2nd NOAA Workshop on Leveraging AI in Environmental Sciences
- Session 26: AI/ML for Information Extraction from Data, Part 2

Kick: Shift-N-Overlap Cascades of Transposed Convolutional Layer for Better Autoencoding Reconstruction on Remote Sensing Imagery

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00 | Before we begin…

This presentation

- May discuss contents **previously published in IEEE© Access journal (Hong and Song, 2020):** IEEEXplore: #9110496, doi: [10.1109/ACCESS.2020.3000557](https://doi.org/10.1109/ACCESS.2020.3000557)
- Describe an **impact of deconvolutional layers in unsupervised autoencoder modeling**

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Kick: Shift-N-Overlap Cascades of Transposed Convolutional Layer for Better Autoencoding Reconstruction on Remote Sensing Imagery

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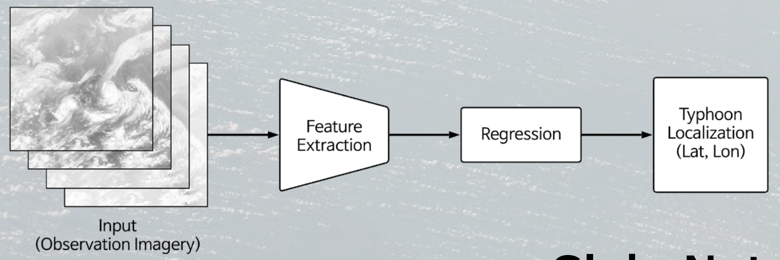
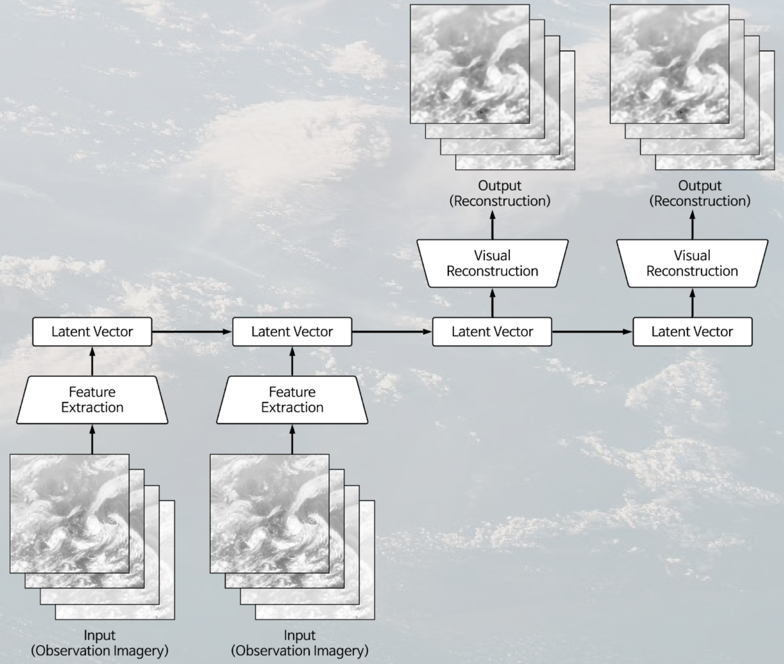
01 | Background

How this research began?

- Fresh attempt to **'extract and predict'** upcoming atmospheric events, from large-scale remote sensing imagery **'rapidly'**
- Preliminary model surveys for **meso-scale weather prediction tasks**
  - **Typhoon Eye Localization**
    (GlobeNet: [arXiv:1708.03417](https://arxiv.org/abs/1708.03417))
  - **Next Sequence of Satellite Images Prediction**
    (PSIque: [arXiv:1711.10644](https://arxiv.org/abs/1711.10644))



