AOMSUC-15 FYSUC-2025
FIFTEENTH ASIA-OCEANIA METEOROLOGICAL SATELLITE USERS' CONFERENCE
THE JOINT 2025 FENGYUN SATELLITE USER CONFERENCE

Research and Applications of Nowcasting Methods Based on Artificial Intelligence

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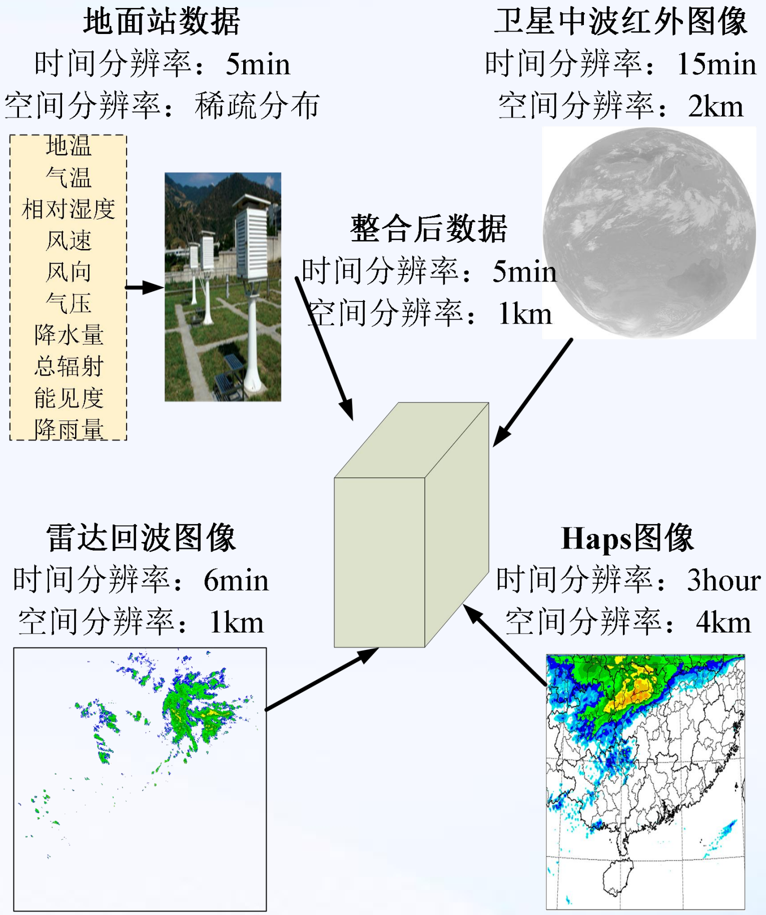
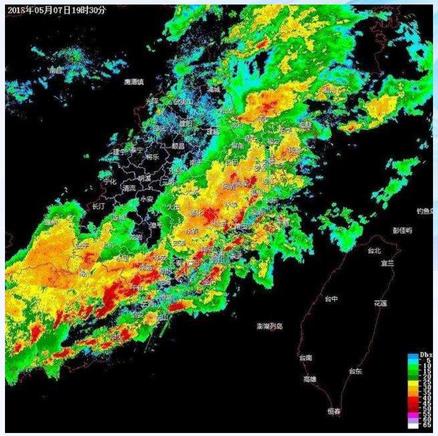
Content

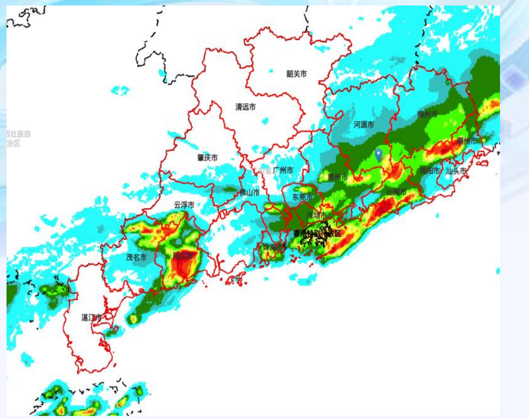
What is nowcasting?

- **Nowcasting：For next 0~6 hour weather prediction, with a very high resolution (minute level and street level)**

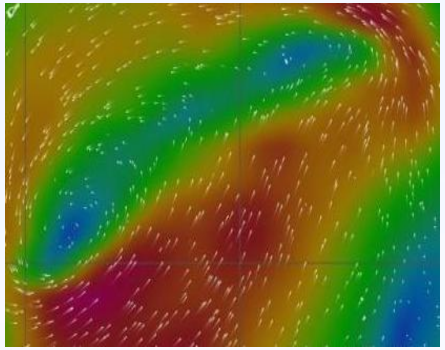




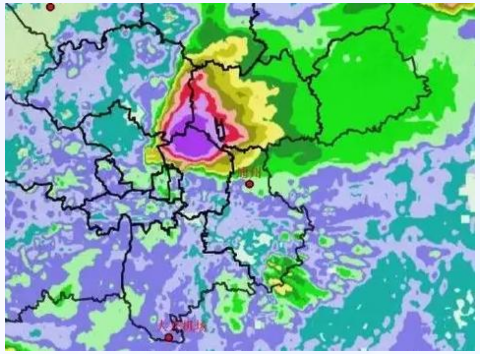
Radar Extrapolation



Rainfall Prediction



Wind Prediction



Hail Prediction

Application Scenarios of Nowcasting

- **Disaster prevention agencies in preventing meteorological disasters**

2024.04.27 广州市遭遇冰雹和龙卷极端天气，造成5人死亡33人受伤

2023.09.07 深圳遭遇极端特大暴雨，累积降雨总量619毫米，打破7项气象记录

2023.07.31 北京遭遇罕见特大暴雨，全市平均降雨量达到331毫米，死亡33人，18人失踪

2021.05.14 武汉突发雷暴大风致8人遇难

2020.05.22 广州突发暴雨致严重内涝

2019.04.11 深圳突发暴雨致11人遇难

Application Scenarios of Nowcasting

- Decision-making in smart agriculture, such as fertilization, and irrigation scheduling

Good timing for fertilization?

Good timing for fertilization?

Irrigation

- Smart agricultural insurance (e.g., coverage for agricultural facilities and crops).

Strong wind damage to agriculture

Flood damage to agriculture

Hail damage

Application Scenarios of Nowcasting

- Smart city development, including applications in travel planning, taxi dispatch, and logistics optimization.

Daily plan

Taxi dispatch

Logistics optimization

Outdoor sports meeting

Outdoor meeting

Logistics optimization

Application Scenarios of Nowcasting

- Operations in aviation, aerospace, and related fields

For plane taking off or landing?

Aviation plan

Flight delay prediction

Flight safety

Flight safety

Launch Weather Operations

Content

Nowcasting of Severe Convections

Severe convection is a destructive meso- and micro-scale weather system often accompanied by heavy rainfall, strong winds, hail, and lightning. Thus, accurate prediction of such phenomena is of critical importance.

- Applications

➢ Prevention of disasters and secondary hazards, such as floods, mudslides, and landslides

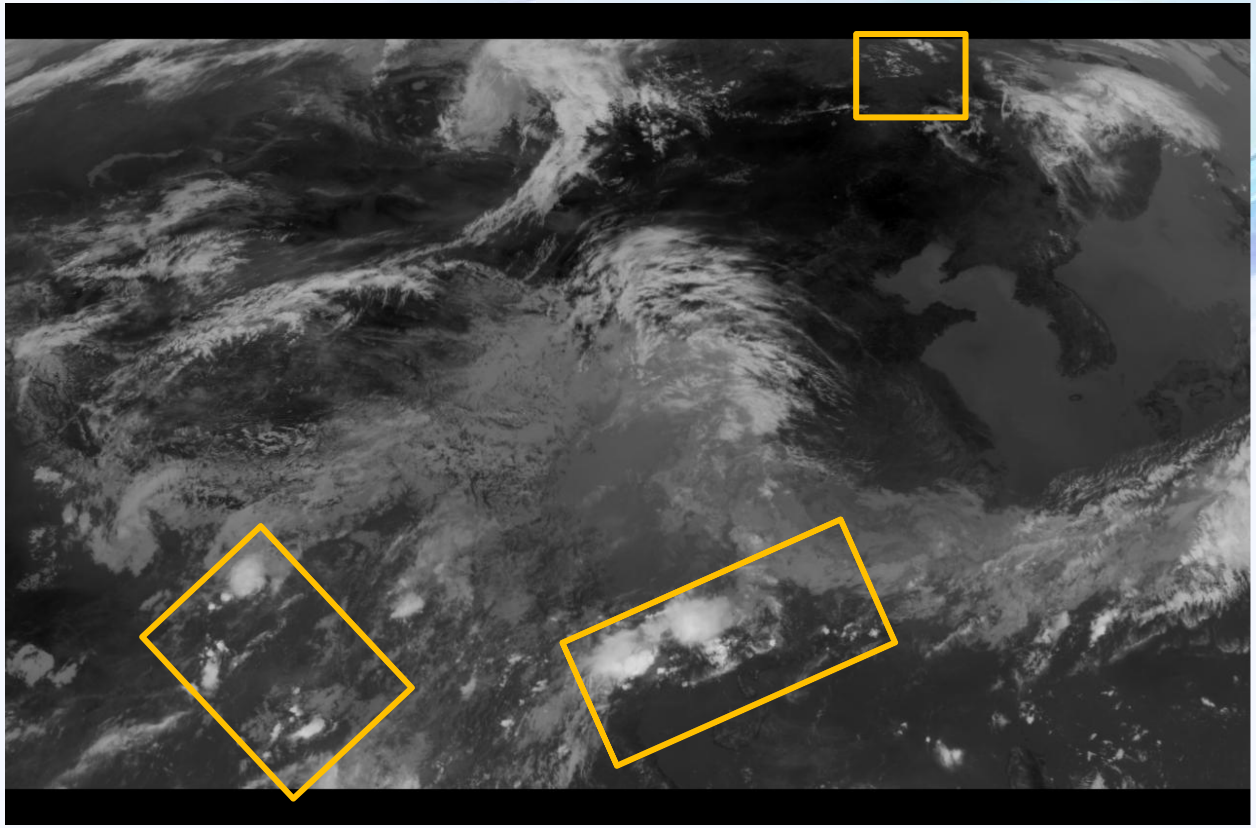
➢ Smart city development by providing daily travel guidance to the public

➢ Smart agriculture by providing essential information for decisions on pesticide application, irrigation, or fertilization

➢ It provides flight operation guidance, such as takeoff/landing decisions, turbulence warnings and avoidance, and flight delay predictions.

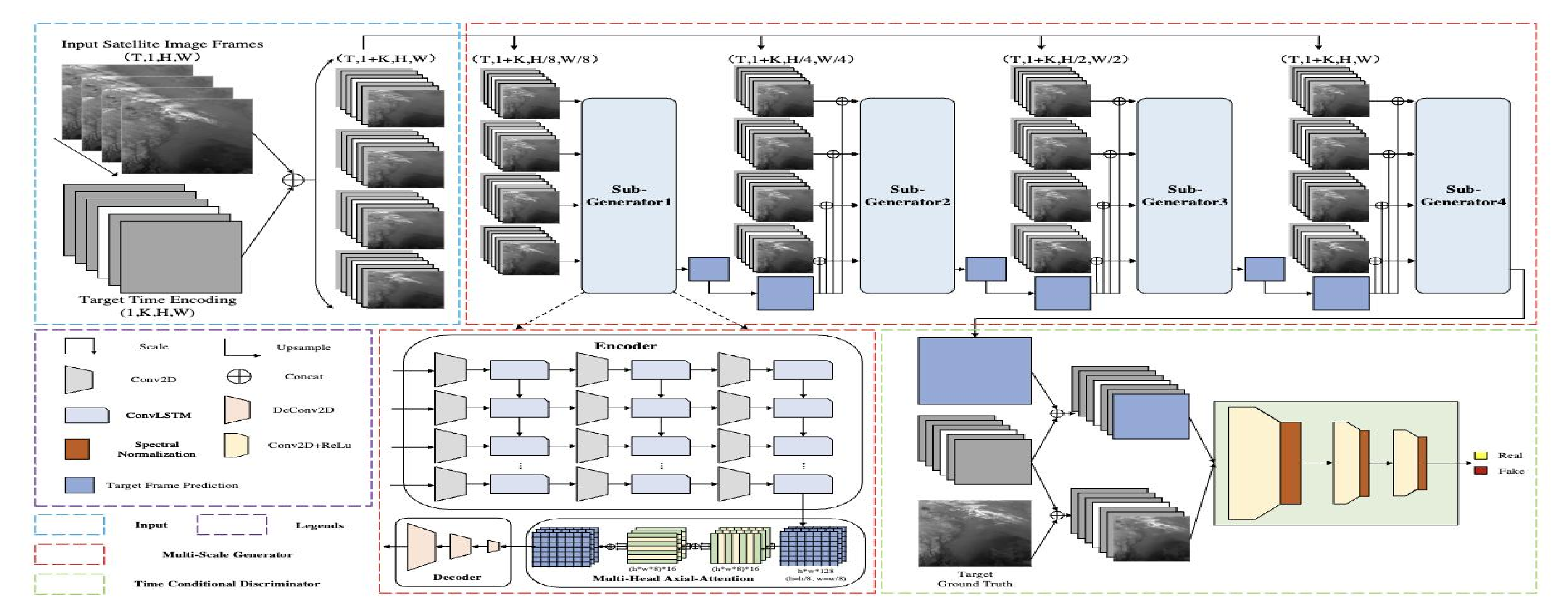
Challenges of Severe Convections Nowcasting

- **Challenges：**
  - small scale
  - short duration
  - complex evolution
  - convection initation



