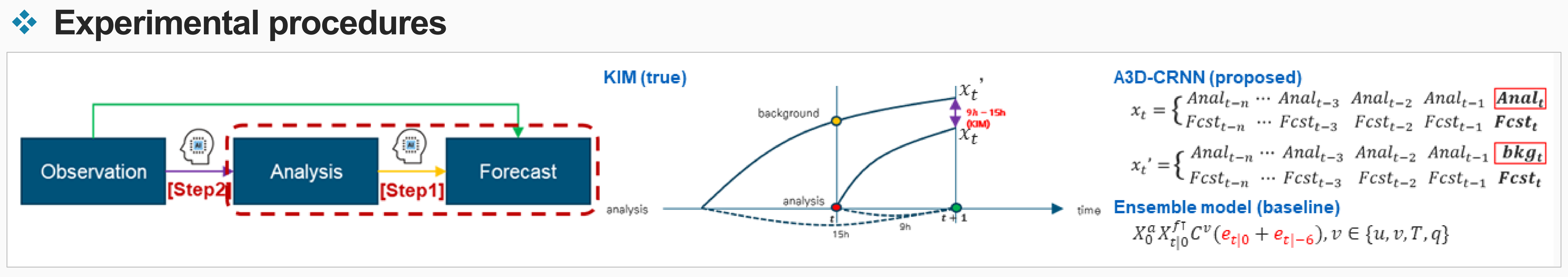


Figure 2. Architecture of the proposed A3D-CRNN model.

3 Experimental Results

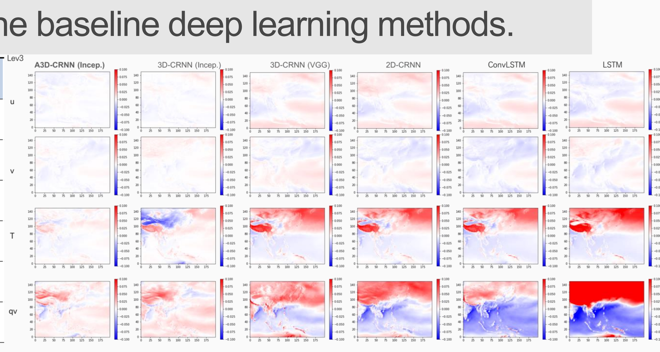
- **Experimental procedures**



Evaluation of the A3D-CRNN performance

Table 1. A performance comparison of the proposed model with the baseline deep learning methods.

Models	MAE	R^2	σ	R
A3D-CRNN (Incep.)	**0.01**	**0.99**	**0.99**	**1.00**
3D-CRNN (Incep.)	0.01	0.99	0.99	0.99
3D-CRNN (VGG)	0.02	0.96	0.96	0.96
2D-CRNN	0.04	0.85	0.85	0.84
ConvLSTM	0.05	0.82	0.82	0.83
LSTM	0.07	0.75	0.75	0.75



- ✓ **Reflecting the various physical properties of atmospheric phenomena contributes to high accuracy**

Evaluation of the estimation system

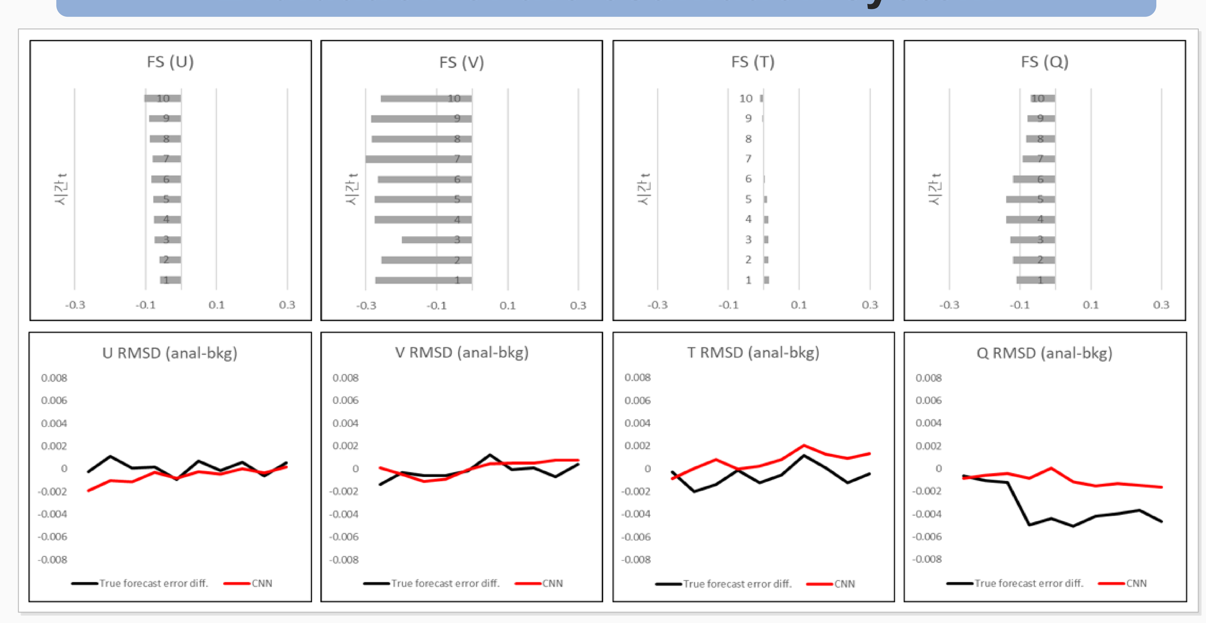


Figure 3. Forecast sensitivity for each variable (u, v, T, qv) estimated over time with the proposed system.