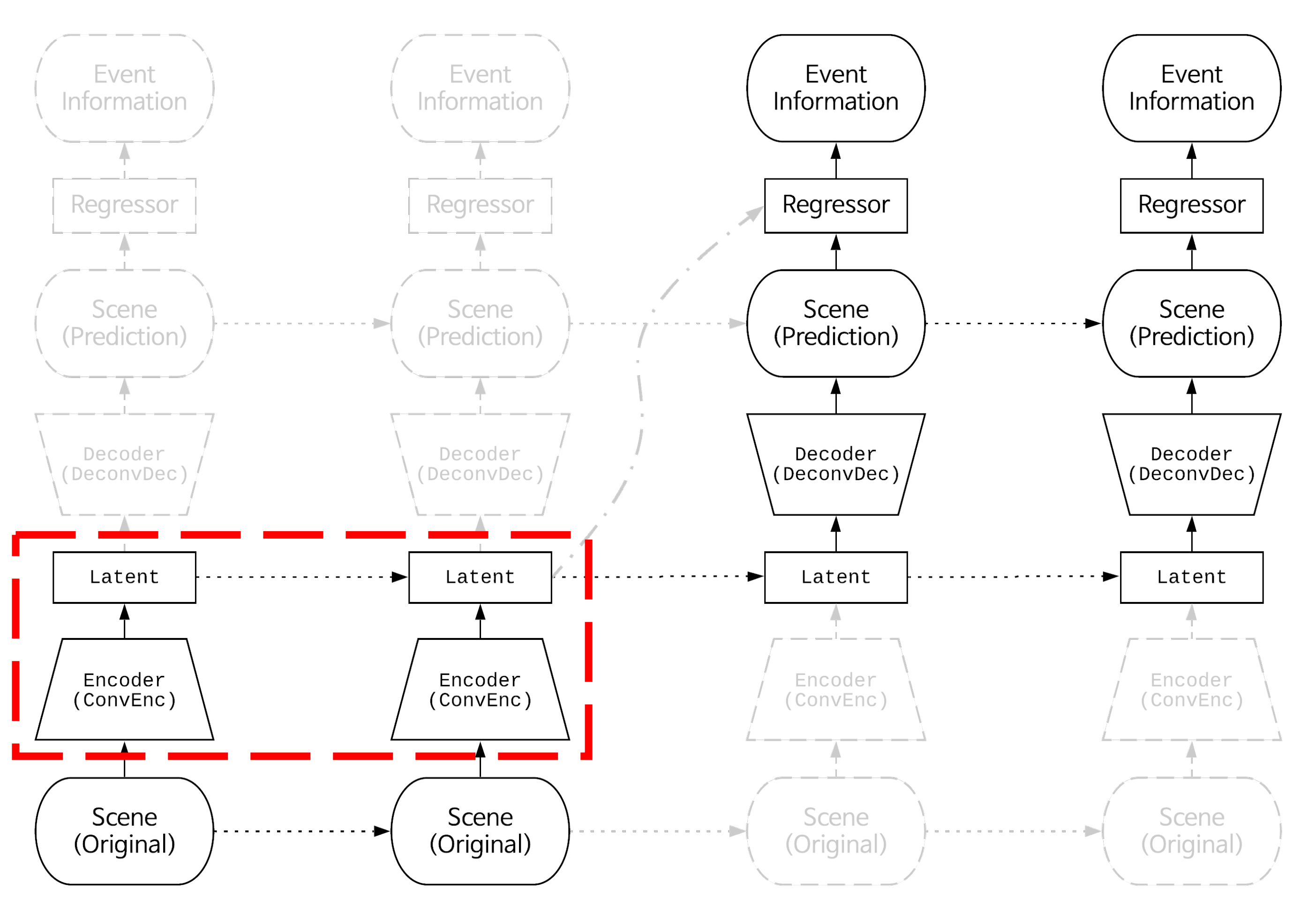
GlobeNet



PSIque

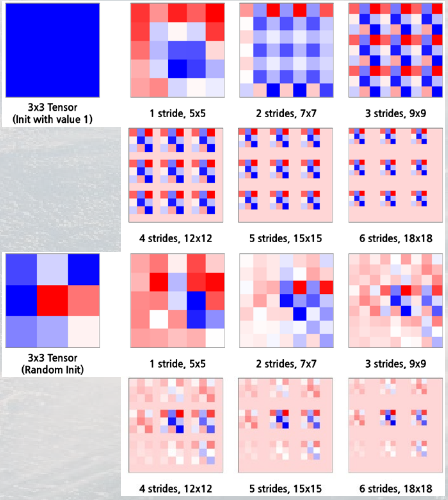
01 | Background

- **Issue #1**: Correlated models **share common part** which trained **separately**

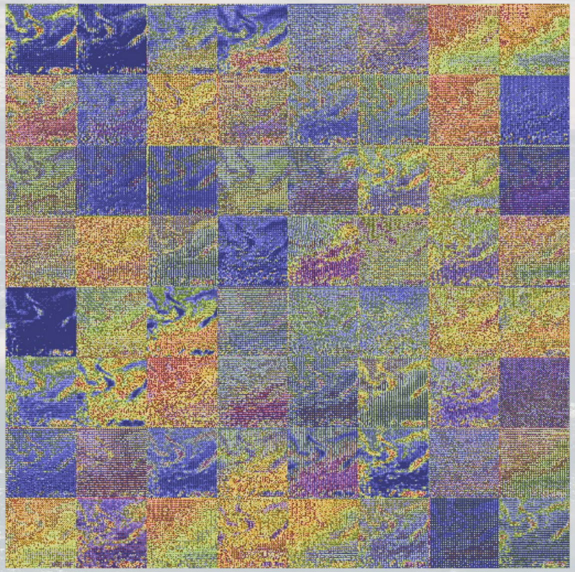


01 | Background

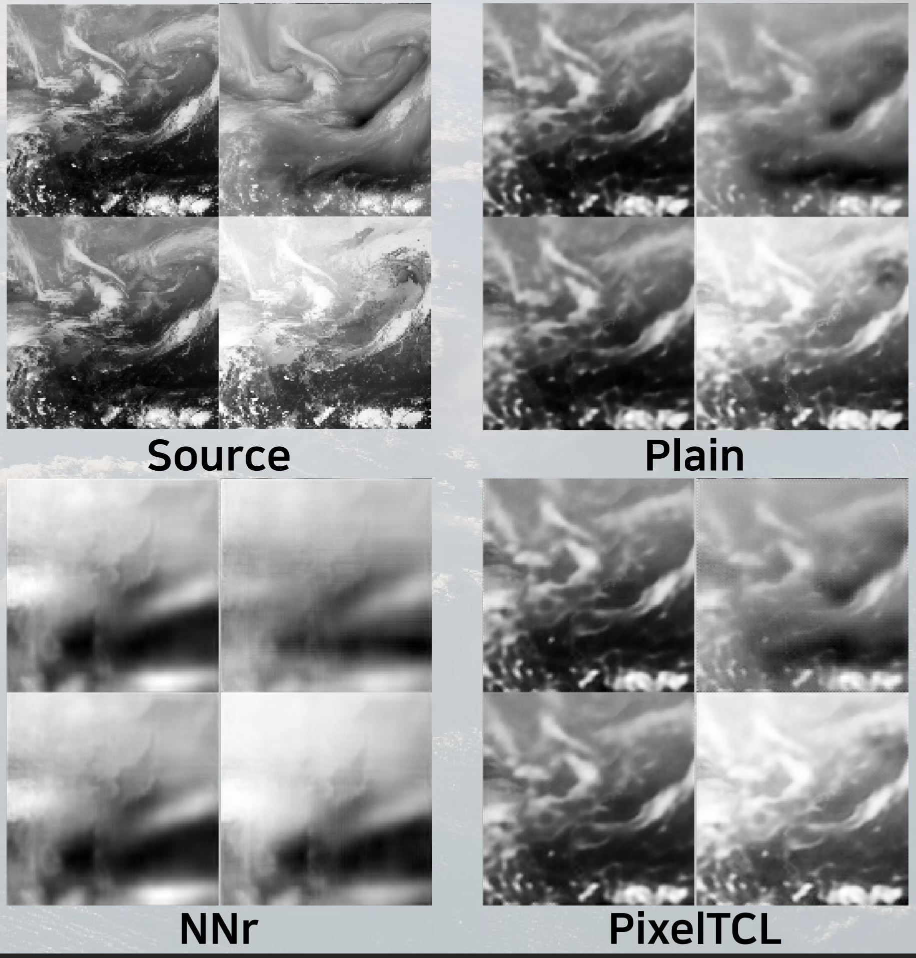
- **Issue #2**: A **deconvolution** process **matters** on **reconstruction quality**



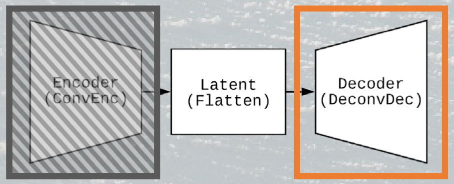
Checkerboard artifacts from deconv.



Reconstruction results from deconv.