Convection Nowcasting: First generation method MSTCGAN

- **MSTCGAN-**Multi-Scale Time Conditional Generative Adversarial Network

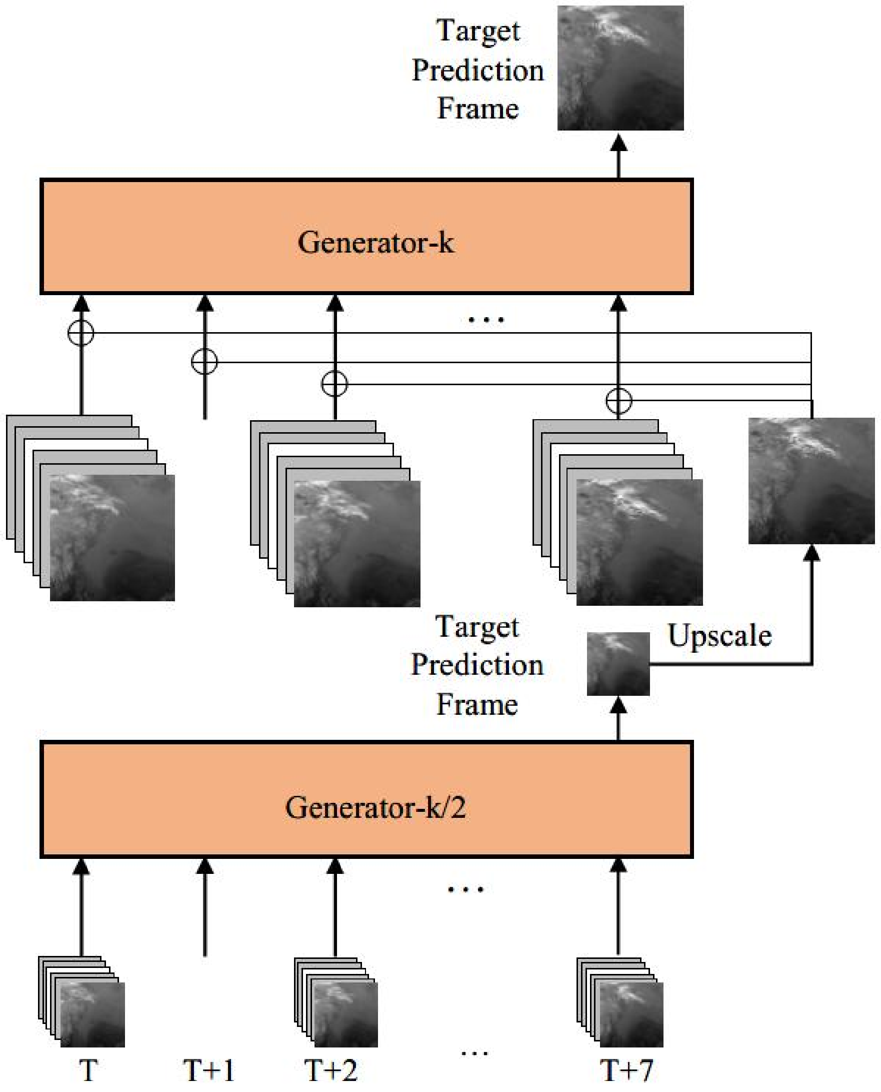


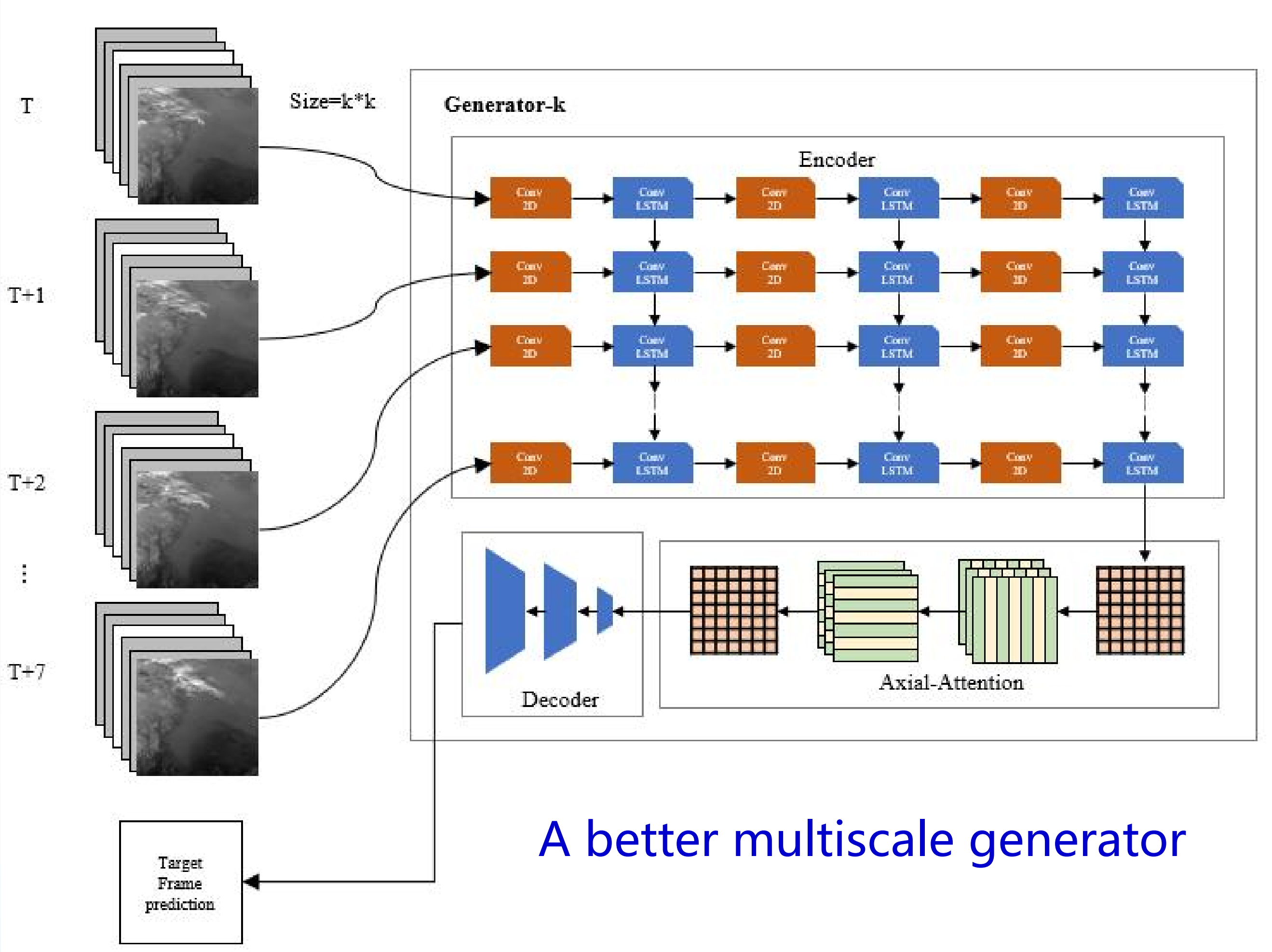
MSTCGAN Method

Kuai Dai, Xutao Li, Yunming Ye, Shanshan Feng, Danyu Qin, Rui Ye: ***MSTCGAN: Multiscale Time Conditional Generative Adversarial Network for Long-Term Satellite Image Sequence Prediction. IEEE Trans. Geosci. Remote. Sens.*** 60: 1-16 (2022)

Convection Nowcasting： First generation mehtod MSTCGAN

- **Generator of MSTCGAN**

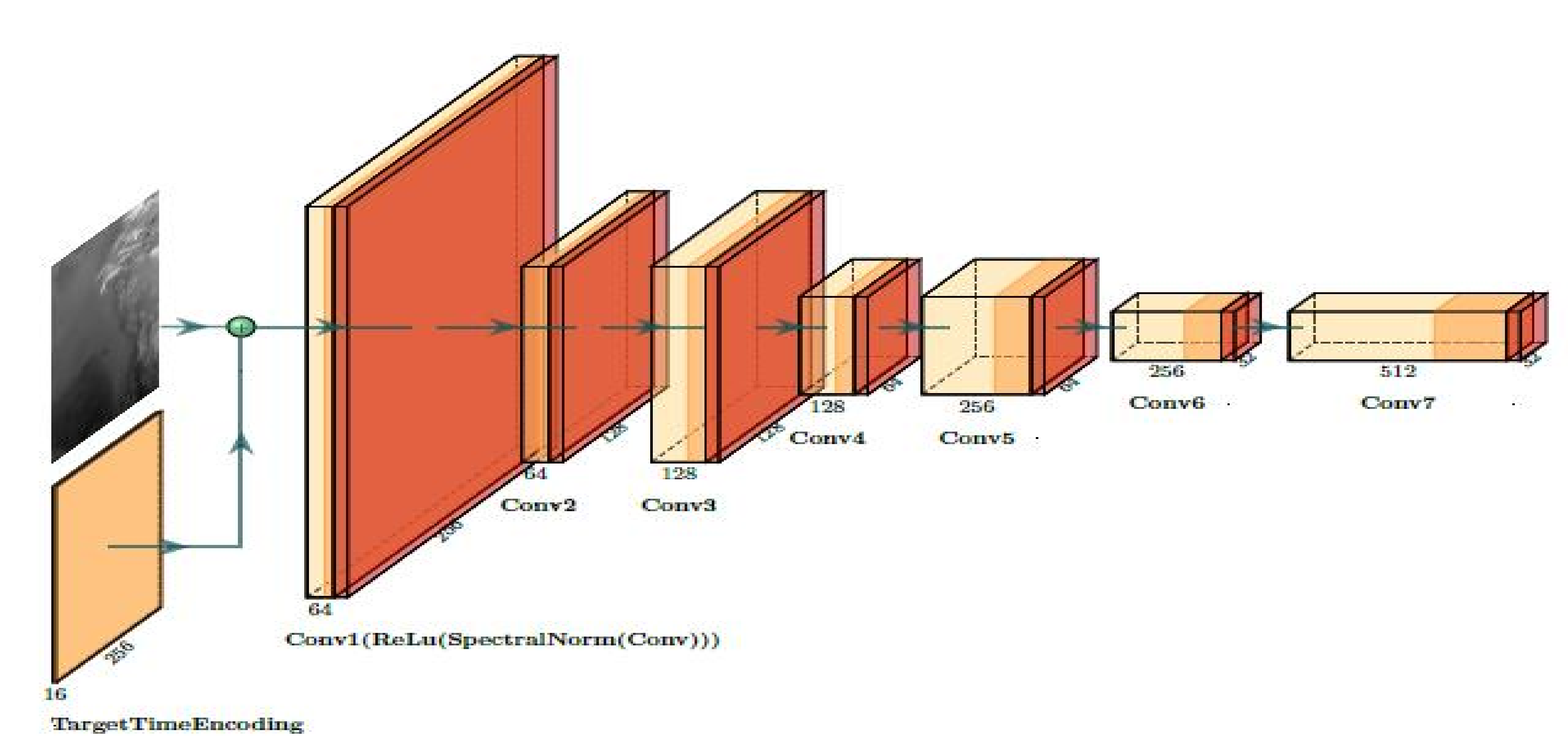




A better multiscale generator

Convection Nowcasting：First generation method MSTCGAN

- **MSTCGAN的生成器结构**



The architecture of discriminator

0~4h Satellite Prediction Comparison

• Results

Input/Output	Model	256*256				512*512				Average			
		↑ PSNR	↓ MSE	↓ MAE	↓ GDL	PSNR	MSE	MAE	GDL	PSNR	MSE	MAE	GDL
8 → 16	Opticalflow-LK	24.40	384.62	12.58	4.98	24.13	404.78	12.85	4.90	24.27	394.70	12.72	4.94
	ConvGRU	24.48	351.85	13.02	4.65	24.06	371.88	13.41	4.50	24.27	361.87	13.22	4.58
	ConvLSTM	25.00	324.39	12.64	4.78	24.28	388.63	13.98	4.64	24.64	356.51	13.31	4.71
	TrajGRU	25.01	341.37	12.93	4.72	23.26	604.79	16.10	5.73	24.14	473.08	14.52	5.23
	PredRNN	25.06	337.12	12.84	4.86	24.12	410.62	14.67	4.64	24.59	373.87	13.75	4.75
	PredRNN++	24.75	337.38	13.33	4.84	24.30	369.76	14.09	4.69	24.53	353.57	13.71	4.77
	MIM	24.67	329.35	13.02	4.84	24.10	375.16	14.18	4.70	24.39	352.26	13.60	4.77
	PhyDNet	24.21	327.41	13.08	4.86	23.26	388.52	13.88	4.93	23.74	357.97	13.48	4.90
	SA-ConvLSTM	24.08	366.74	13.99	13.63	23.31	449.29	15.72	13.74	23.70	408.02	14.86	13.69
	Conv-TT-LSTM	25.07	430.53	13.39	4.58	24.87	434.12	13.12	4.43	24.97	432.33	13.26	4.51
	MSTCGAN	25.41	280.91	11.06	4.68	24.33	326.25	12.96	4.53	24.87	303.58	12.01	4.61

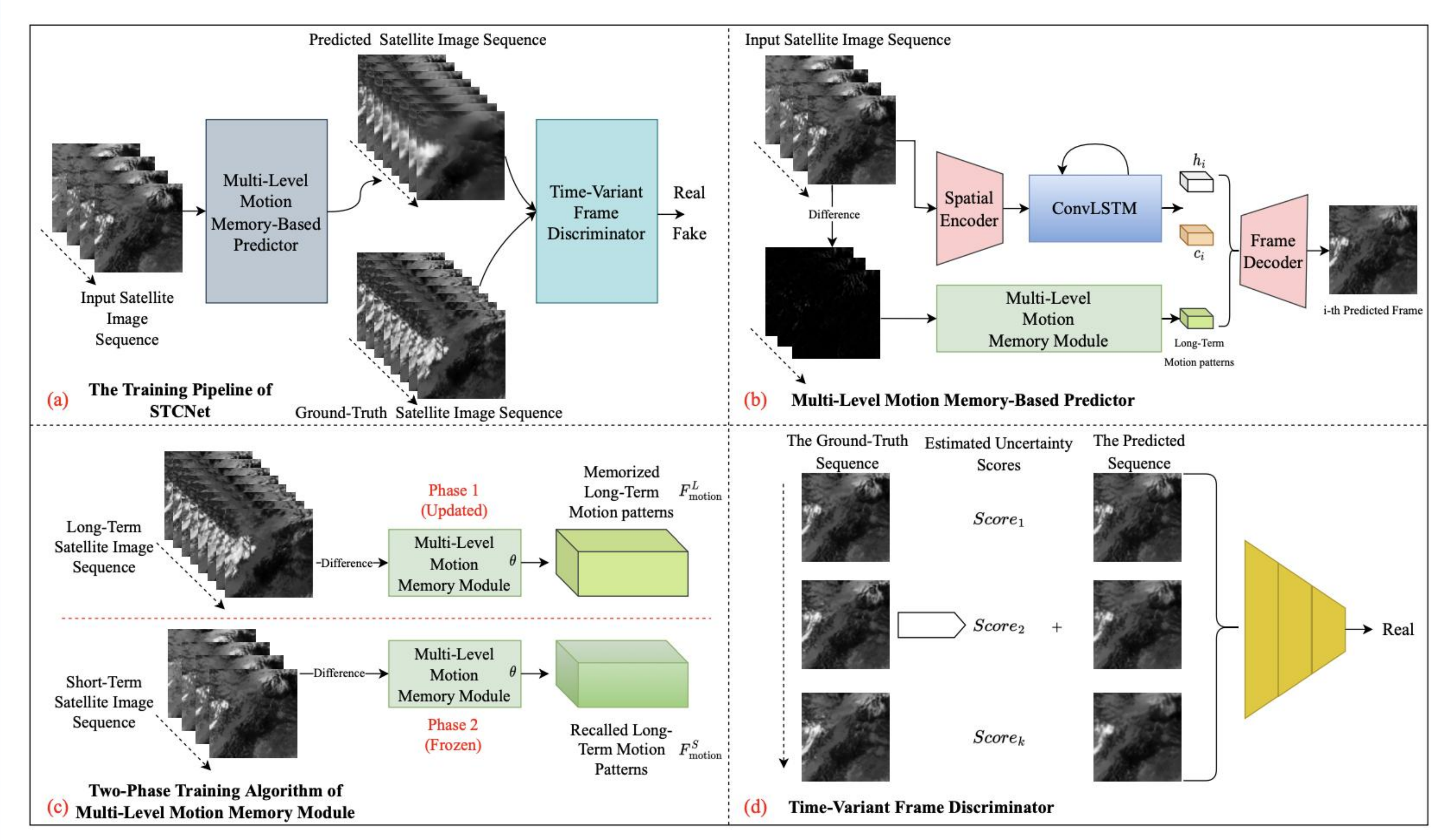
Conclusion: The MSTCGAN usually performs better than existing deep learning models and optical flow model, which means the prediction location of MSTCGAN on clouds is more accurate.