- ✓ **The RMSD from the proposed model showed similar trend to the true forecast error difference.**

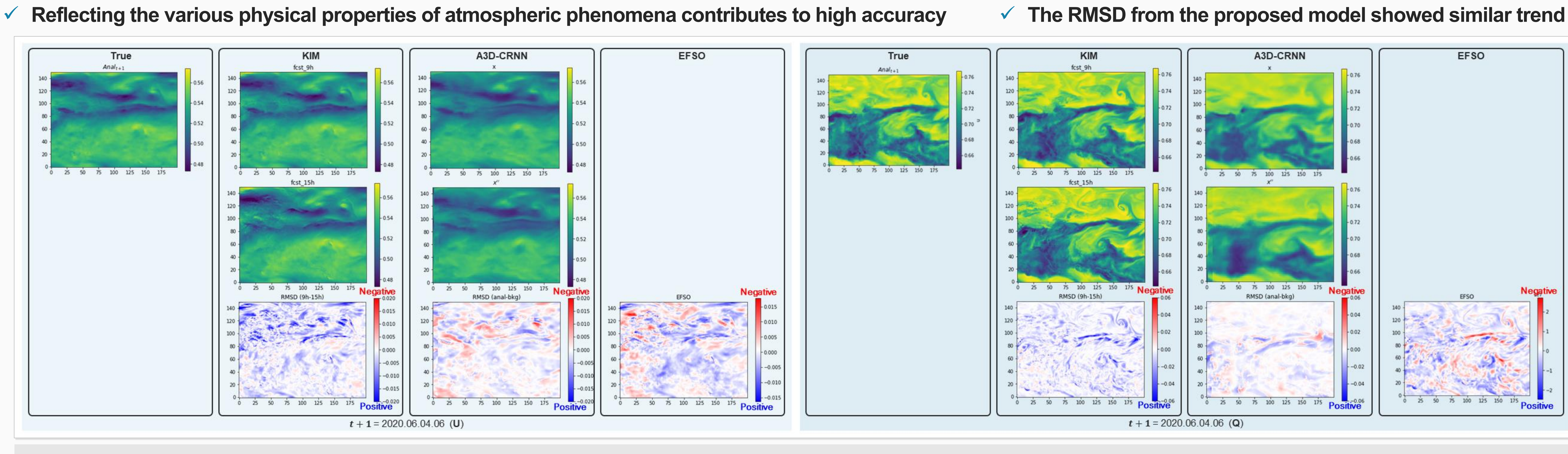
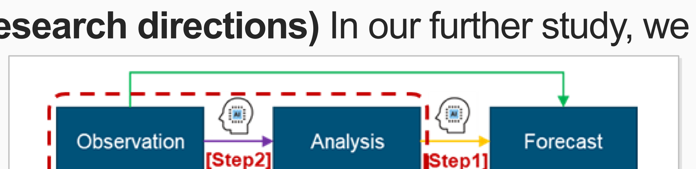


Figure 4. Comparison of the spatial distribution of forecast sensitivities of the baseline system (EFSO) and the proposed system (A3D-CRNN) in each meteorological variable.

- ✓ **It is difficult for our system to completely explain the true forecast error difference of KIM.**
- ✓ **However, the spatial distribution estimated by EFSO also shows the same result as our system.**
- ✓ **Although our AI-based system that predicts the forecast field based on the time-series pattern of the analysis field, and the EFSO system use different approaches for estimating the forecast sensitivity, their results have similar patterns.**

4 Conclusions & Future directions

- **(Conclusion)** We have proposed a novel AI-based approach, named the Attentive 3D-convolutional RNN, which enables the assessment of the propagation impact of the analysis field to the forecast field.
- **(Conclusion)** This end-to-end method complements the current research that relies on numerical and assimilation system biases.
- **(Limitations)** The proposed method learned based on the output of the KIM model only can be applied to grid-type data, and requires more experiments to evaluate the estimated sensitivity.
- **(Research directions)** In our further study, we extend the proposed model to estimate the observation impacts on the analysis field (Step 2).



① To reflect various meteorological variables collected from multiple observations, heterogeneous data processing techniques and multimodal fusion algorithms can be used.
② To learn non-grid and irregular observations, we can apply graph neural networks or advanced convolutional kernels.
③ Differential equation-inspired deep learning can be used to understand various meteorological phenomena in continuous-time dynamics with different time intervals.

The 24th International TOVS Study Conference (ITSC-24), Tromso, Norway, 16-22 March 2023