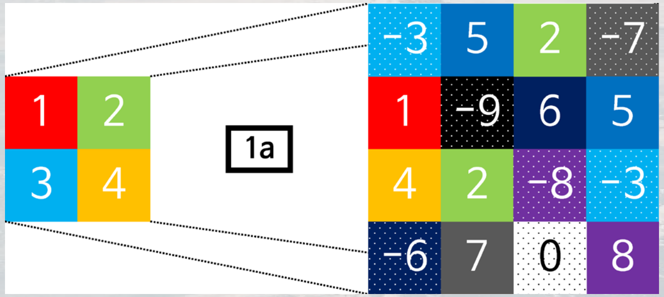


- **Every deconvolutional process MUST produce checkerboard artifacts**
- Furthermore, **variations of deconvolutional** process on decoder provide **considerable differences with fixed encoder operation** during End-to-End learning
- Therefore, **reconstruction quality** in **convolutional-based autoencoder** is **highly dependent on decoder**

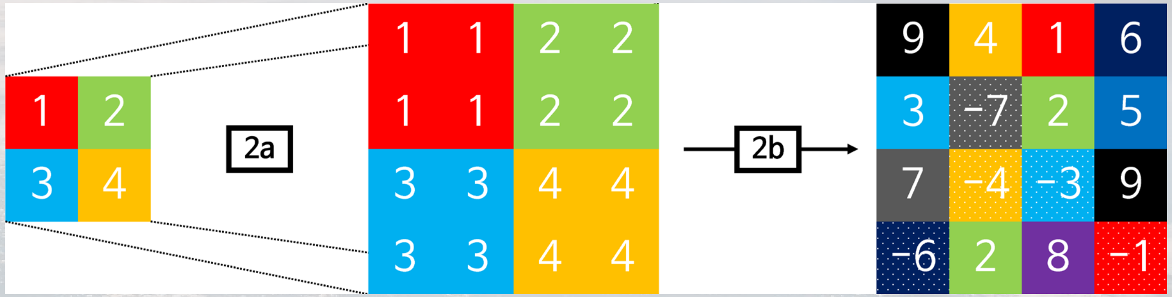


02 | Methods | Related works

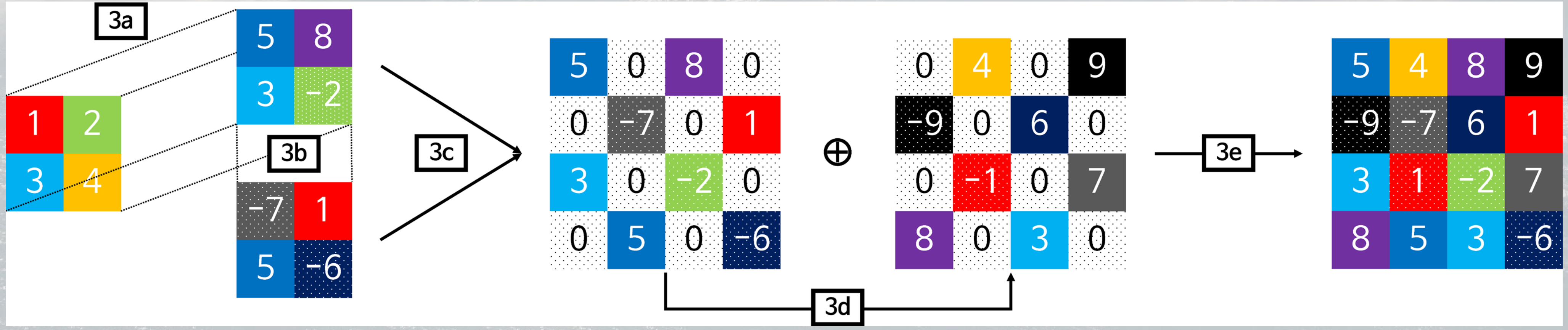
Plain Deconvolution
(Zeiler et al., 2010)



Nearest-Neighbor Resize Deconvolution
(Odena et al., 2016)

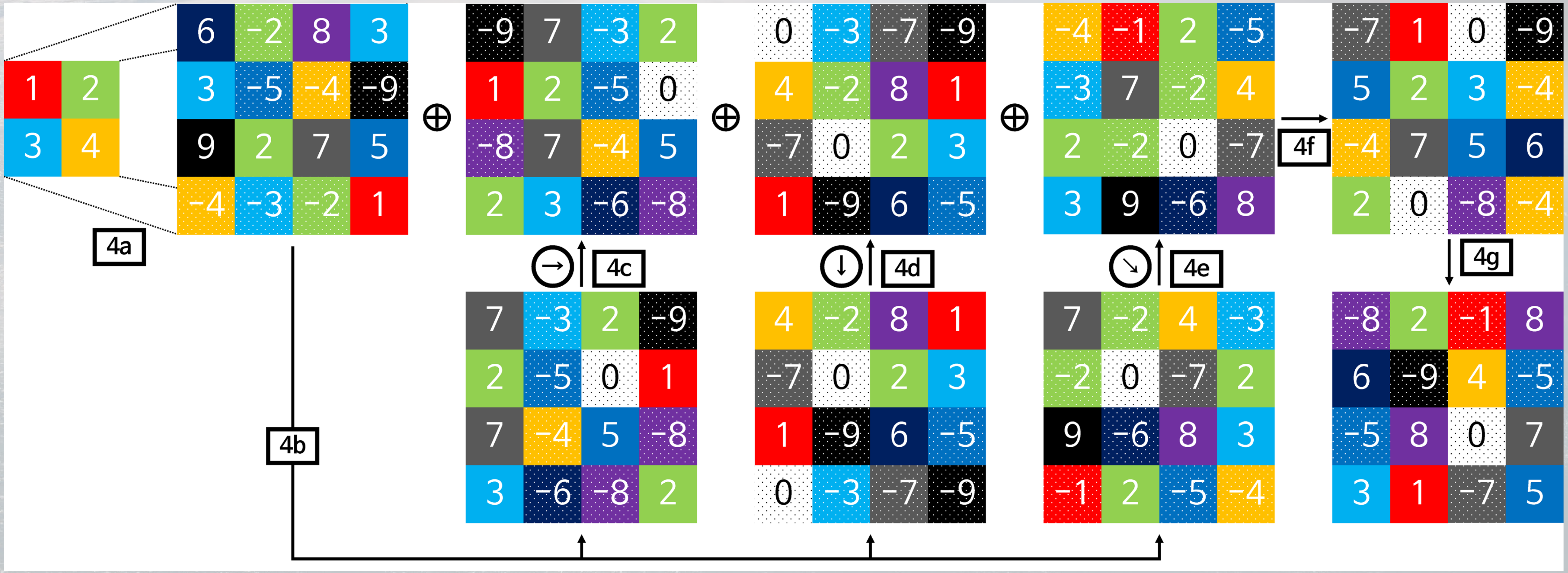


Pixel Transposed Convolution
(Gao et al., 2020)