0~4h Satellite Sequence Prediction Comparison

• Visual Comparison

Convection Nowcasting: Second generation method STCNet

- **Spatial temporal consistence network (STCNet)**

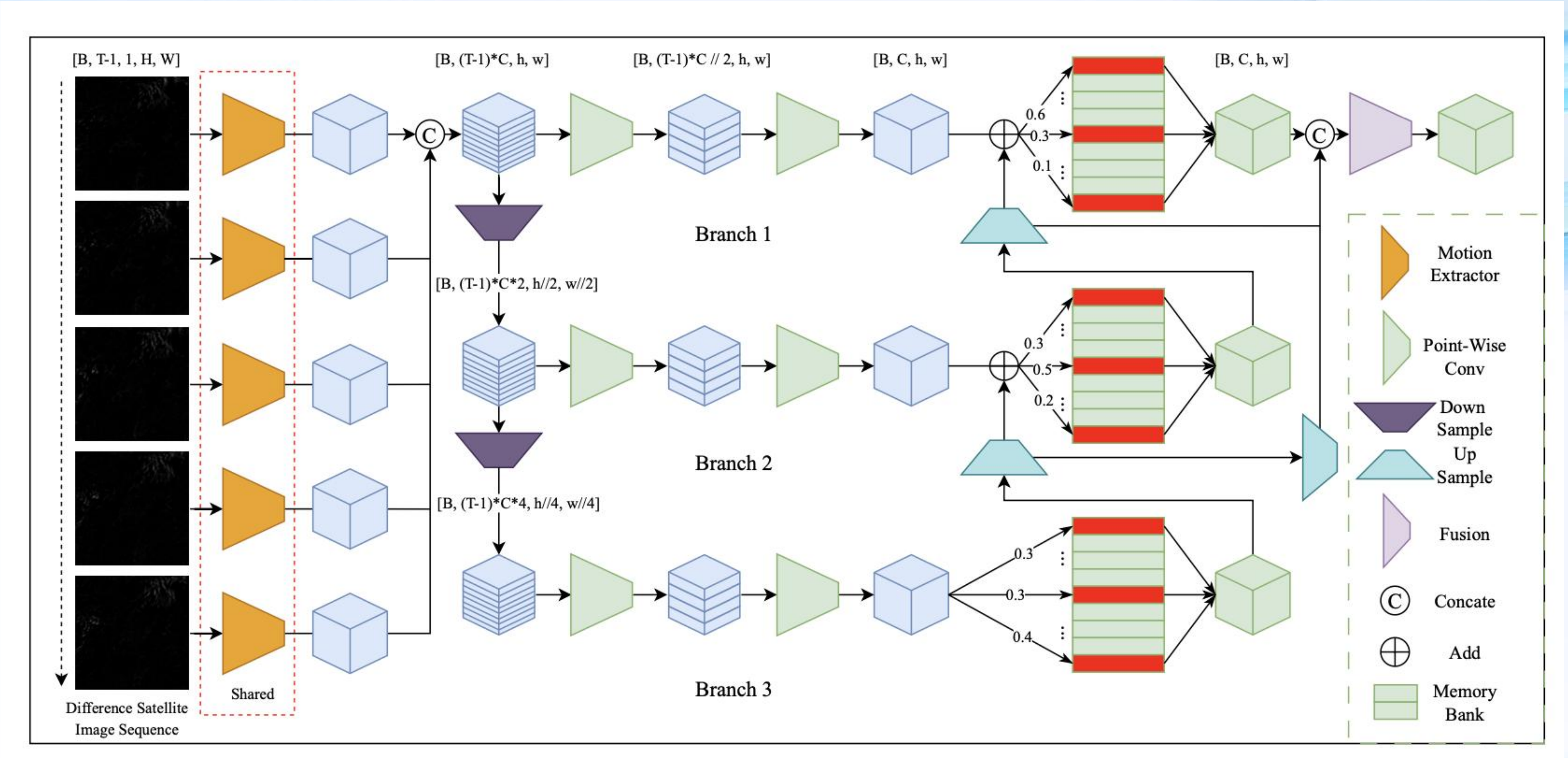


While MSTCGAN improves the visual quality of predicted sequences, it fails to accurately model the temporal correlations in satellite sequences, resulting in less coherent movement of convective clouds.

To enhance visual quality while ensuring the coherence of convective cloud motion, this project attempts to integrate memory networks with a generative adversarial network architecture in designing the extrapolation model Spatial-Temporal Consistency Network (STCNet).

Convection Nowcasting：Second generation method STCNet

- **Spatial temporal consistence network（STCNet）**



To accurately predict complex motion patterns in satellite image sequences while ensuring temporal consistency, this project designs a multi-level motion memory module to capture hierarchical long-term motion patterns and guide the predictor in forecasting.

Multi-Level Motion Memory Module 多层运动记忆模块

Kuai Dai, Xutao Li, Chi Ma, Shenyuan Lu, Yunming Ye, Di Xian, Lin Tian, Danyu Qin: ***Learning Spatial-Temporal Consistency for Satellite Image Sequence Prediction. IEEE Trans. Geosci. Remote. Sens***. 61: 1-17 (2023)

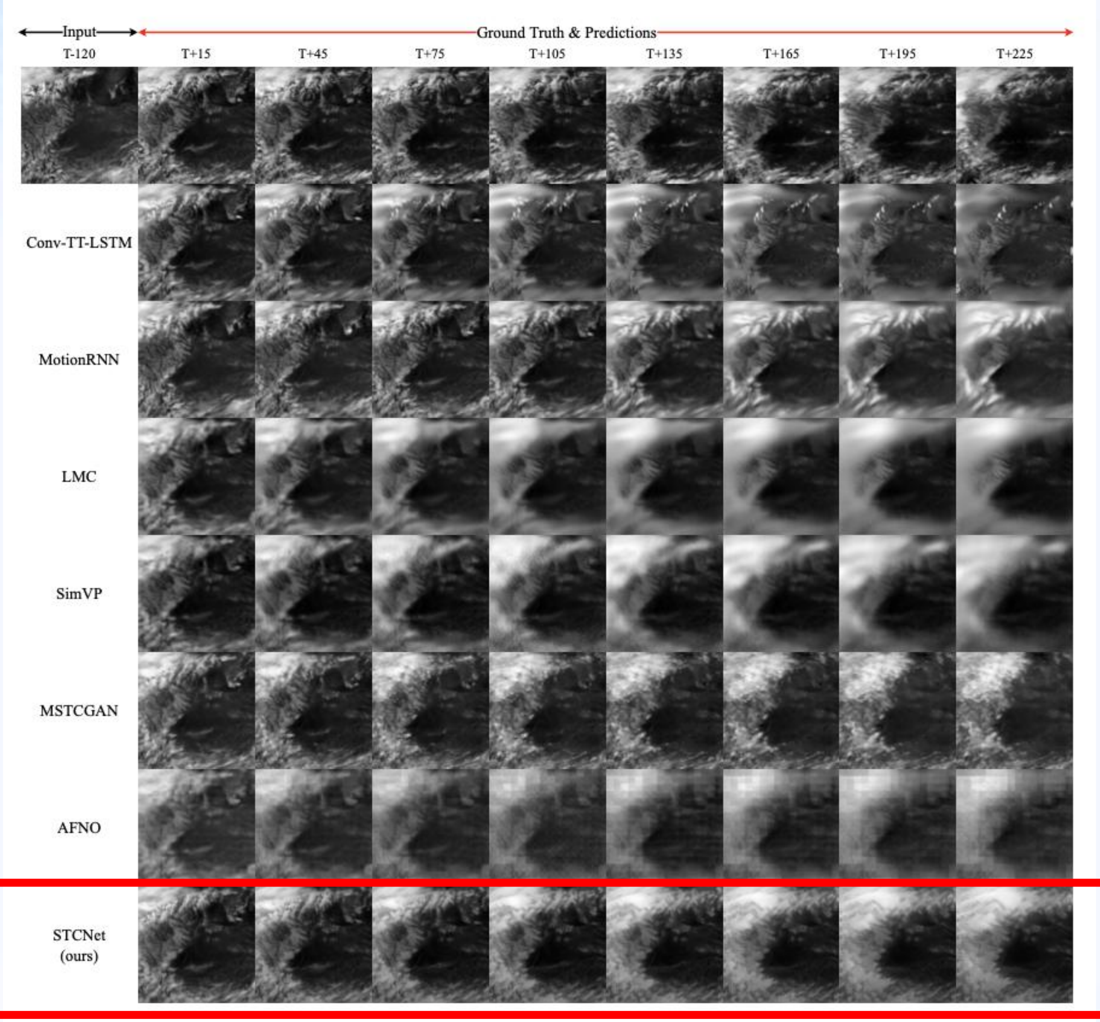
0~4h Satellite Prediction Comparison

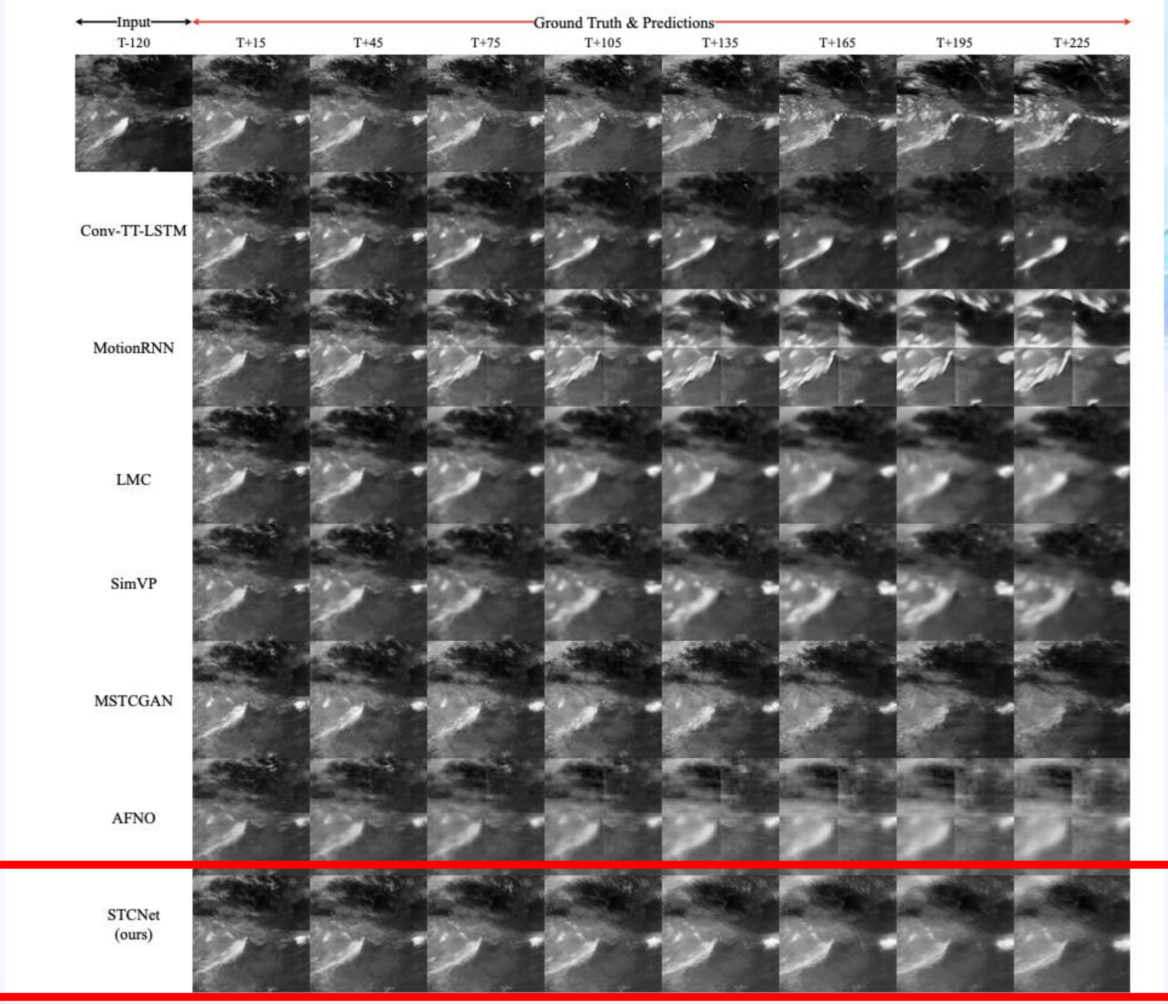
- 量化结果对比

Model	Size Free	256 × 256					512 × 512					Average				
		↑ PSNR	↓ MSE	↓ MAE	↓ GDL	↓ LPIPS	PSNR	MSE	MAE	GDL	LPIPS	PSNR	MSE	MAE	GDL	LPIPS
Opticalflow-LK [19]	Yes	24.40	384.62	12.58	4.98	**0.172**	24.13	404.78	12.85	4.90	**0.169**	24.27	394.70	12.72	4.94	**0.171**
ConvGRU [27]	Yes	24.48	351.85	13.02	4.65	0.352	24.06	371.88	13.41	4.50	0.357	24.27	361.87	13.22	4.58	0.355
ConvLSTM [41]	Yes	25.00	324.39	12.64	4.78	0.384	24.28	388.63	13.98	4.64	0.396	24.64	356.51	13.31	4.71	0.390
TrajGRU [57]	No	25.01	341.37	12.93	4.72	0.357	23.26	604.79	16.10	5.73	0.381	24.14	473.08	14.52	5.23	0.369
PredRNN [23]	Yes	25.06	337.12	12.84	4.86	0.434	24.12	410.62	14.67	4.64	0.412	24.59	373.87	13.75	4.75	0.423
PredRNN++ [24]	Yes	24.75	337.38	13.33	4.84	0.406	24.30	369.76	14.09	4.69	0.411	24.53	353.57	13.71	4.77	0.409
MIM [25]	Yes	24.67	329.35	13.02	4.84	0.405	24.10	375.16	14.18	4.70	0.413	24.39	352.26	13.60	4.77	0.409
PhyDNet [45]	No	24.21	327.41	13.08	4.86	0.461	23.26	388.52	13.88	4.93	0.463	23.74	357.97	13.48	4.90	0.462
SA-ConvLSTM [26]	Yes	24.08	366.74	13.99	13.63	0.449	23.31	449.29	15.72	13.74	0.452	23.70	408.02	14.86	13.69	0.451
Conv-TT-LSTM [58]	Yes	25.07	430.53	13.39	**4.58**	0.293	24.87	434.12	13.12	**4.43**	0.299	24.97	432.33	13.26	**4.51**	0.296
MotionRNN [28]	No	24.48	495.41	13.83	**4.59**	0.350	23.21	632.43	16.12	4.64	0.379	23.85	563.92	14.98	4.62	0.365
LMC [46]	Yes	26.52	234.15	9.76	4.96	0.446	**26.31**	**243.18**	**9.79**	4.82	0.457	**26.42**	**238.67**	**9.78**	4.89	0.452
SimVP [42]	Yes	**26.59**	**223.77**	**9.69**	4.80	0.447	25.90	269.69	10.83	4.65	0.450	26.25	246.73	10.26	4.73	0.449
MSTCGAN [34]	Yes	25.41	280.91	11.06	4.68	0.233	24.33	326.25	12.96	4.53	0.262	24.87	303.58	12.01	4.61	0.248
AFNO [50]	No	25.22	271.63	11.32	8.25	0.431	24.46	331.59	12.52	8.58	0.470	24.84	301.61	11.92	8.42	0.451
STCNet (Ours)	Yes	**27.00**	**211.31**	**8.97**	4.61	**0.161**	**26.81**	**218.47**	**8.89**	**4.47**	**0.166**	**26.91**	**214.89**	**8.93**	**4.54**	**0.164**

0~4h Satellite Sequence Prediction Comparison

• Visual Comparison

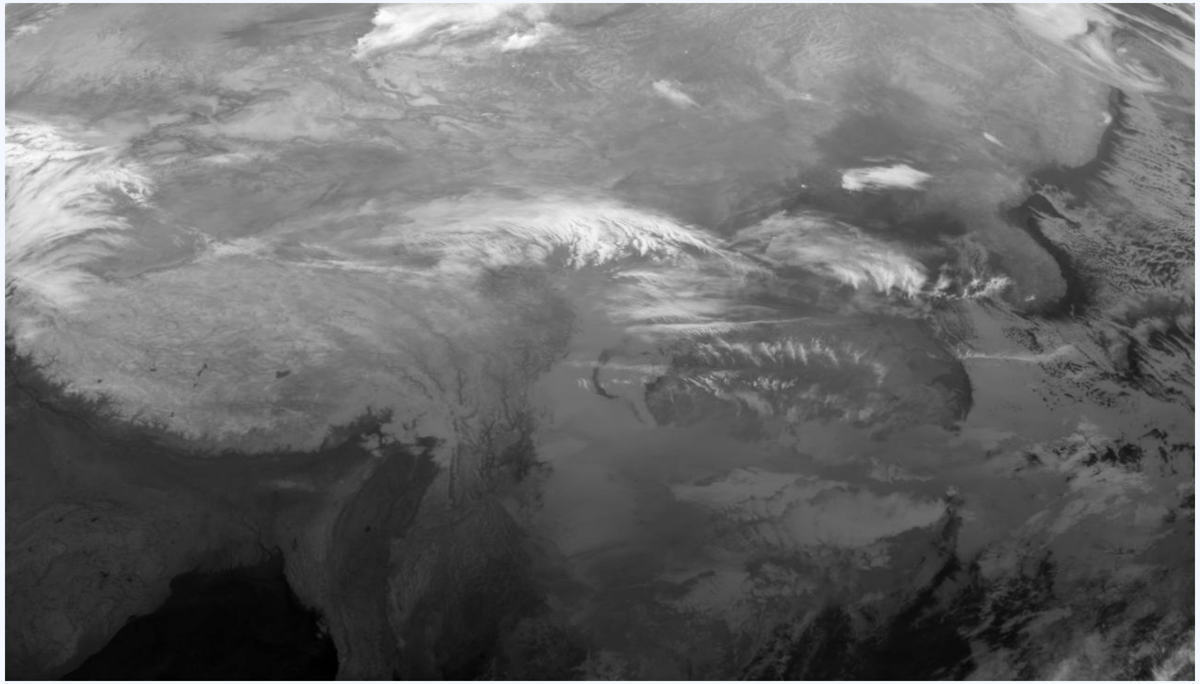




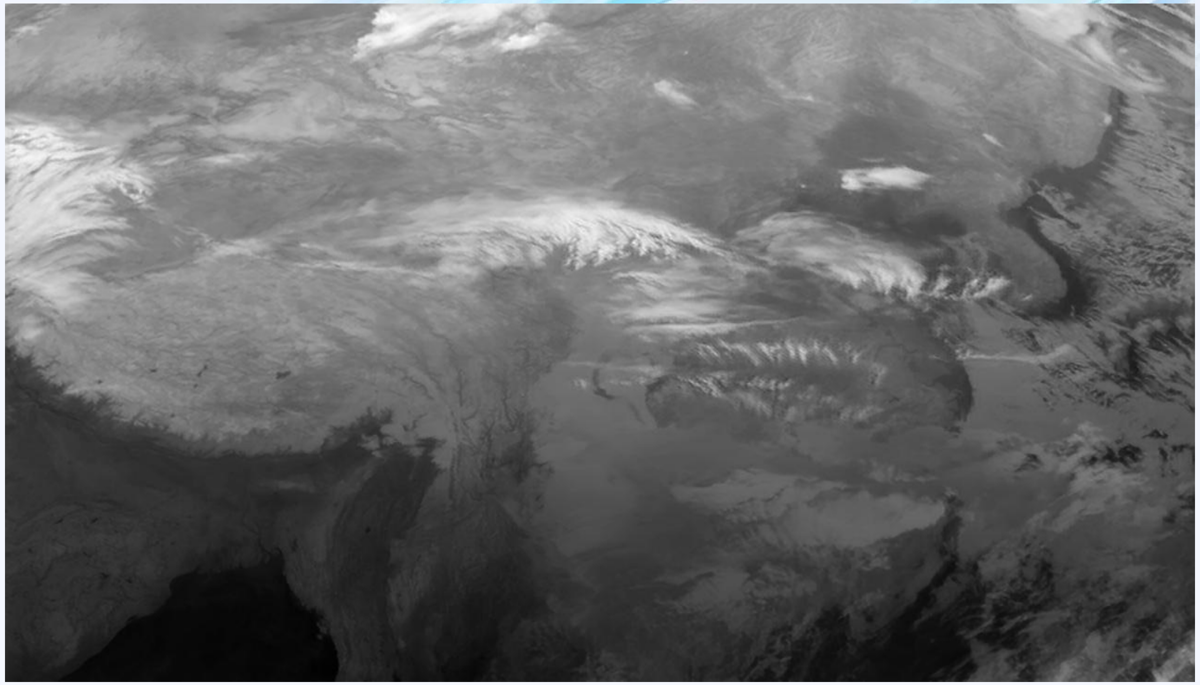
Conclusion: STCNet can more accurately predict the location of convection clouds, which maintains the visual effects and accuracy at the same time.

0~4h Satellite Sequence Prediction Comparison

- **Visual Sequence Prediction**



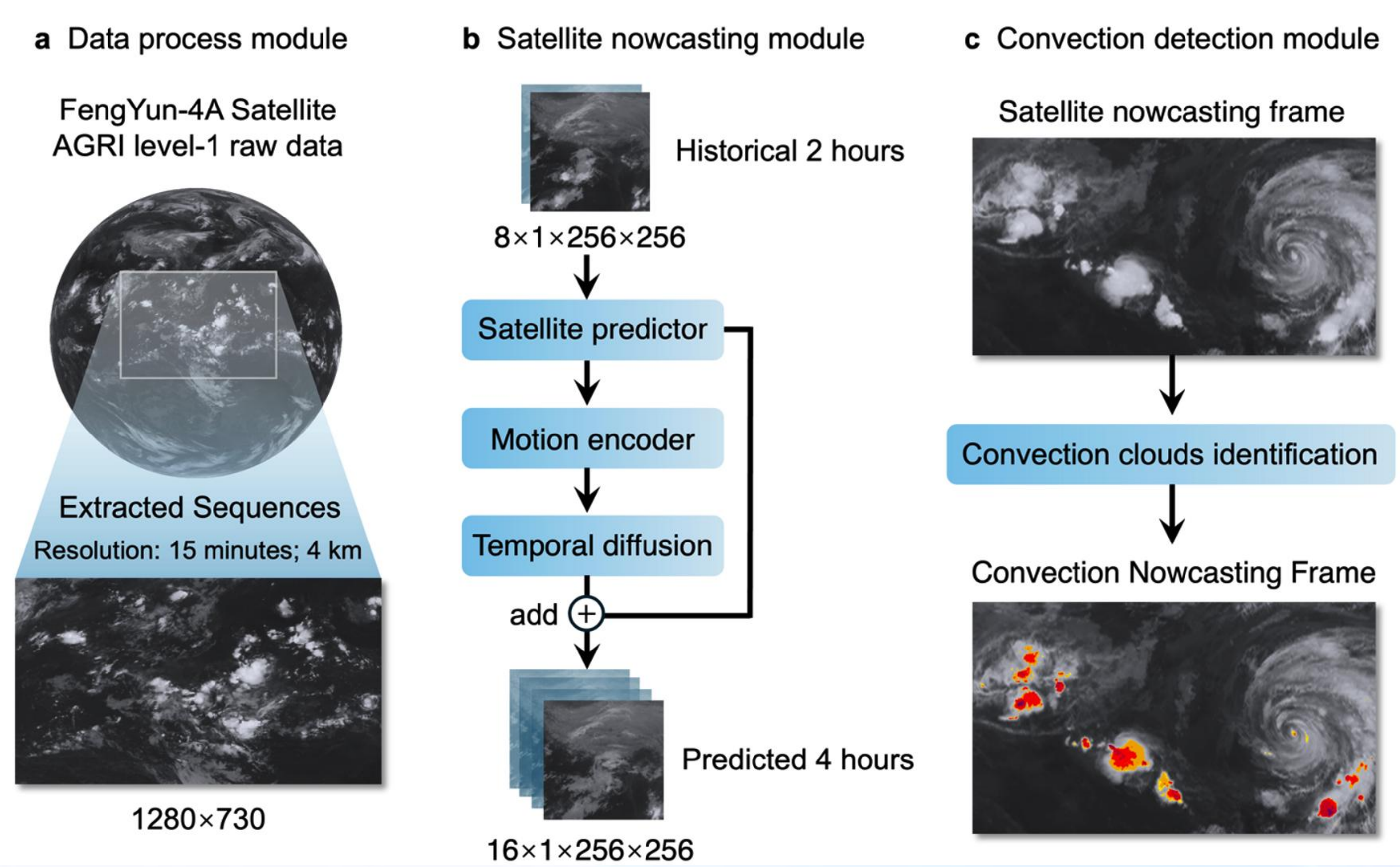
Ground Truth

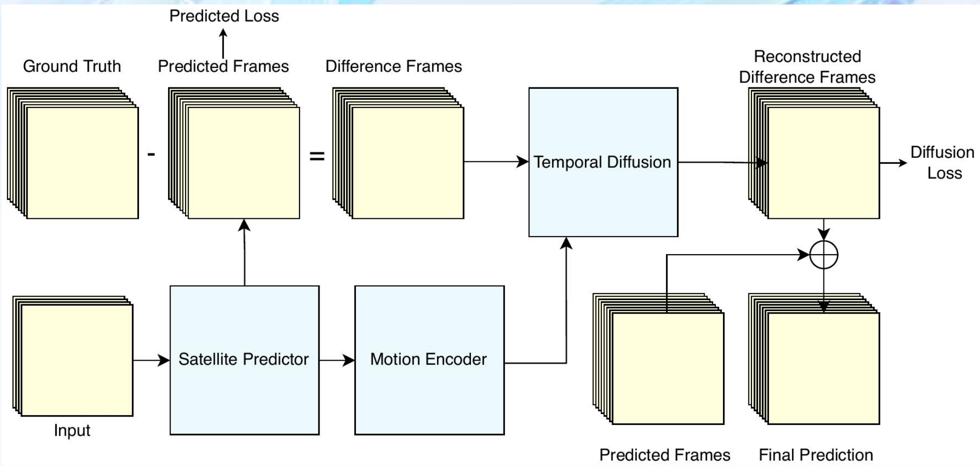


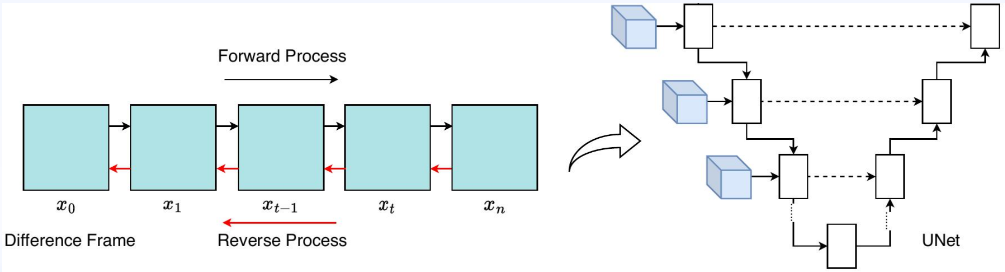
Predicted (STCNet)

Convection Nowcasting: Third generation method DDMS

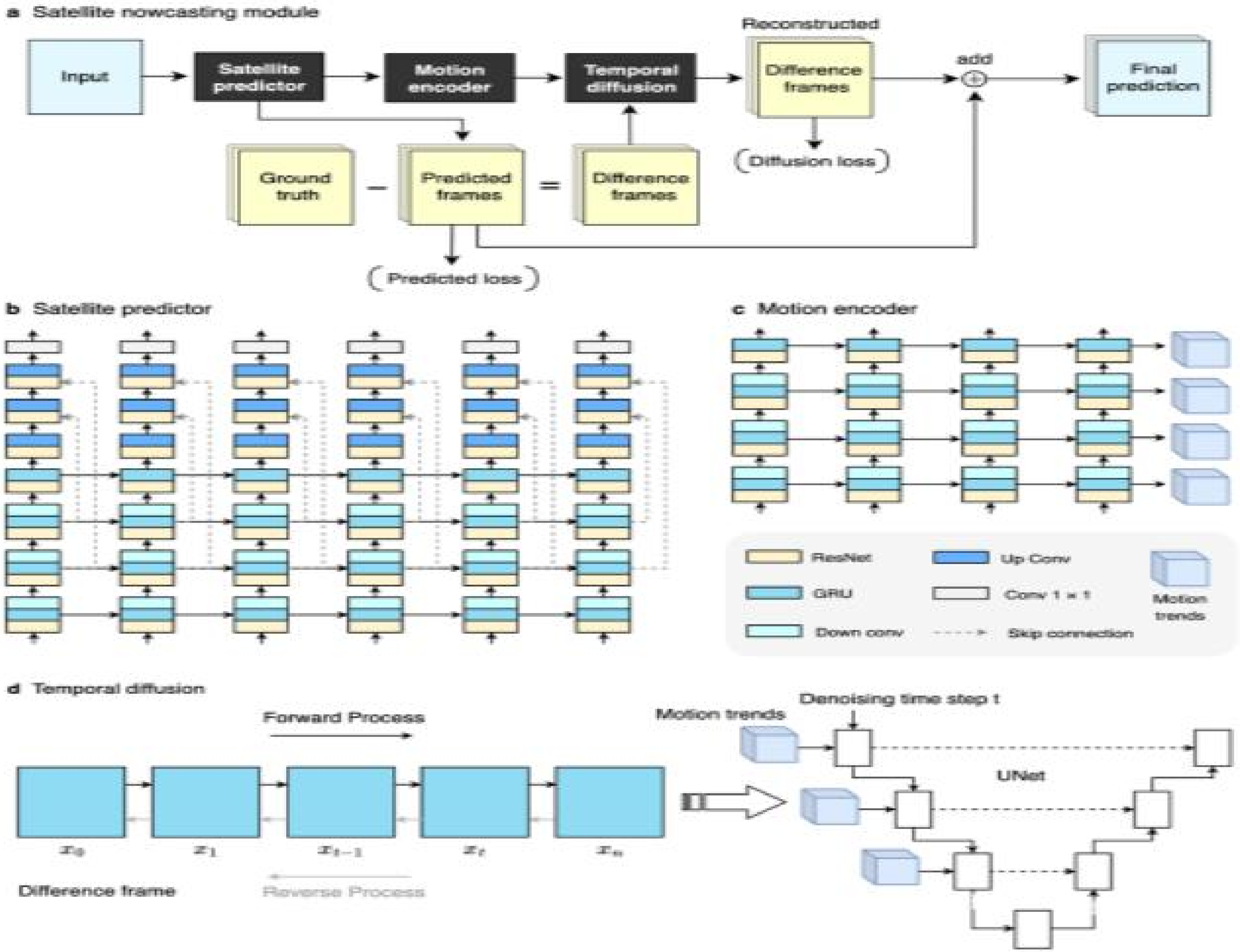
- **A deep defusion method of satellite (DDMS)**
- **0~4 hour prediction of convection ≥ 0.32**