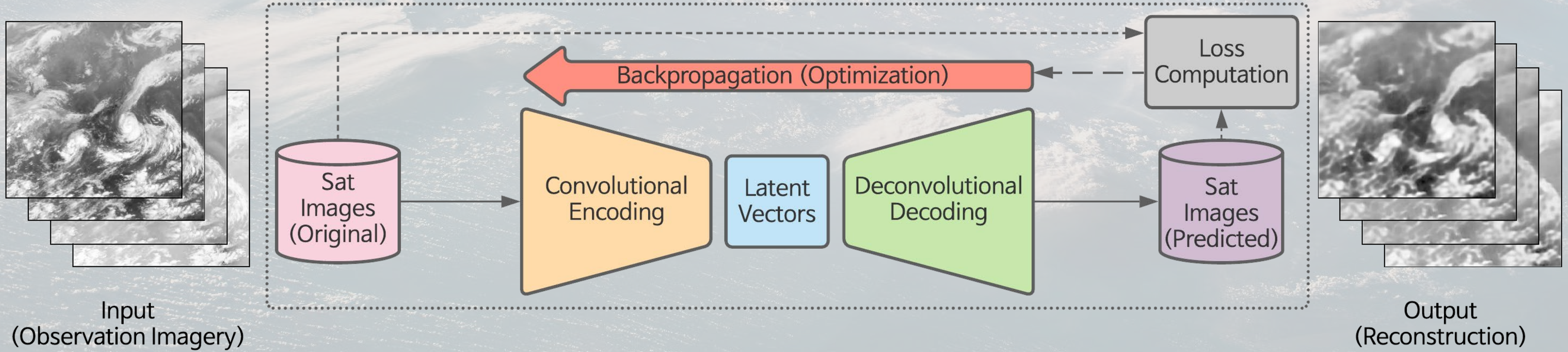
02 | Methods | Our solution

Shift-N-Overlap Cascaded Deconvolution



02 | Methods | Overall

- An **unsupervised autoencoder** model can **extract principal factors** and **learn** both **key visual features** and **desired data distribution** by **itself**
- A **universal and versatile encoder-decoder** model is demanded for **multi-purpose prediction tasks** from **wide observation area**



03 | Target Data | MTSAT1R/2,COMS

- Preparation of homogeneous observation dataset

COMS-1:128.2° E(COMS-1/OSCAR)

MTSAT-1R: 140° E (Himawari-6/OSCAR)

MTSAT-2: 145° E (Himawari-7/OSCAR)

Homogeneous Satellite Instruments (MI, JAMI, IMAGER)

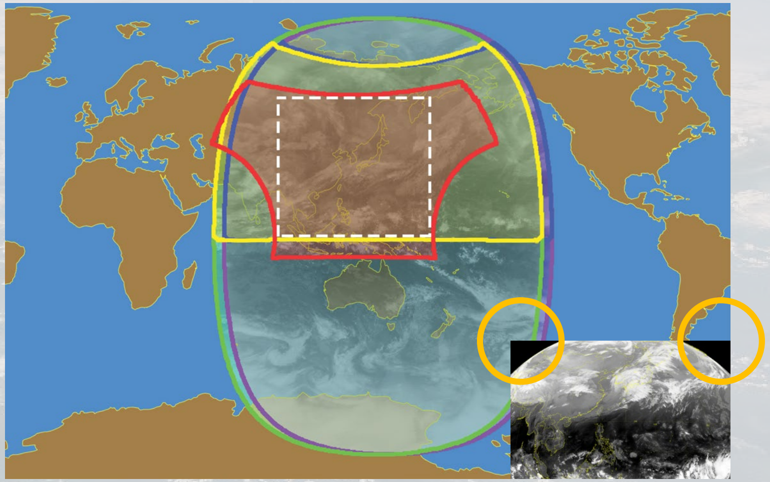
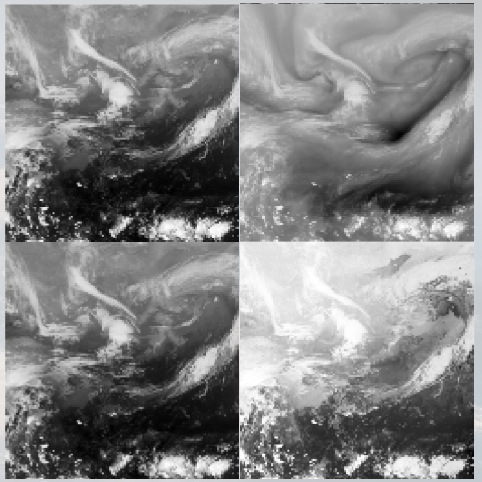