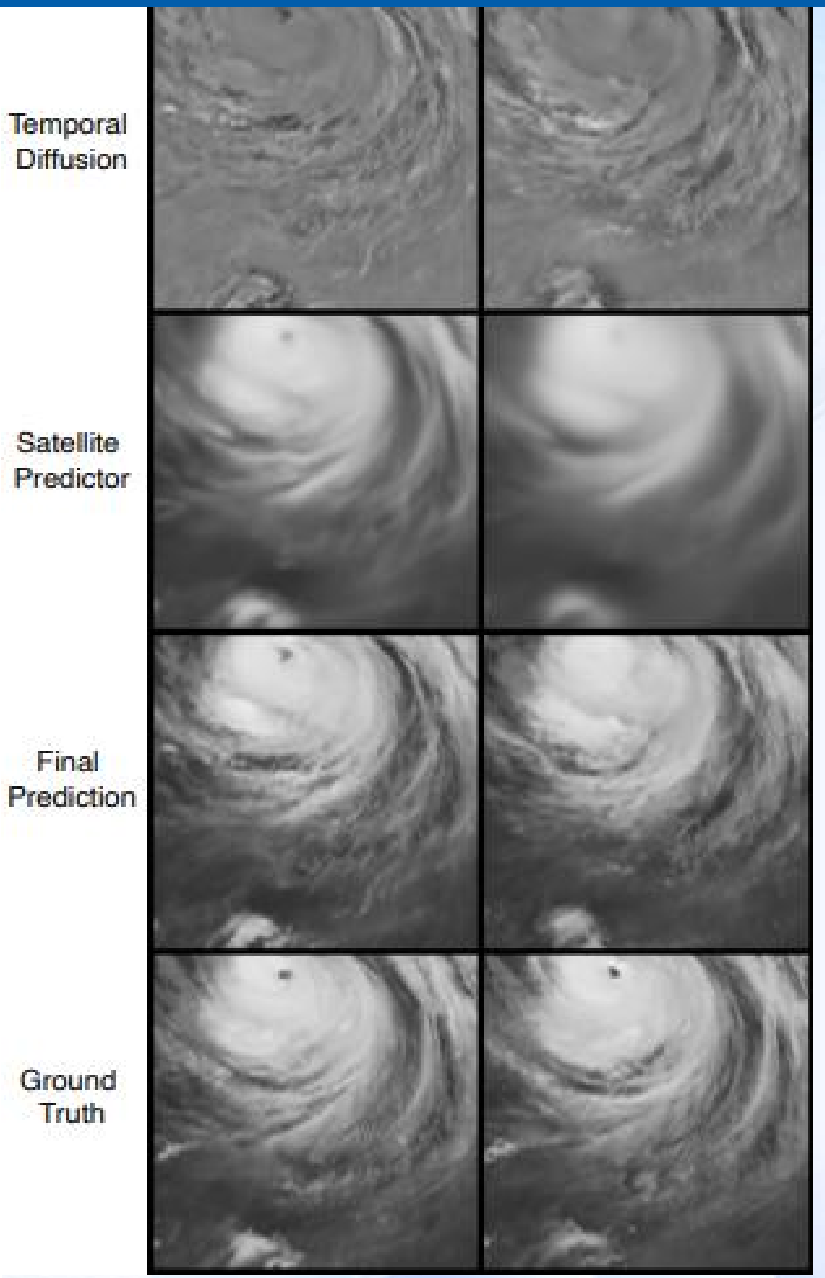






Convection Nowcasting：Third generation method DDMS





0~4h Satellite Prediction Comparison

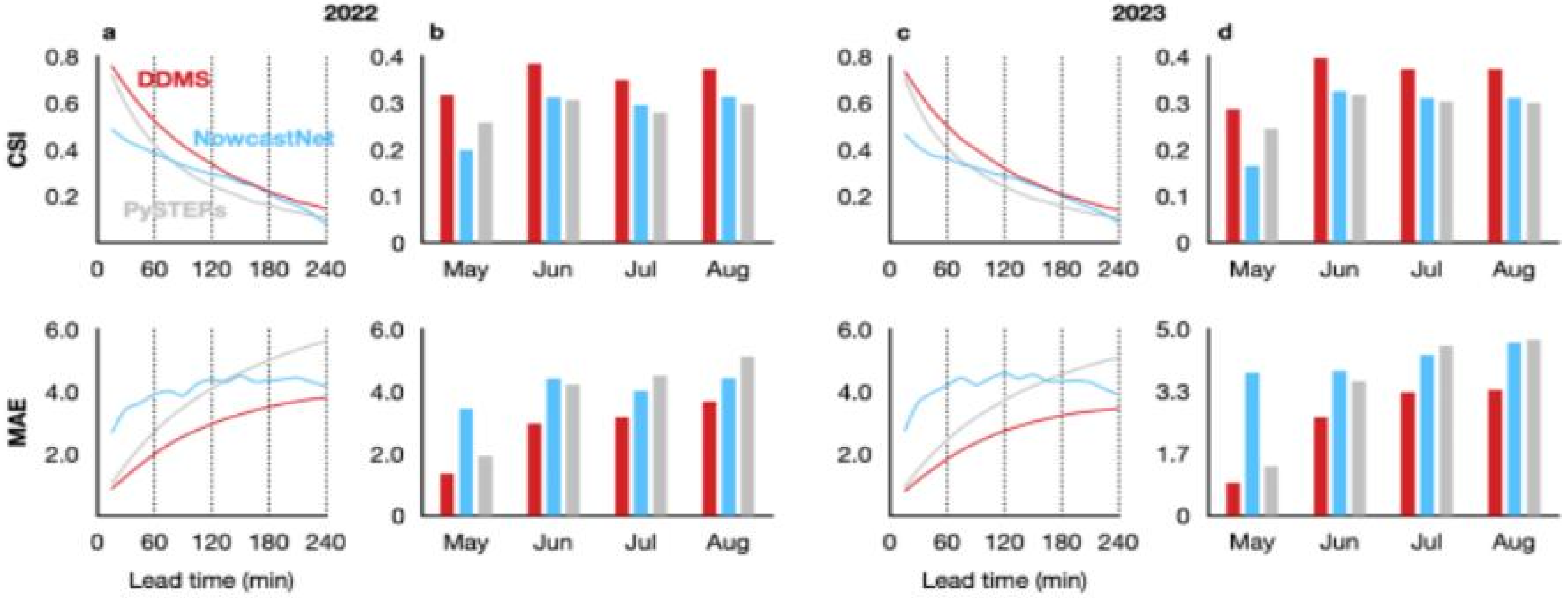


Fig. 2 **Quantitative evaluation of DDMS.** Curves of the critical success index (CSI) and mean absolute error (MAE) with nowcasting lead time averaged from May to August in 2022 **(a)** and 2023 **(c)**. Histograms of the CSI and MAE respectively for 2022 **(b)** and 2023 **(d)** May, June, July, and August. Red (blue, grey) curves and bars indicate DDMS (NowcastNet, pySTEPS).

June 16, 2022 Case study

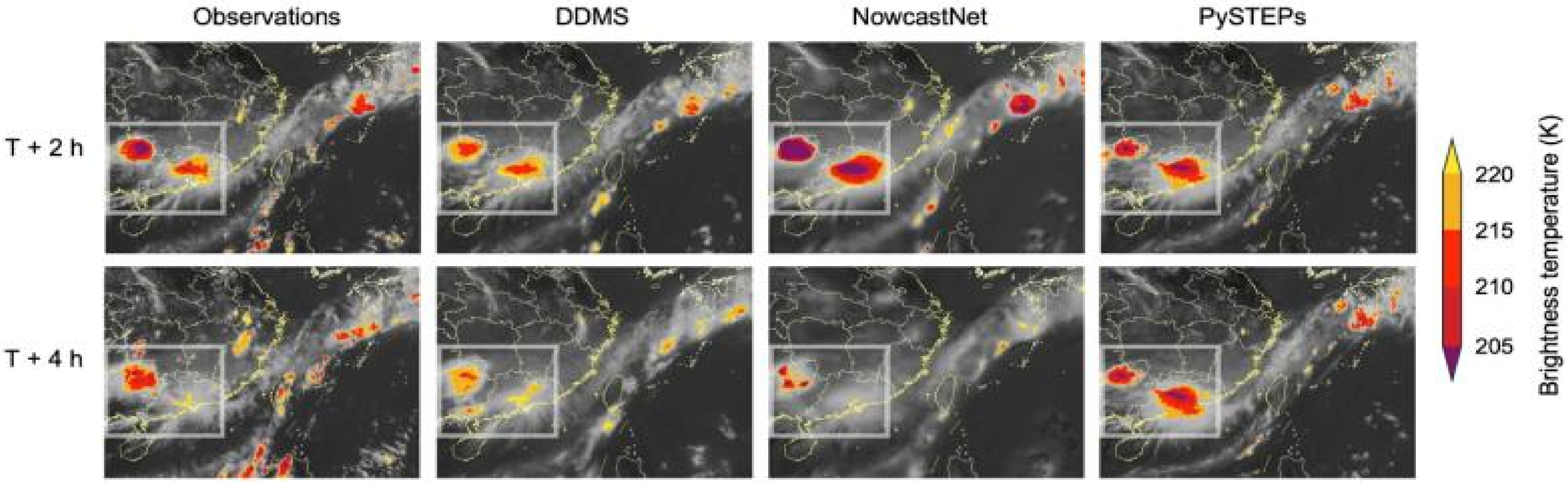


Fig. 3 Case evaluation of a severe convection event with extreme rainstorm starting on 16 June 2022 in South China. This convection event is also accompanied by floods warning of the Pearl River. The color denotes the predicted brightness temperature (K) of convective clouds. The locations of the extreme event are marked with white boxes. The samples are cropped to highlight local details. The state-of-the-art AI-based nowcasting baseline method NowcastNet significantly underestimates the motion tendency of convective clouds 4 hours later. The traditional baseline approach pySTEPS fails to model the growth and death of convective clouds and significantly overestimates the motion tendency of convective clouds. The two methods fail to deliver satisfactory 4-hour convection nowcasting, while our proposed DDMS produces much more accurate nowcasting results.

July 28, 2023 Case study (Beijing)

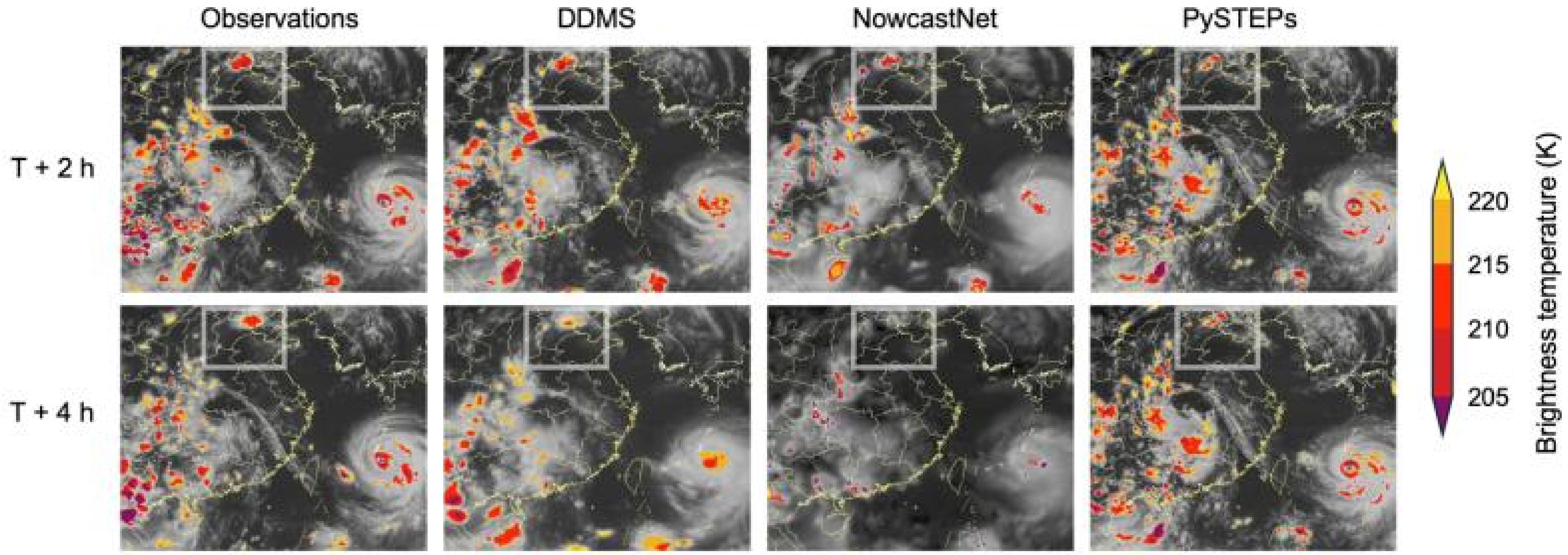
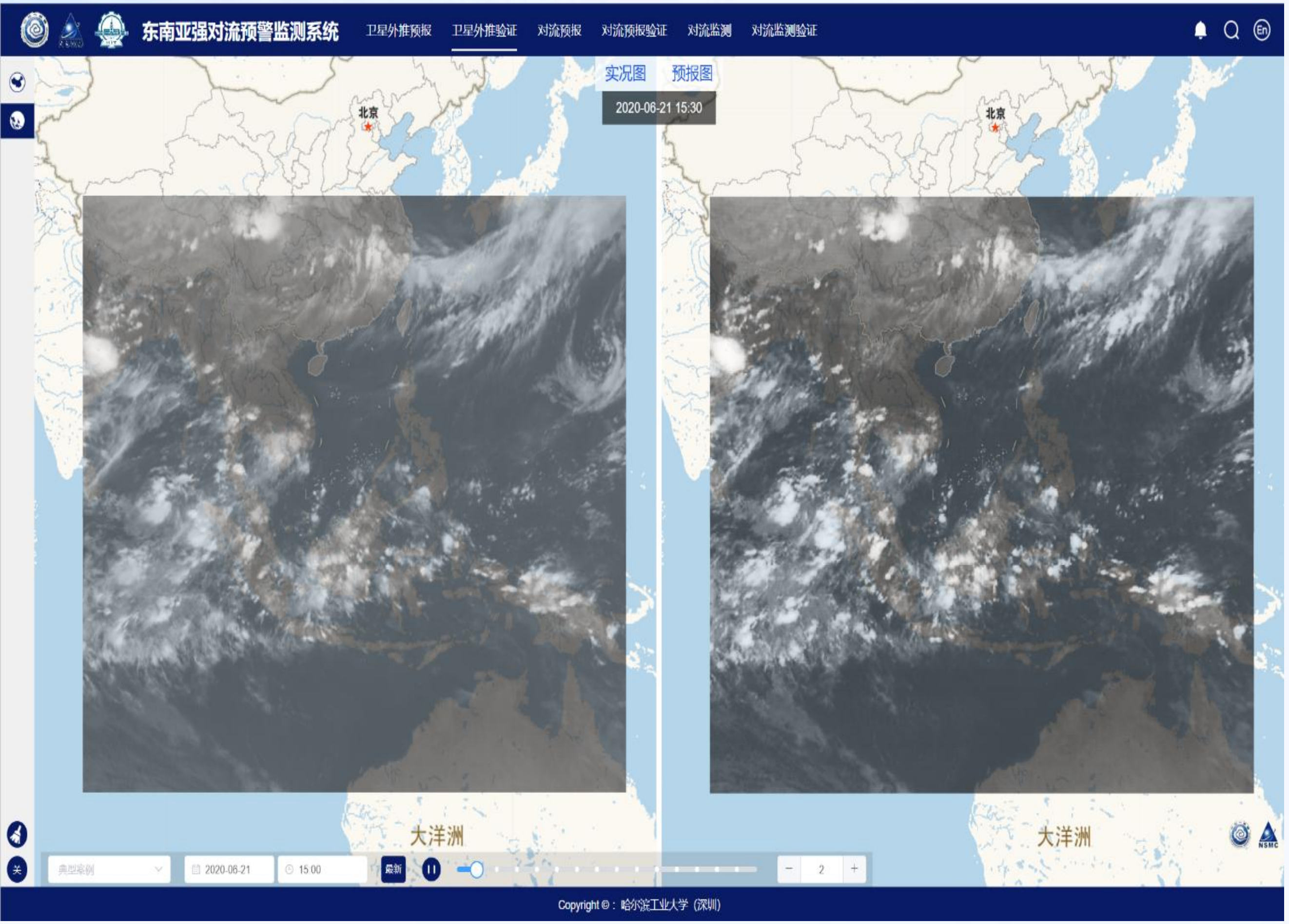
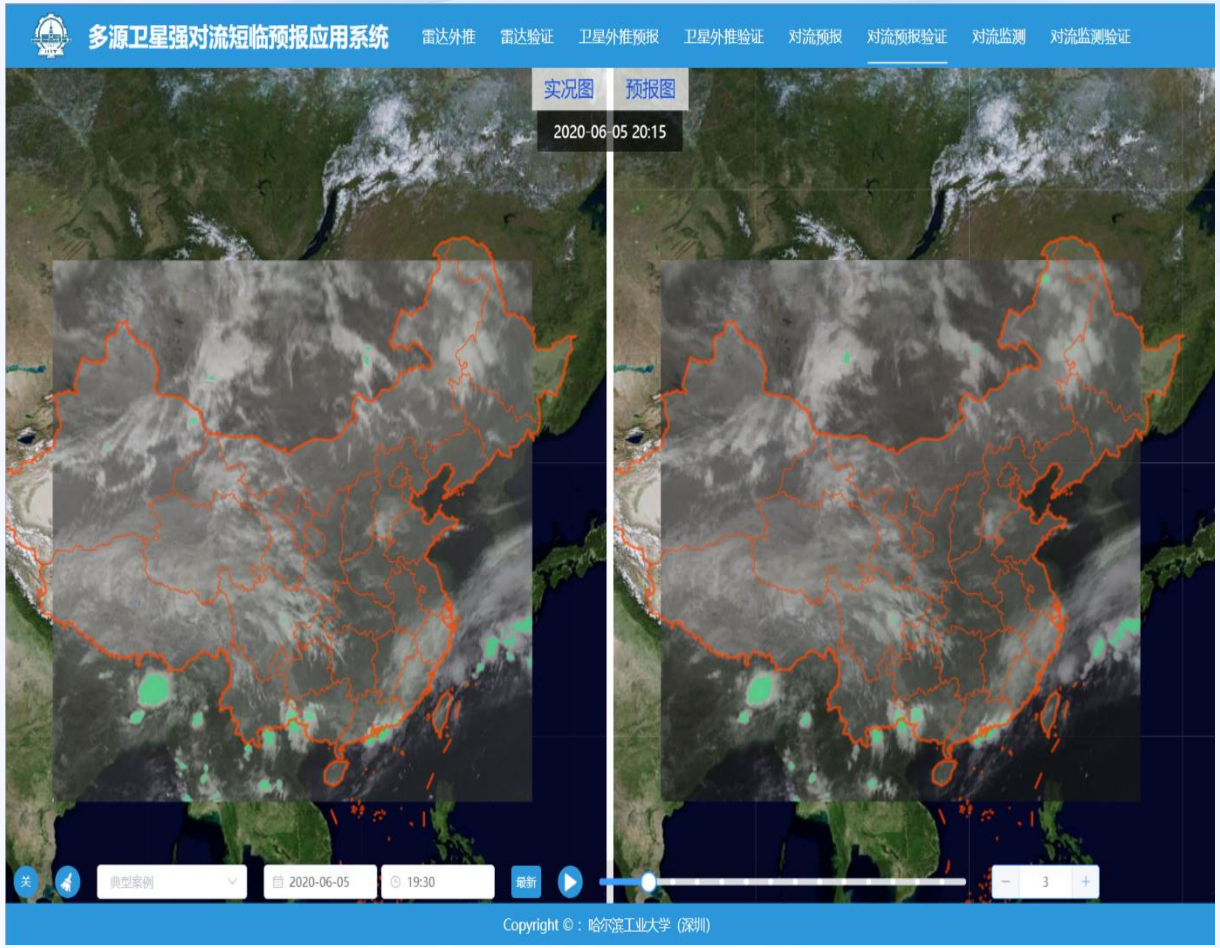