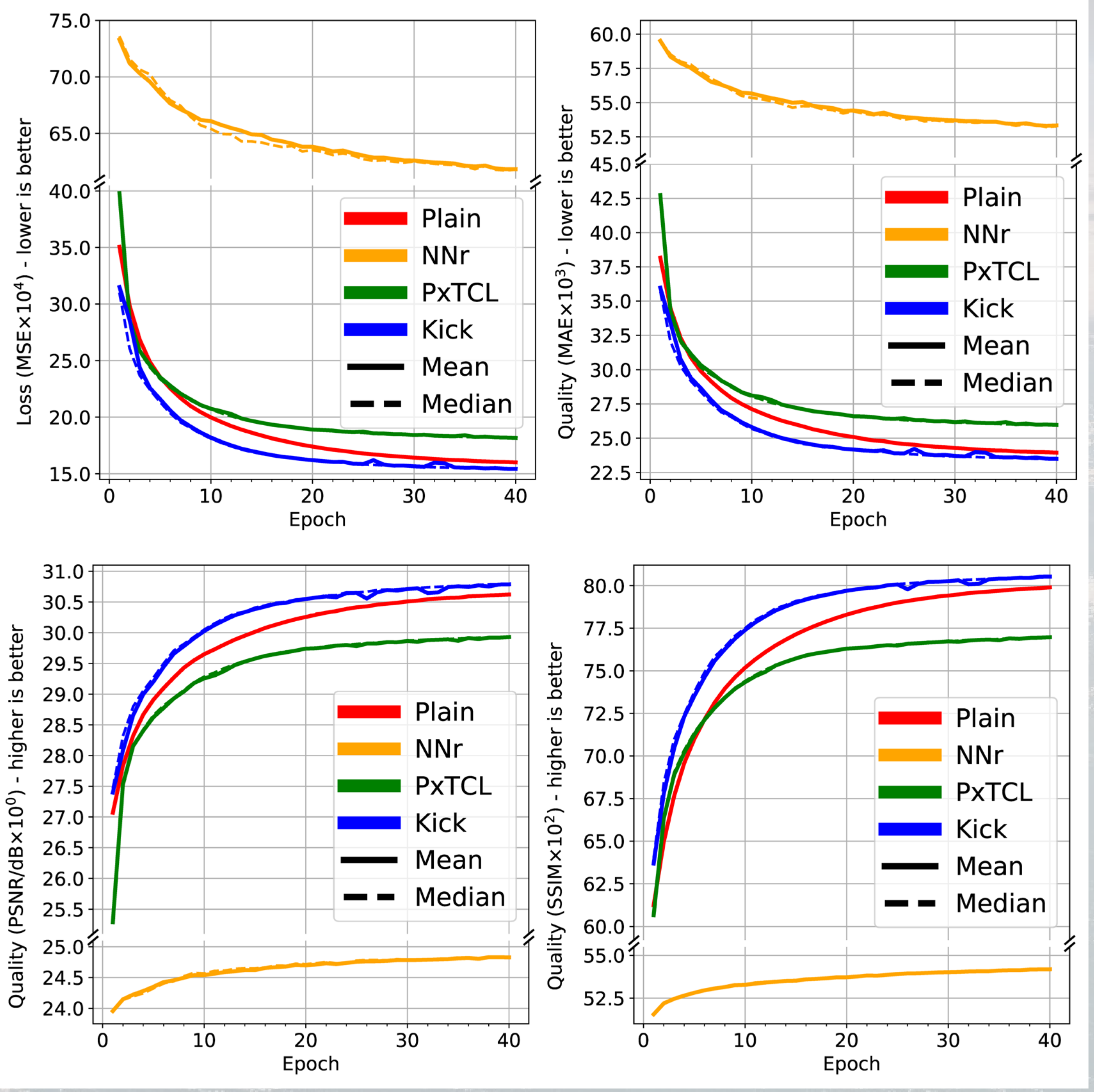
Image rearrangement and reprojection



Final image arrangement

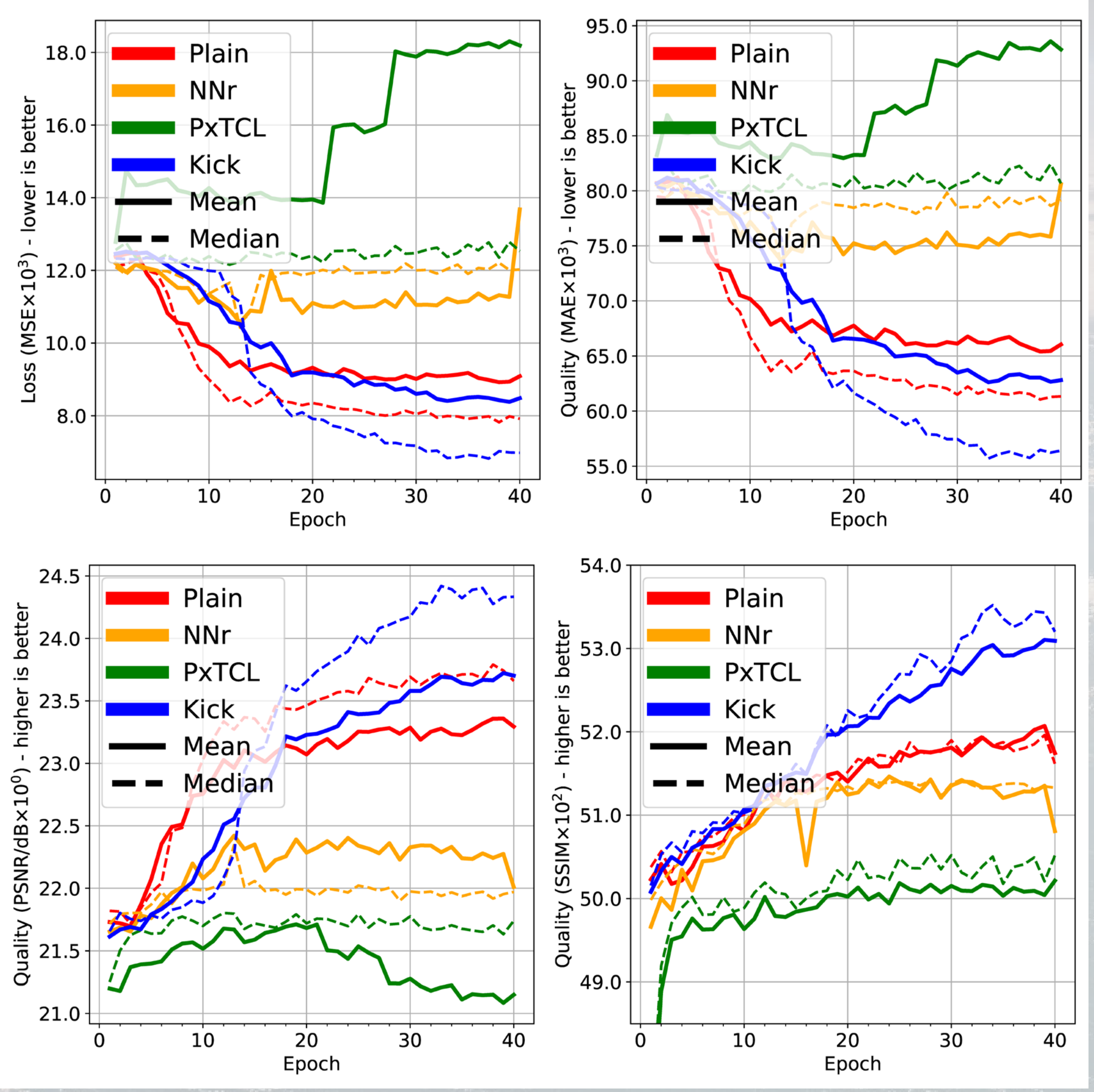
- Each satellite program **operates on limited operational plan** (due to a durability)
- **Observation area reprojection is mandatory,** due to the **reconstruction tendency of void space** in autoencoders
- **Additional image rearrange is required due to the discrete mission orbit**
- **Entire Duration: 2006~2017Y (307,808 images) / Valid, Test: 2014~2017Y**

04 | Results | Convolutional AE



- Model Training Configurations
  - Model:
    Convolutional Autoencoder (ConvAE)
  - Loss/Metric: Mean-squared (MSE)
  - Learning rate: 1e-3
  - Epoch: 40
  - Opt.: Adam (Adaptive Moment Estimation)
- Results
  - **Better performance metrics** than any **other deconvolutional models**
  - Fastest model convergence within epochs

04 | Results | Adversarial AE



- Model Training Configurations
  - Model: **Adversarial Autoencoder (AdvAE)**
  - Loss/Metric: Mean-squared (MSE)
  - Learning rate: 1e-3
  - Epoch: 40
  - Opt.: Adam (Adaptive Moment Estimation)
- Results
  - **Better performance metrics** than any **other deconvolutional models**
  - **Significant loss fluctuation** is observed due to the **model complexity**