Fig. 4 Case evaluation of a severe convection event with extreme rainstorm starting on 29 July 2023 in Beijing-Tianjin-Hebei region of China. This convection event is affected by the typhoon Dusuirei (in the rightdown corner). The color denotes the predicted brightness temperature of convective clouds. The locations of the extreme event are marked with white boxes. The samples are cropped to highlight local details. Again, DDMS delivers accurate nowcasting results while the state-of-the-art baselines fail to do this.

A FY-4A\4B Severe Convection Prediction System

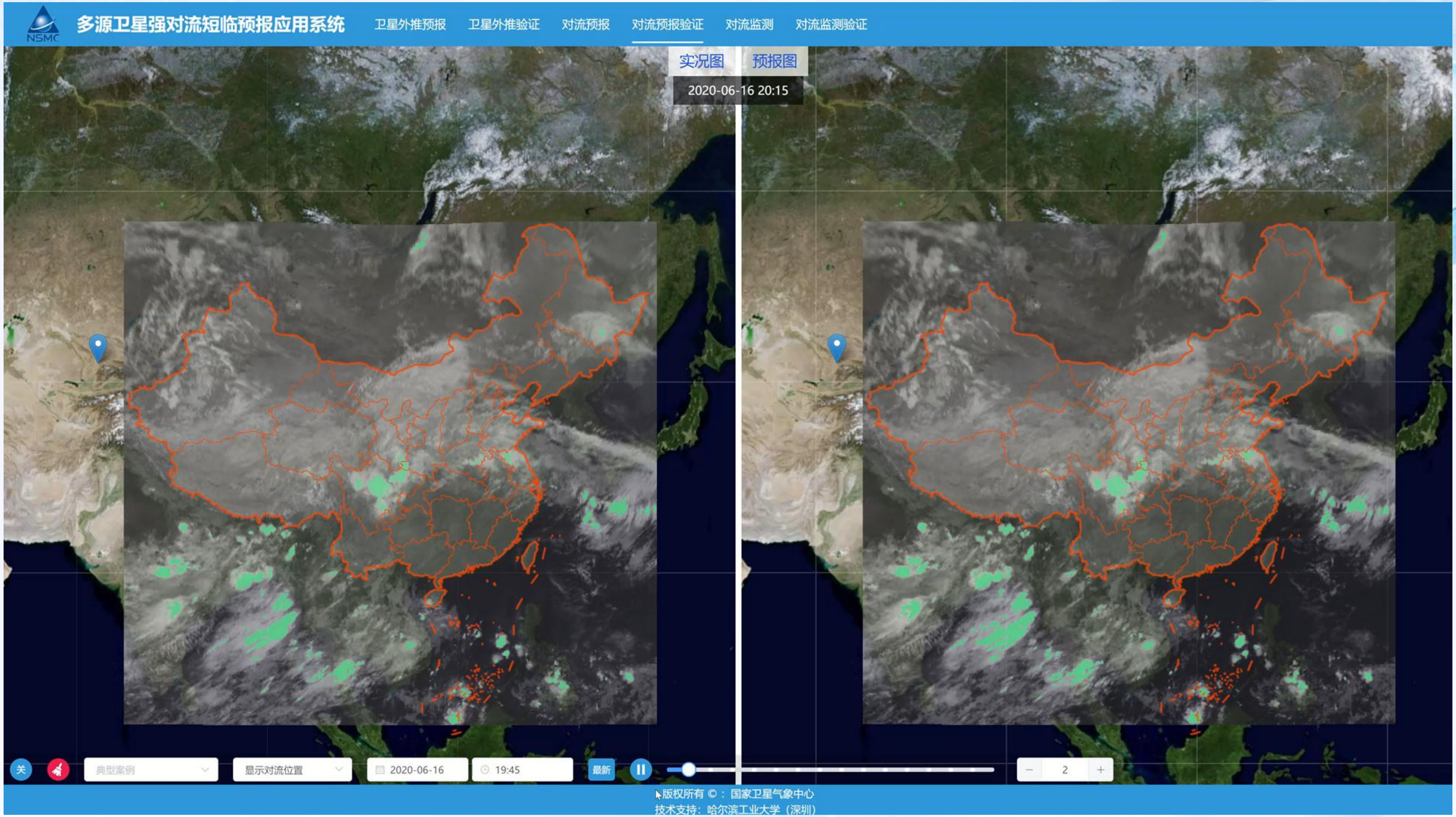


South China Convection Nowcasting Early Warning System



Multi-Satellite based Convection Nowcasting Systems

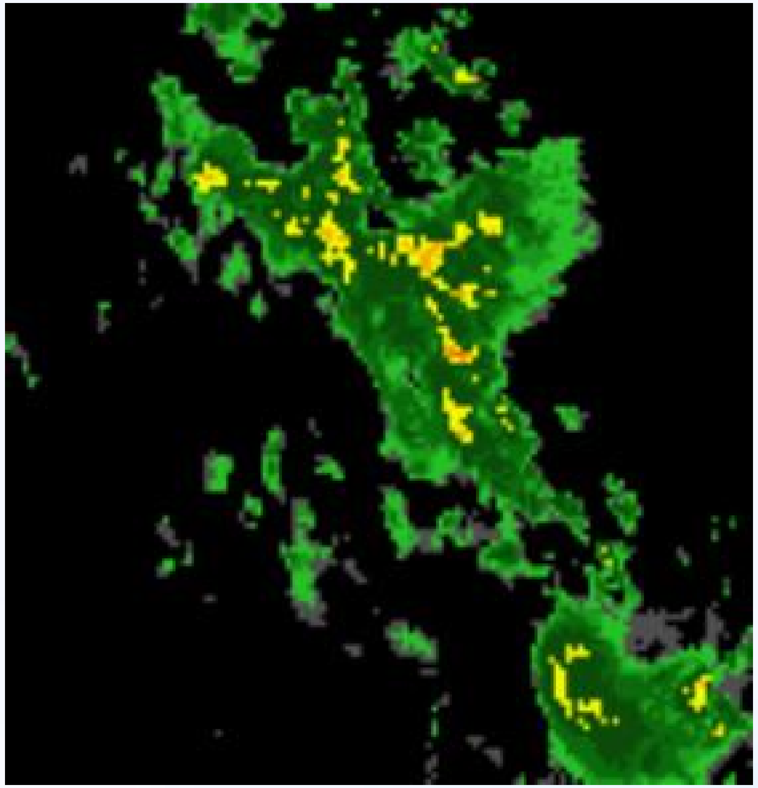
A FY-4A\4B Severe Convection Prediction System



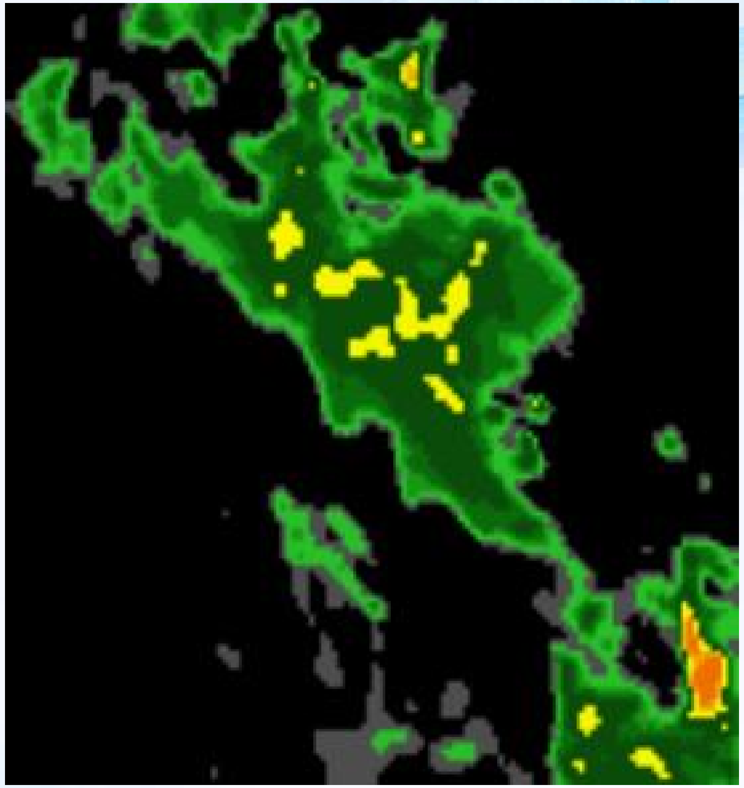
Content

Challenges in Deep Learning-Based Nowcasting Methods on Radar Data

- 1：As the prediction goes on, the image become very blurry
- 2：As the prediction goes on, the high echo part is badly underestimate
- 3：As the prediction goes on, the prediction locations of clouds are not accurate



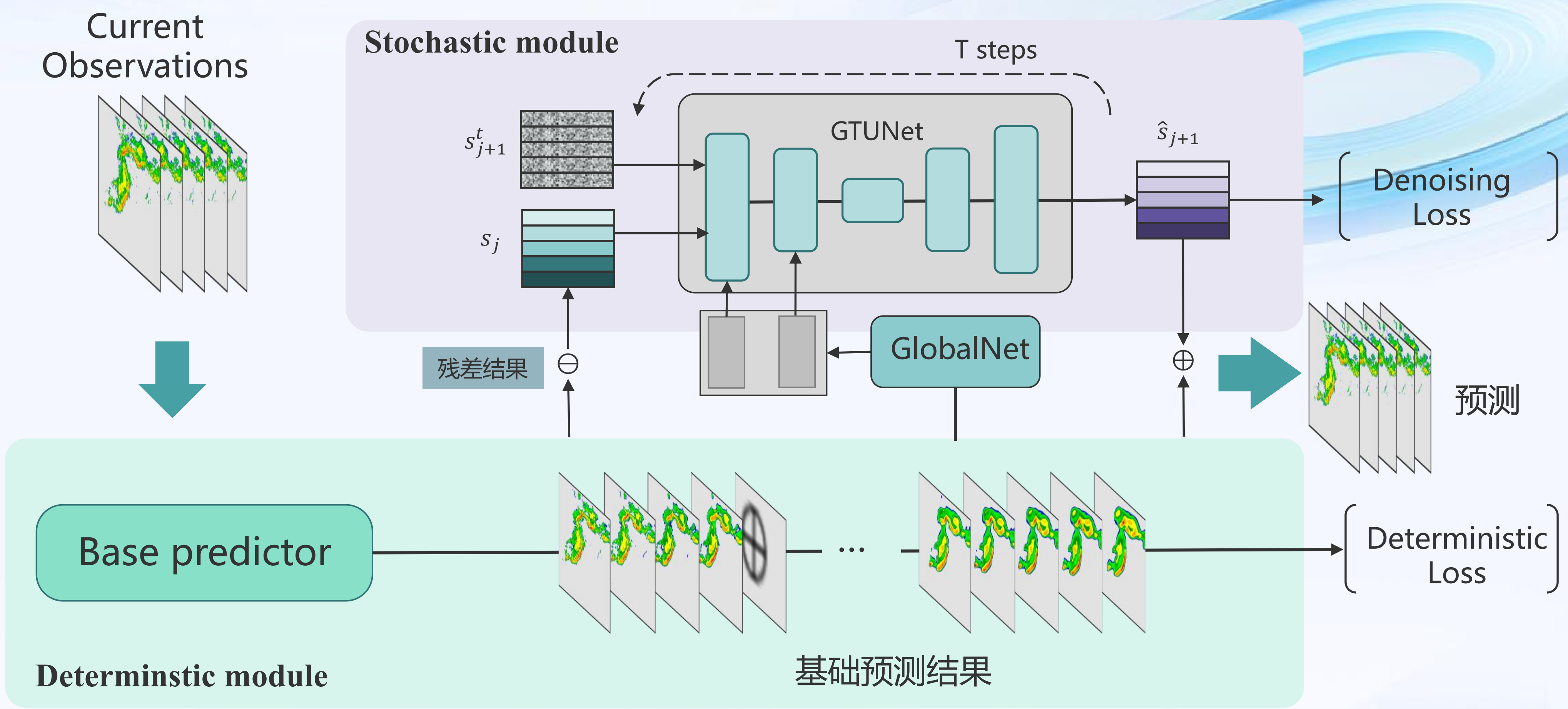
实况



预报

DiffCast: A Nowcasting Method Based on Deep Residual Diffusion Model

- Based on the Reynolds decomposition theory from fluid dynamics, a novel nowcasting framework, DiffCast, is proposed, which decomposes the system into an overall motion part and a local stochastic part



Demin Yu, Xutao Li, Yunming Ye, Baoquan Zhang, Chuyao Luo, Kuai Dai, Rui Wang, Xunlai Chen: ***DiffCast: A Unified Framework via Residual Diffusion for Precipitation Nowcasting. CVPR 2024***: 27758-27767

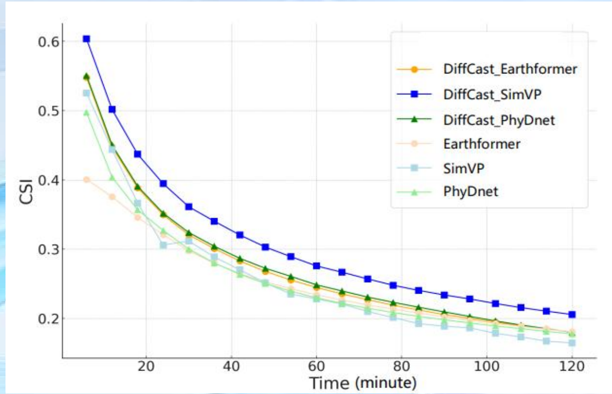
Experiment Results

Table 1. Experiment results on four radar datasets. Relative improvements are shown with brackets.