04 | Results | Error Metrics

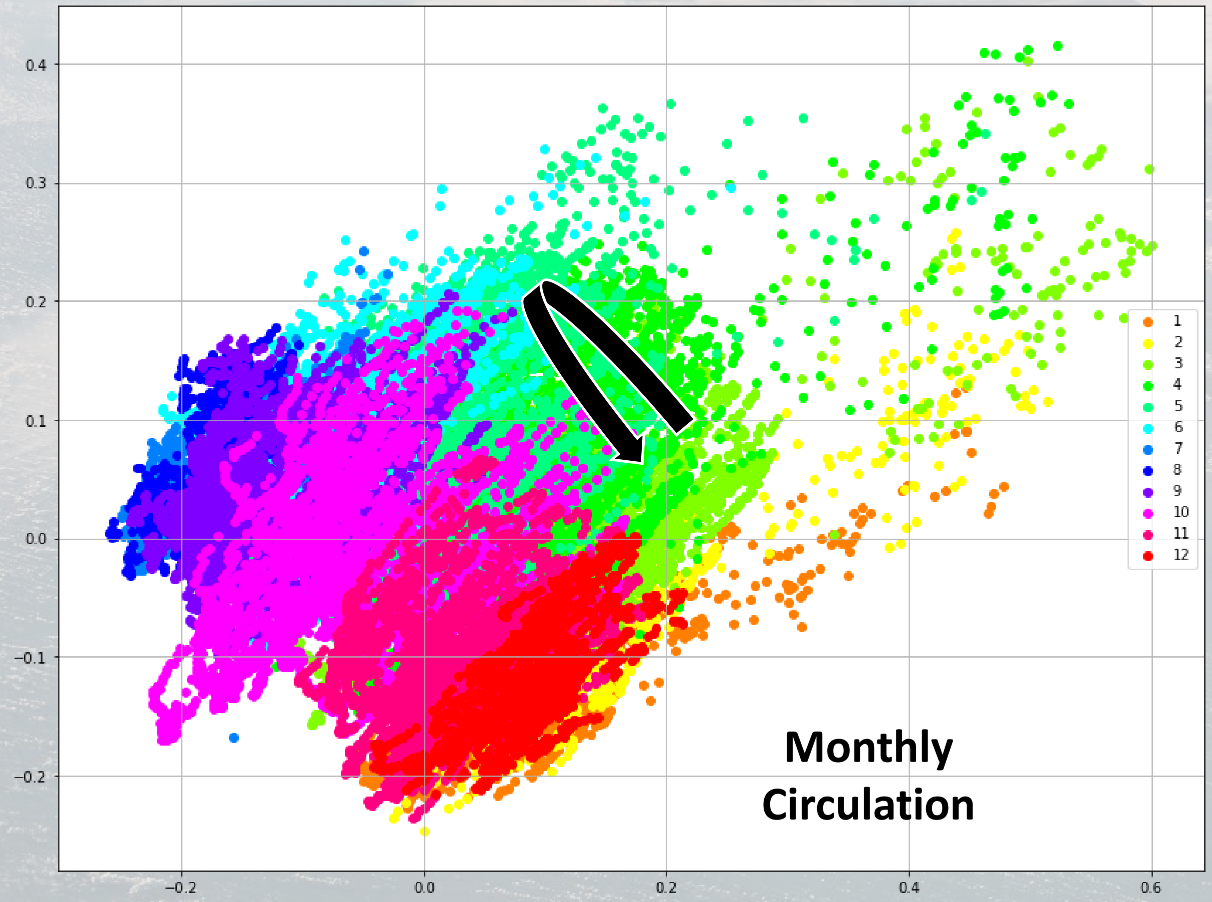
- **Result of Average (50 discrete cold-start)** model training and evaluation
- **NNr** shows weak perf on **ConvAE**, and **PixelTCL** show weak perf on **AdvAE**

	Convolutional Autoencoders (ConvAE)				Adversarial Autoencoders (AdvAE)			
Metric	Plain (Baseline)	NNr	PixelTCL	Kick **(Ours)**	Plain (Baseline)	NNr	PixelTCL	Kick **(Ours)**
MSE	0.00086 (0.00001)	0.00375 (0.00006) [−336.0%]	0.00102 (0.00001) [−18.6%]	**0.00085 (0.00001)** [+1.2%]	0.00510 (0.00101)	0.00821 (0.01564) [−61.0%]	0.01179 (0.02076) [−131.2%]	**0.00493 (0.00109)** [+3.3%]
MAE	0.01726 (0.00012)	0.04024 (0.00049) [−133.1%]	0.01912 (0.00012) [−10.8%]	**0.01708 (0.00015)** [+1.0%]	0.04803 (0.00598)	0.05834 (0.03272) [−21.5%]	0.06929 (0.04973) [−44.3%]	**0.04649 (0.00661)** [+3.2%]
PSNR	33.71803 (0.05058)	27.72582 (0.09519) [−17.8%]	32.77205 (0.03890) [−2.8%]	**33.79470 (0.04102)** [+0.2%]	26.36942 (0.95127)	25.21174 (2.34726) [−4.4%]	24.23747 (3.05105) [−8.1%]	**26.60216 (1.05993)** [+0.9%]
SSIM	0.84087 (0.00051)	0.63357 (0.00135) [−24.7%]	0.81317 (0.00074) [−3.3%]	**0.84415 (0.00055)** [+0.4%]	0.61335 (0.02124)	0.60970 (0.04198) [−0.6%]	0.60392 (0.01087) [−1.5%]	**0.62000 (0.00585)** [+1.1%]