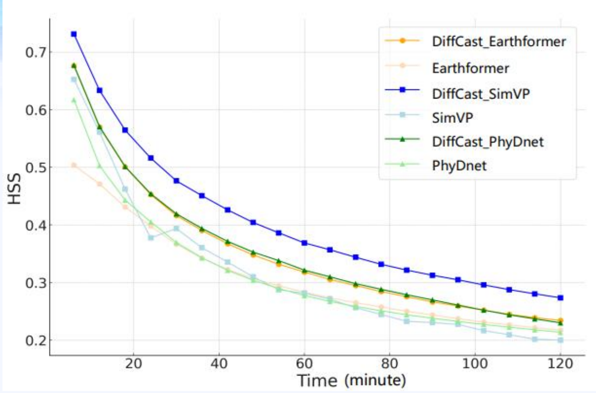
Method	SEVIR ↑CSI	SEVIR ↑CSI-pool4	SEVIR ↑CSI-pool16	SEVIR ↑HSS	SEVIR ↓LPIPS	SEVIR ↑SSIM	MeteoNet ↑CSI	MeteoNet ↑CSI-pool4	MeteoNet ↑CSI-pool16	MeteoNet ↑HSS	MeteoNet ↓LPIPS	MeteoNet ↑SSIM
SimVP[9]	0.2662	0.2844	0.3452	0.3369	0.3914	0.6304	0.3346	0.3383	0.4143	0.4568	0.3523	0.7557
DiffCast_SimVP	**0.3077**	**0.4122**	**0.5683**	**0.4033**	**0.1812**	**0.6354**	**0.3511**	**0.5081**	**0.7155**	**0.4846**	**0.1198**	**0.7887**
	(+15.59%)	**(+44.94%)**	**(+64.63%)**	**(+19.71%)**	**(+53.70%)**	**(+0.79%)**	**(+4.93%)**	**(+50.19%)**	**(+72.70%)**	**(+6.09%)**	**(+65.99%)**	**(+4.37%)**
Earthformer[8]	0.2513	0.2617	0.2910	0.3073	0.4140	**0.6773**	0.3296	0.3428	0.4333	0.4604	0.3718	0.7899
DiffCast_Earthformer	**0.2823**	**0.3868**	**0.5362**	**0.3623**	**0.1818**	0.6420	**0.3402**	**0.5020**	**0.7092**	**0.4696**	**0.1236**	**0.7967**
	(+12.34%)	**(+47.80%)**	**(+84.26%)**	**(+17.90%)**	**(+56.09%)**	(-5.21%)	**(+3.22%)**	**(+46.44%)**	**(+63.67%)**	**(+2.00%)**	**(+66.76%)**	**(+0.86%)**
MAU[3]	0.2463	0.2566	0.2861	0.3004	0.3933	0.6361	0.3232	0.3304	0.4165	0.4451	0.3089	0.7897
DiffCast_MAU	**0.2716**	**0.3789**	**0.5414**	**0.3506**	**0.1874**	**0.6729**	**0.3490**	**0.5030**	**0.7114**	**0.4822**	**0.1213**	0.7665
	(+10.27%)	**(+47.66%)**	**(+89.23%)**	**(+16.71%)**	**(+52.35%)**	**(+5.79%)**	**(+7.98%)**	**(+52.24%)**	**(+70.80%)**	**(+8.34%)**	**(+60.73%)**	(-2.94%)
ConvGRU[27]	0.2416	0.2554	0.3050	0.2834	0.3766	**0.6532**	0.3400	0.3578	0.4473	0.4667	0.2950	**0.7832**
DiffCast_ConvGRU	**0.2772**	**0.3809**	**0.5463**	**0.3551**	**0.1880**	0.6188	**0.3512**	**0.4930**	**0.7001**	**0.4862**	**0.1244**	0.7761
	(+14.74%)	**(+49.14%)**	**(+79.11%)**	**(+25.30%)**	**(+50.08%)**	(-5.27%)	**(+3.29%)**	**(+37.79%)**	**(+56.52%)**	**(+4.18%)**	**(+57.83%)**	(-0.91%)
PhyDnet[11]	0.2560	0.2685	0.3005	0.3124	0.3785	**0.6764**	0.3384	0.3824	0.4986	0.4673	0.2941	**0.8022**
DiffCast_PhyDnet	**0.2757**	**0.3797**	**0.5296**	**0.3584**	**0.1845**	0.6320	**0.3472**	**0.5066**	**0.7200**	**0.4802**	**0.1234**	0.7788
	(+7.70%)	**(+41.42%)**	**(+76.24%)**	**(+14.72%**	**(+51.2%)**	(-6.56%)	**(+2.60%)**	**(+32.48%)**	**(+44.40%)**	**(+2.76%)**	**(+58.04%)**	(-2.92%)
MCVD[34]	0.2148	0.3020	0.4706	0.2743	0.2170	0.5265	0.2336	0.3841	0.6128	0.3393	0.1652	0.5414
PreDiff[10]	0.2304	0.3041	0.4028	0.2986	0.2851	0.5185	0.2657	0.3854	0.5692	0.3782	0.1543	0.7059
STRPM[4]	0.2512	0.3243	0.4959	0.3277	0.2577	0.6513	0.2606	0.4138	0.6882	0.3688	0.2004	0.5996

Method	Shanghai_Radar ↑CSI	Shanghai_Radar ↑CSI-pool4	Shanghai_Radar ↑CSI-pool16	Shanghai_Radar ↑HSS	Shanghai_Radar ↓LPIPS	Shanghai_Radar ↑SSIM	CIKM ↑CSI	CIKM ↑CSI-pool4	CIKM ↑CSI-pool16	CIKM ↑HSS	CIKM ↓LPIPS	CIKM ↑SSIM
SimVP[9]	0.3841	0.4467	0.5603	0.5183	0.2984	0.7764	**0.3021**	0.3530	0.4677	**0.3948**	0.3134	0.6324
DiffCast_SimVP	**0.3955**	**0.5116**	**0.6576**	**0.5296**	**0.1571**	**0.7902**	0.2999	**0.3657**	**0.5260**	0.3874	**0.2223**	**0.6391**
	(+2.97%)	**(+14.53%)**	**(+17.37%)**	**(+2.18%)**	**(+47.35%)**	**(+1.78%)**	(-0.73%)	**(+3.60%)**	**(+12.47%)**	(-1.87%)	**(+29.07%)**	**(+1.06%)**
Earthformer[8]	0.3575	0.4008	0.4863	0.4843	0.2564	0.7750	**0.3153**	0.3547	0.4927	0.3828	0.3857	**0.6510**
DiffCast_Earthformer	**0.3751**	**0.4855**	**0.6212**	**0.5069**	**0.1586**	**0.7851**	0.3099	**0.3807**	**0.5509**	**0.3947**	**0.2259**	0.6313
	(+4.92%)	**(+21.13%)**	**(+27.74%)**	**(+4.67%)**	**(+38.14%)**	**(+1.30%)**	(-1.71%)	**(+7.33%)**	**(+11.81%)**	**(+3.11%)**	**(+41.43%)**	(-3.03%)
MAU[3]	0.3996	0.4695	0.5787	0.5356	0.2735	0.7303	0.2936	0.3152	0.4144	0.3660	0.3999	0.6277
DiffCast_MAU	**0.4089**	**0.5212**	**0.6658**	**0.5475**	**0.1618**	**0.7879**	**0.3158**	**0.3803**	**0.5443**	**0.4085**	**0.2205**	**0.6498**
	(+2.33%)	**(+11.01%)**	**(+15.05%)**	**(+2.22%)**	**(+40.84%)**	**(+7.89%)**	**(+7.56%)**	**(+20.65%)**	**(+31.35%)**	**(+11.61%)**	**(+44.86%)**	**(+3.52%)**
ConvGRU[27]	0.3612	0.4439	0.5596	0.4899	0.2564	0.7795	0.3092	0.3533	0.4686	**0.4007**	0.3135	0.6601
DiffCast_ConvGRU	**0.3738**	**0.4923**	**0.6596**	**0.4945**	**0.1563**	**0.7809**	**0.3143**	**0.3681**	**0.5117**	0.3967	**0.2201**	**0.6418**
	(+3.49%)	**(+10.90%)**	**(+17.87%)**	**(+0.94%)**	**(+39.04%)**	**(+0.18%)**	**(+1.65%)**	**(+4.19%)**	**(+9.20%)**	(-1.00%)	**(+29.79%)**	**(+2.77%)**
PhyDnet[11]	0.3653	0.4552	0.5980	0.4957	0.1894	0.7751	0.3037	0.3442	0.4655	0.3931	0.3631	**0.6540**
DiffCast_PhyDnet	**0.3671**	**0.4907**	**0.6493**	**0.4986**	**0.1574**	**0.7780**	**0.3131**	**0.3836**	**0.5550**	**0.3990**	**0.2270**	0.6156
	(+0.49%)	**(+7.80%)**	**(+8.58%)**	**(+0.59%)**	**(+16.90%)**	**(+0.37%)**	**(+3.10%)**	**(+11.45%)**	**(+19.23%)**	**(+1.50%)**	**(+37.48%)**	(-5.87%)
MCVD[34]	0.2872	0.3984	0.5675	0.4036	0.2081	0.5119	0.2513	0.3095	0.4955	0.3294	0.2528	0.5358
PreDiff[10]	0.3583	0.4389	0.5448	0.4849	0.1696	0.7557	0.3043	0.3681	0.5117	0.3967	0.2201	0.6418
STRPM[4]	0.3606	0.4944	0.6783	0.4931	0.1681	0.7724	0.2984	0.3590	0.5020	0.3870	0.2397	0.6443

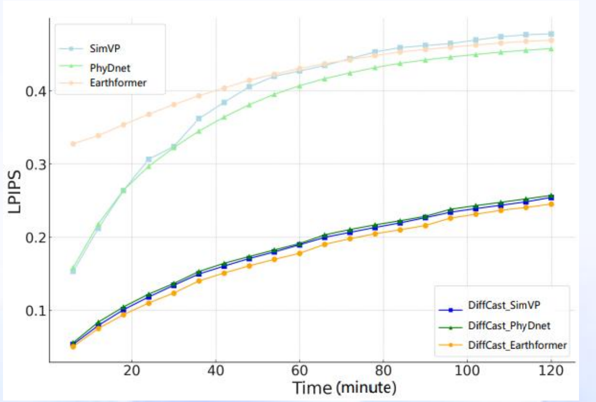
CSI

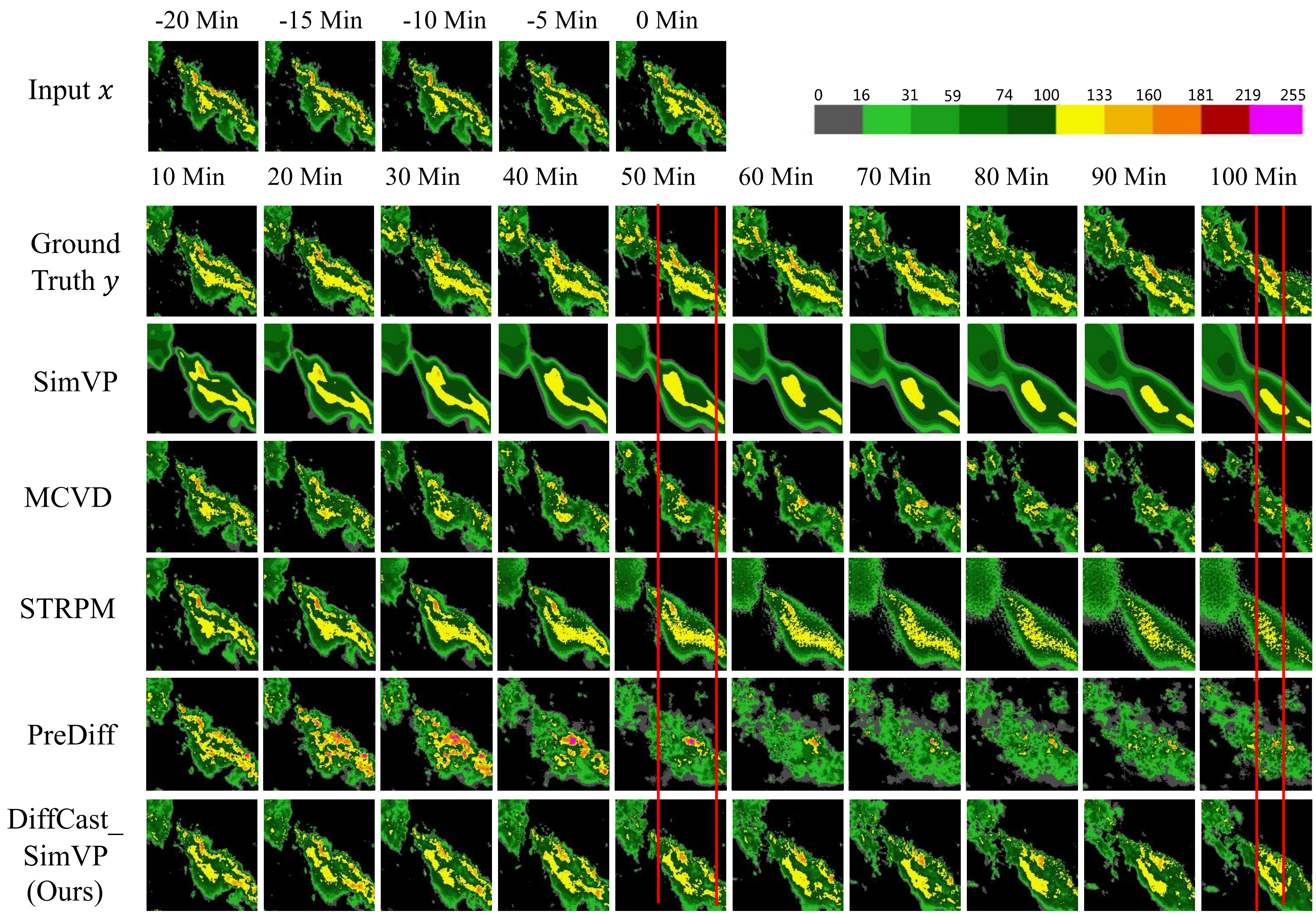


HSS



LPIPS





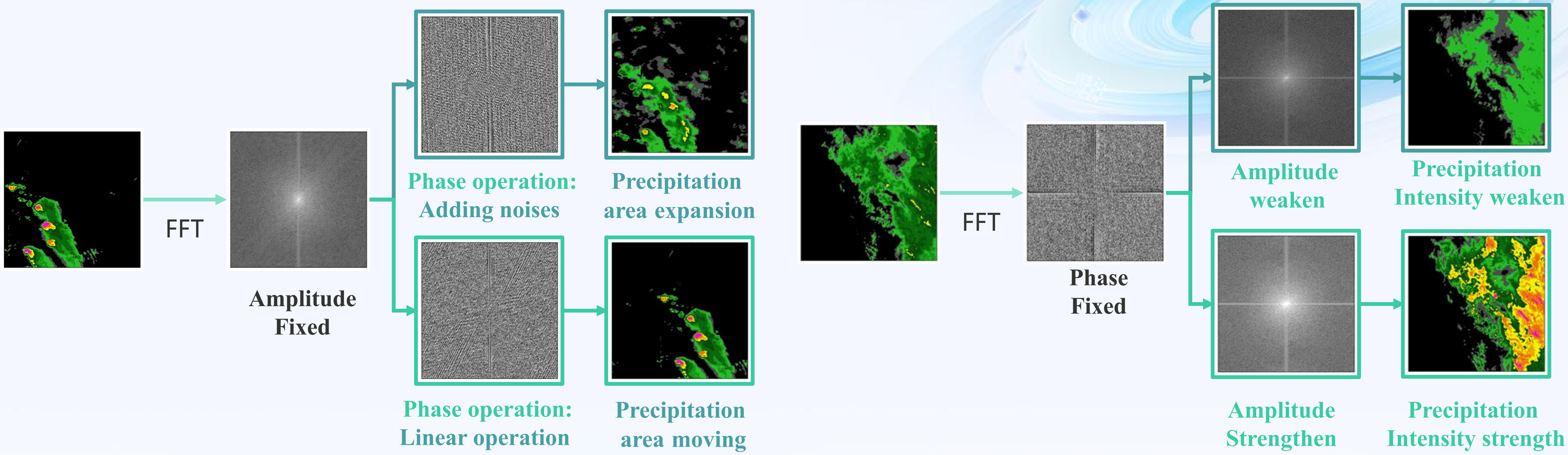
Diffcast shows a better performance:

1) A better prediction on high echo value part, which usually denotes strong stomrs;

2) A better prediction on image quality, with more details.