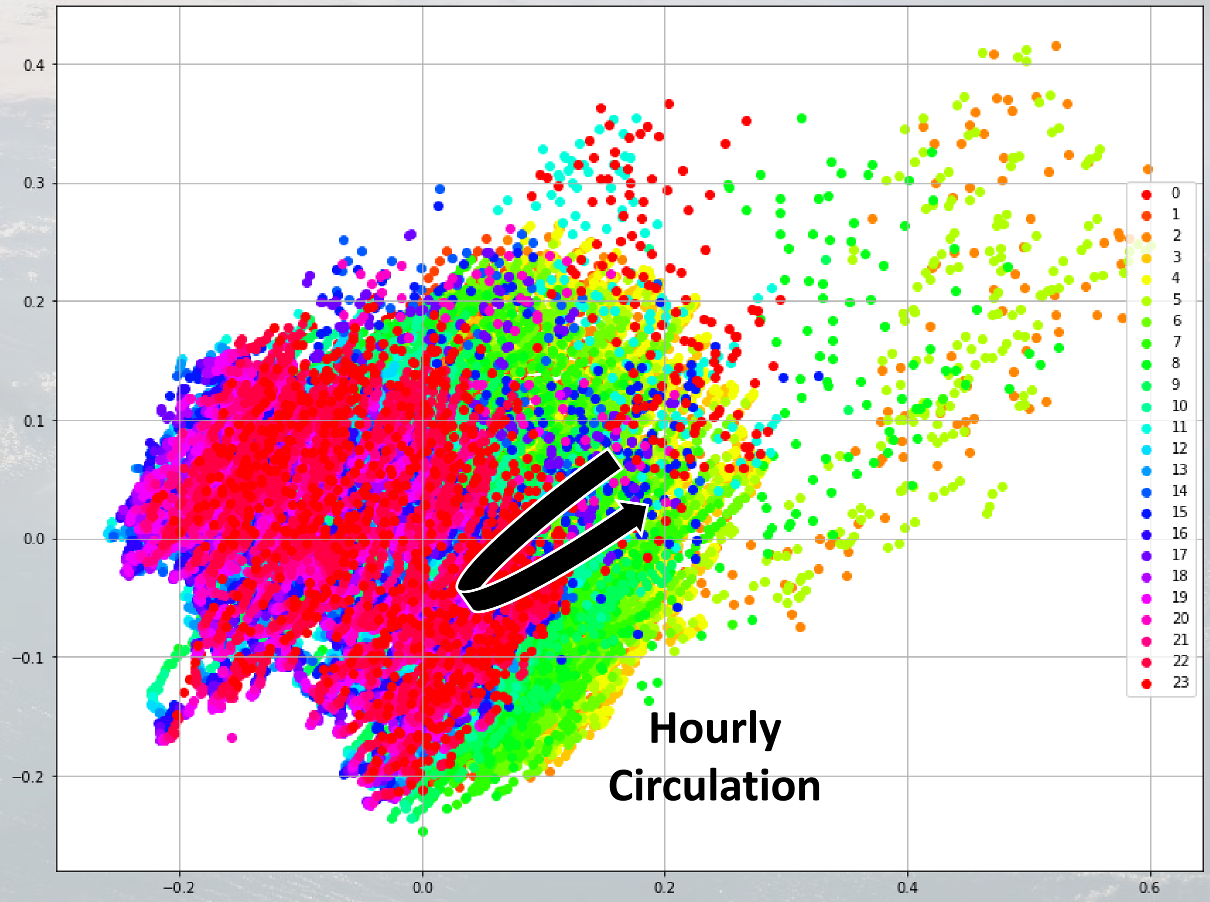
04 | Results | Yearly Circulation

- **Latent Information** (below is PCA-ed) can capture **hourly and monthly circulation** very well

Test (Y2015/Y2017)
Data: Hourly (UTC 00H~23H) | Label: Monthly (M01~M12)



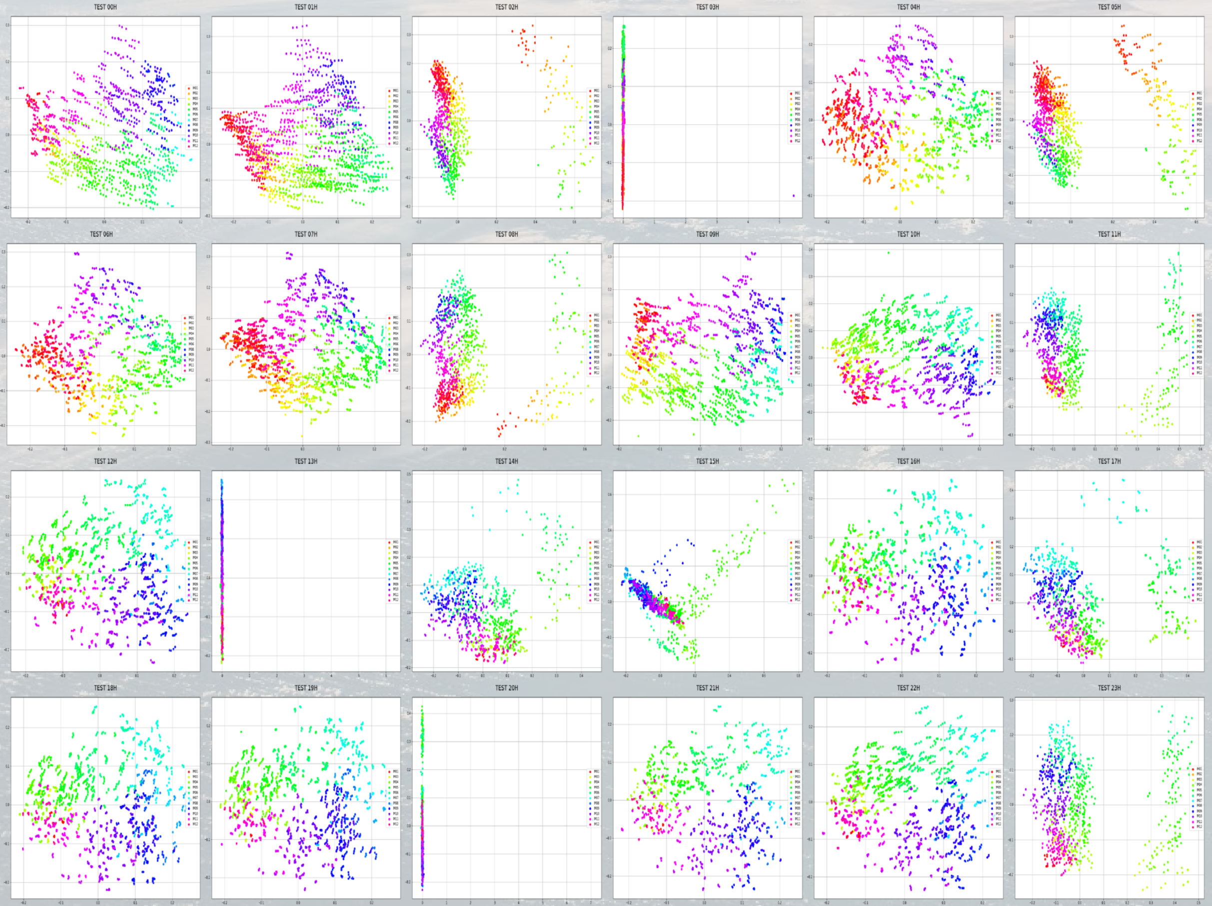
Test (Y2015/Y2017)
Data: Monthly (M01~M12) | Label: Hourly (UTC 00H~23H)



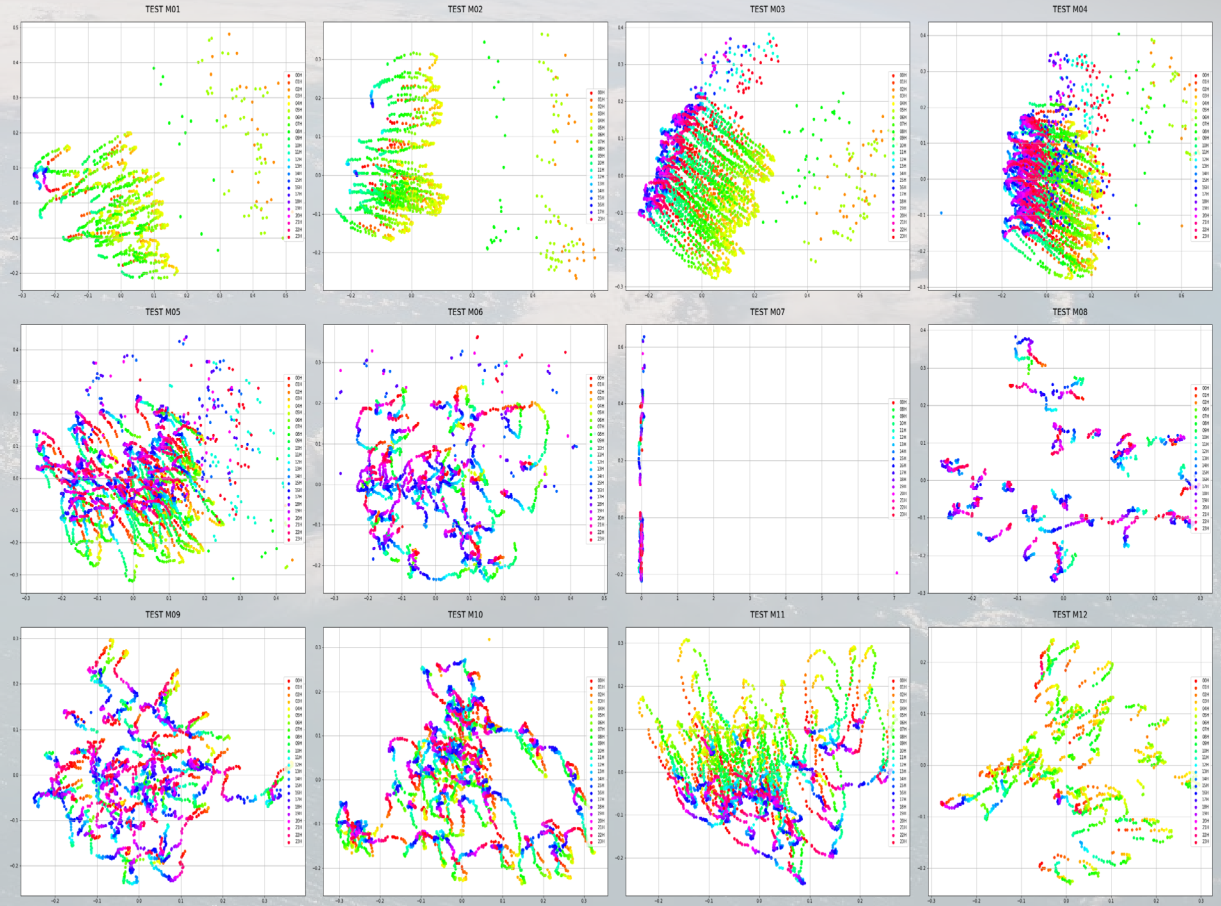
04 | Results | Hourly and Monthly Circulation

- **Latent Information** (below is PCA-ed) can capture **hourly and monthly circulation** very well

Test (Y2015/Y2017)
Data: Hourly (UTC 00H~23H) | Label: Monthly (M01~M12)



Test (Y2015/Y2017)
Data: Monthly (M01~M12) | Label: Hourly (UTC 00H~23H)



05 | Conclusion | Contributions

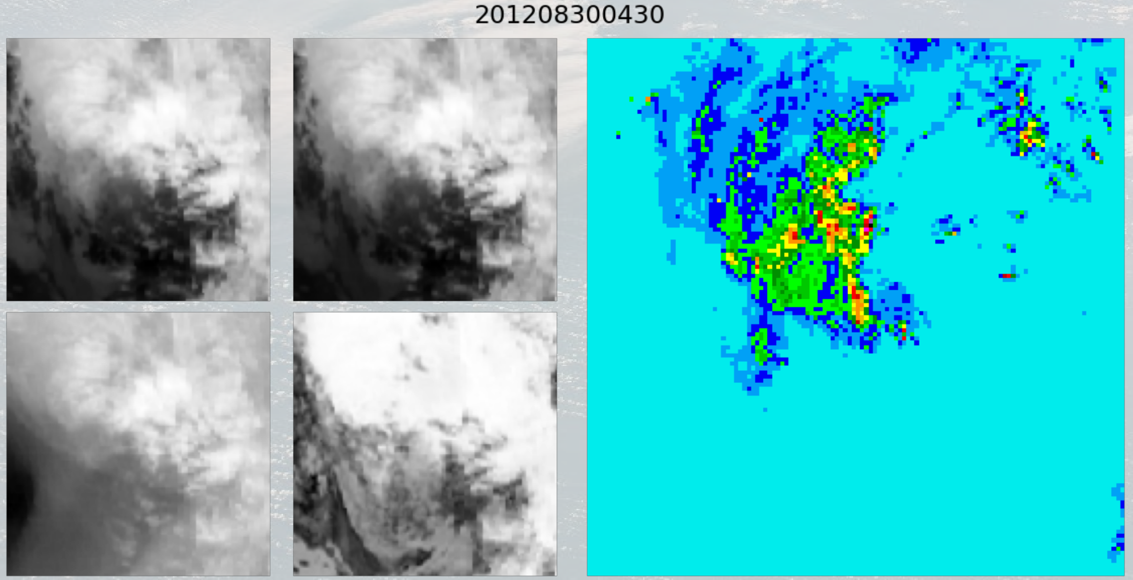
- This work revealed that **a change in the decoder part** of autoencoder could **vary the entire learning of weather representations** without **changing the encoder part**.

- This work is providing a previously-trained convolutional autoencoder model for **understanding 4-channel geostationary satellite images** using autoencoders.

- This work enhanced an **image reconstruction performance** by very unique deconvolutional layer named 'Kick' **to minimize checkerboard artifacts** issue.

05 | Conclusion | Future works

- **Application on Real-world Prediction** using **Pre-trained Convolutional AE** (currently working on radar echo image generation task)
- **Large-scale Image Research Dataset Processing** with **Distributed-Parallel Computing Acceleration** on Open Research Collaboration Platforms



Geostationary Satellite Images   MAPLE Rain Echo Estimation

RAPIDS → data·on → kubernetes

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Acknowledgments

❖**Data Provision**

MTSAT-1R/2 observation data were provided by the **Center for Environmental Remote Sensing (CEReS)**, Chiba University, Japan. COMS-1 observation data were provided by the **National Meteorological Satellite Center (NMSC)** of Korea Meteorological Administration (KMA).

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Thank you for listening! Any questions?

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