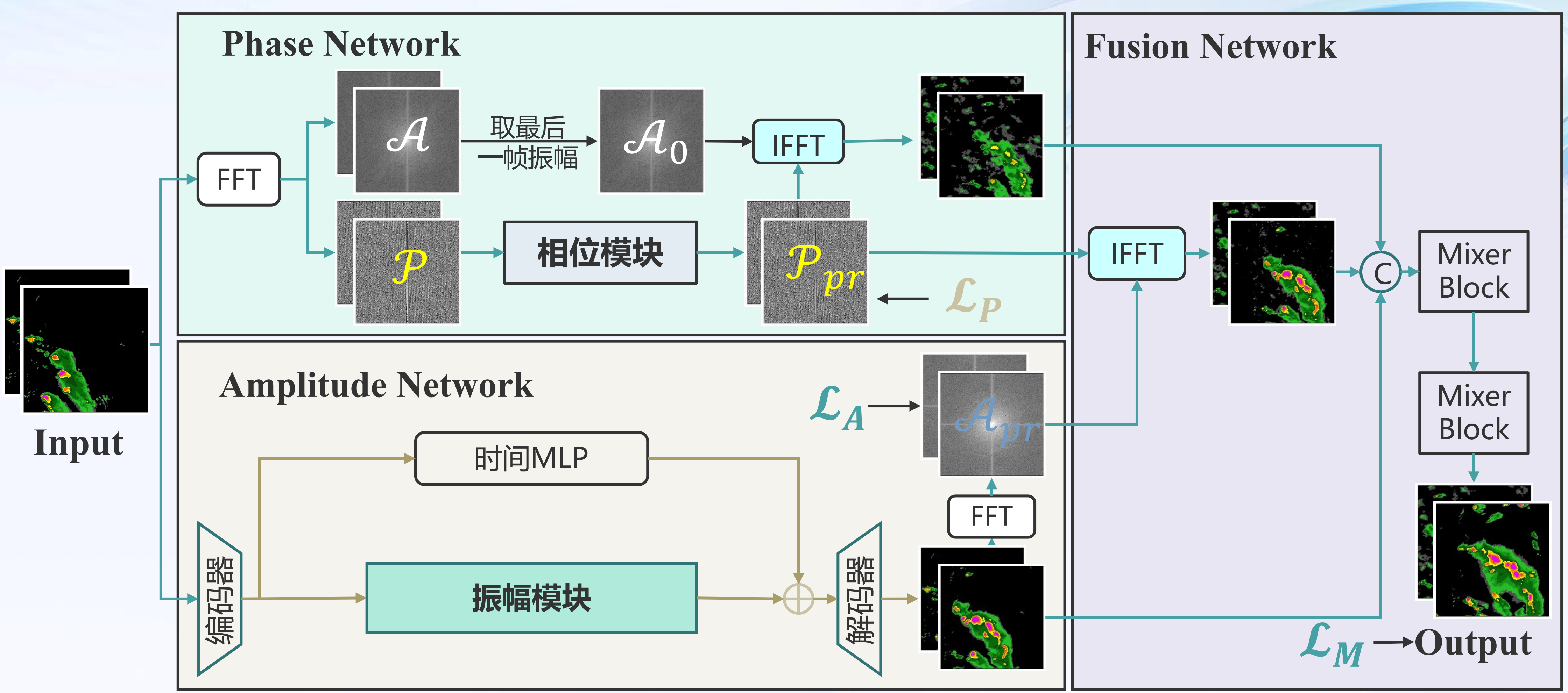
Precipitation Nowcasting Model with Amplitude-Phase Decoupling：AlphaPre

- **Our idea：Spectral domain analysis shows that radar image amplitude and phase relate to precipitation, allowing for the independent modeling of its positional and intensity changes.**



Lin K, Zhang B, Yu D, et al. *AlphaPre: Amplitude-Phase Disentanglement Model for Precipitation Nowcasting.CVPR*, 2025.

Model Architecture of AlphaPre

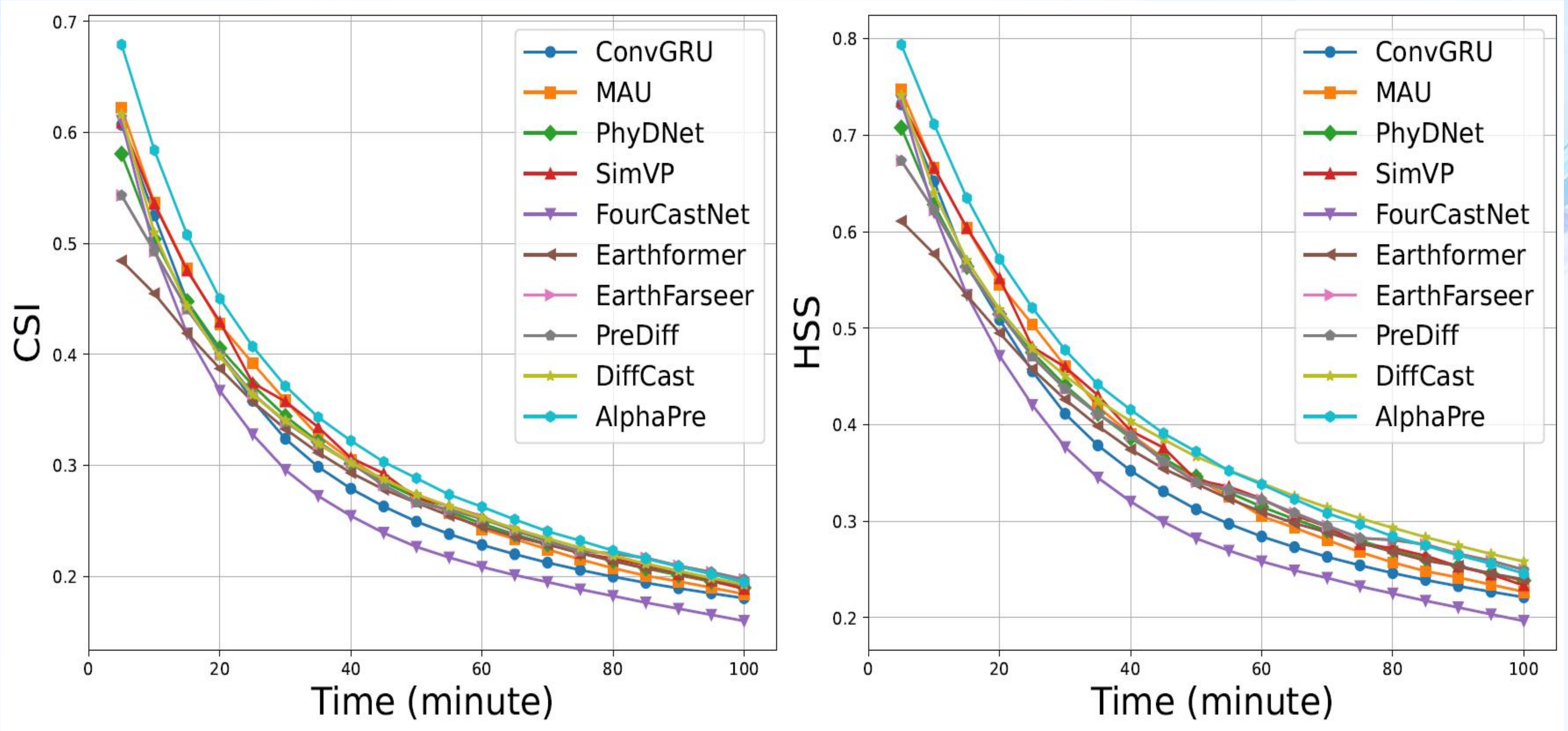


Experiment Results

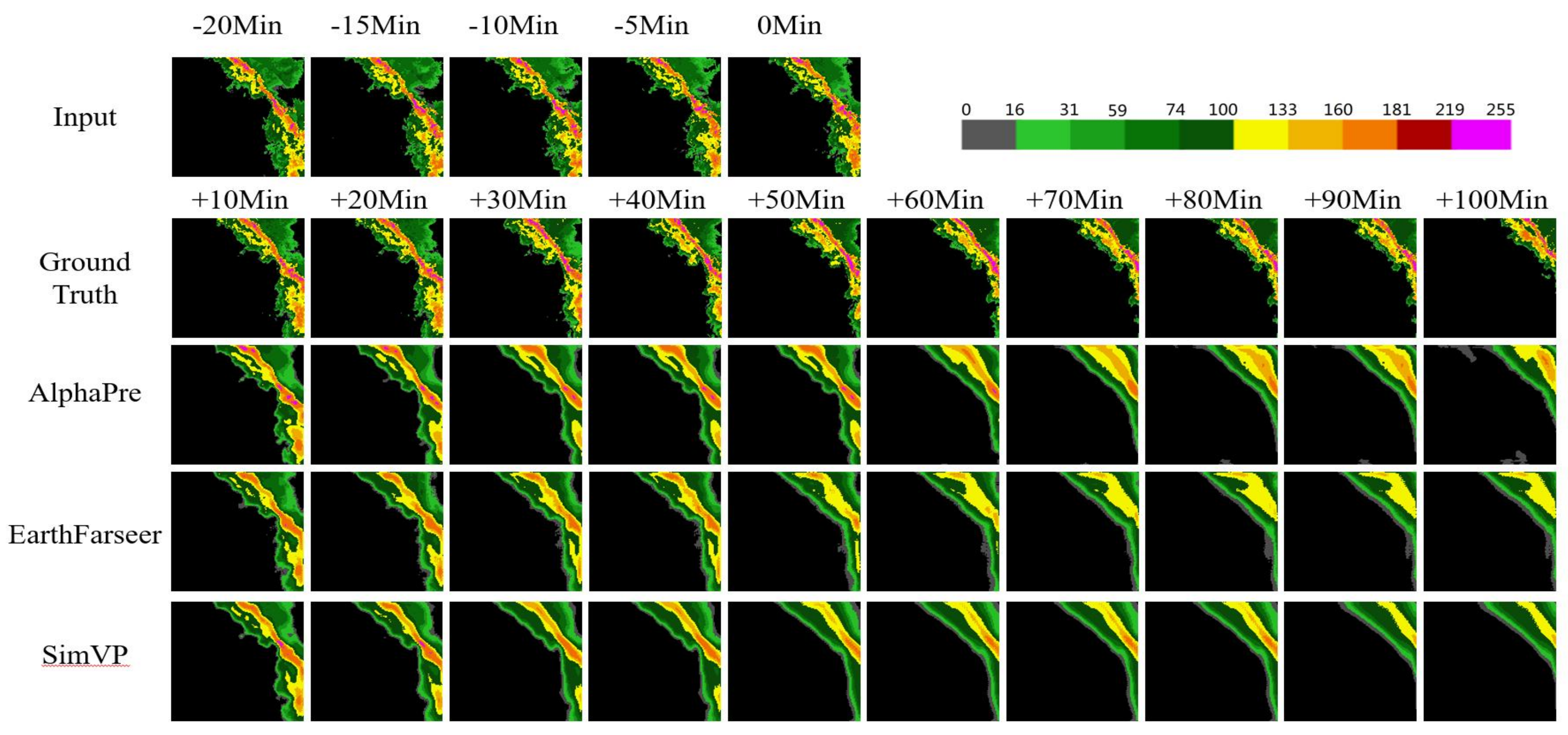
	Type	SEVIR						MeteoNet					
		CSI-M↑	CSI-181↑	CSI-219↑	HSS↑	SSIM↑	MSE↓	CSI-M↑	CSI-24↑	CSI-32↑	HSS↑	SSIM↑	MSE↓
ConvGRU	ND	0.2903	0.0879	0.0350	0.3619	0.6100	368.34	0.3401	0.2990	0.1431	0.4667	0.7833	12.85
MAU	ND	0.3076	0.1071	0.0516	0.3863	0.6505	355.48	0.3233	0.2839	0.0997	0.4452	0.7897	12.92
SimVP	ND	0.3108	0.1106	0.0517	0.3924	0.6508	383.56	0.3351	0.3002	0.1130	0.4573	0.7804	13.45
FourCastNet	ND	0.2686	0.0717	0.0339	0.3355	0.5976	410.27	0.3027	0.2533	0.1085	0.4216	0.6450	15.05
Earthformer	ND	0.2892	0.0844	0.0245	0.3665	0.6633	360.11	0.3205	0.2884	0.1237	0.4491	0.7772	14.43
PhyDNet	D	0.3017	0.1040	0.0278	0.3812	0.6532	357.63	0.3384	0.3194	0.1366	0.4673	0.7823	14.48
EarthFarseer	D	0.3004	0.0992	0.0413	0.3829	0.6327	388.91	0.3404	0.3170	0.1372	0.4726	0.7542	14.10
NowcastNet	D	0.2791	0.0770	0.0351	0.3512	0.6839	412.94	0.3427	0.3206	0.1598	0.4751	0.7879	15.64
DiffCast	D	0.3050	0.1300	**0.0582**	0.3996	0.6482	559.59	0.3512	0.3340	0.1808	0.4846	0.7887	17.93
AlphaPre	D	**0.3259**	**0.1332**	0.0545	**0.4110**	**0.6884**	**345.18**	**0.3824**	**0.3633**	**0.2002**	**0.5164**	**0.7968**	**12.74**

	Type	Shanghai						CIKM					
		CSI-M↑	CSI-35↑	CSI-40↑	HSS↑	SSIM↑	MSE↓	CSI-M↑	CSI-35↑	CSI-40↑	HSS↑	SSIM↑	MSE↓
ConvGRU	ND	0.3612	0.3163	0.2062	0.4899	0.7796	33.56	0.3091	0.2009	0.1259	0.4006	0.6507	37.13
MAU	ND	0.3983	0.3621	0.2417	0.5346	0.7195	30.40	0.3039	0.2054	0.1241	0.3928	0.6325	40.74
SimVP	ND	0.3850	0.3549	0.2382	0.5194	0.7795	34.40	0.3052	0.2044	0.1321	0.3955	0.6538	38.06
FourCastNet	ND	0.3571	0.3108	0.2073	0.4868	0.5598	32.10	0.2980	0.1849	0.1015	0.3801	0.4359	36.14
Earthformer	ND	0.3503	0.3178	0.1872	0.4844	0.7298	35.57	0.3077	0.2039	0.1369	0.4001	0.6267	36.49
PhyDNet	D	0.3654	0.3236	0.2176	0.4957	0.7751	36.41	0.3038	0.2052	0.1287	0.3931	0.6541	39.56
EarthFarseer	D	0.3926	0.3608	0.2343	0.5330	0.5405	32.68	0.3000	0.2046	0.1259	0.3911	0.6373	39.87
NowcastNet	D	0.3953	0.3608	0.2450	0.5334	0.7902	33.56	0.2991	0.1940	0.1188	0.3865	**0.6713**	40.96
DiffCast	D	0.4089	0.3740	0.2606	0.5476	0.7879	36.35	0.3159	0.2009	**0.1457**	0.4085	0.6499	42.78
AlphaPre	D	**0.4178**	**0.3854**	**0.2615**	**0.5534**	**0.7951**	**28.02**	**0.3194**	**0.2068**	0.1416	**0.4137**	0.6568	**35.18**

Experiment Results

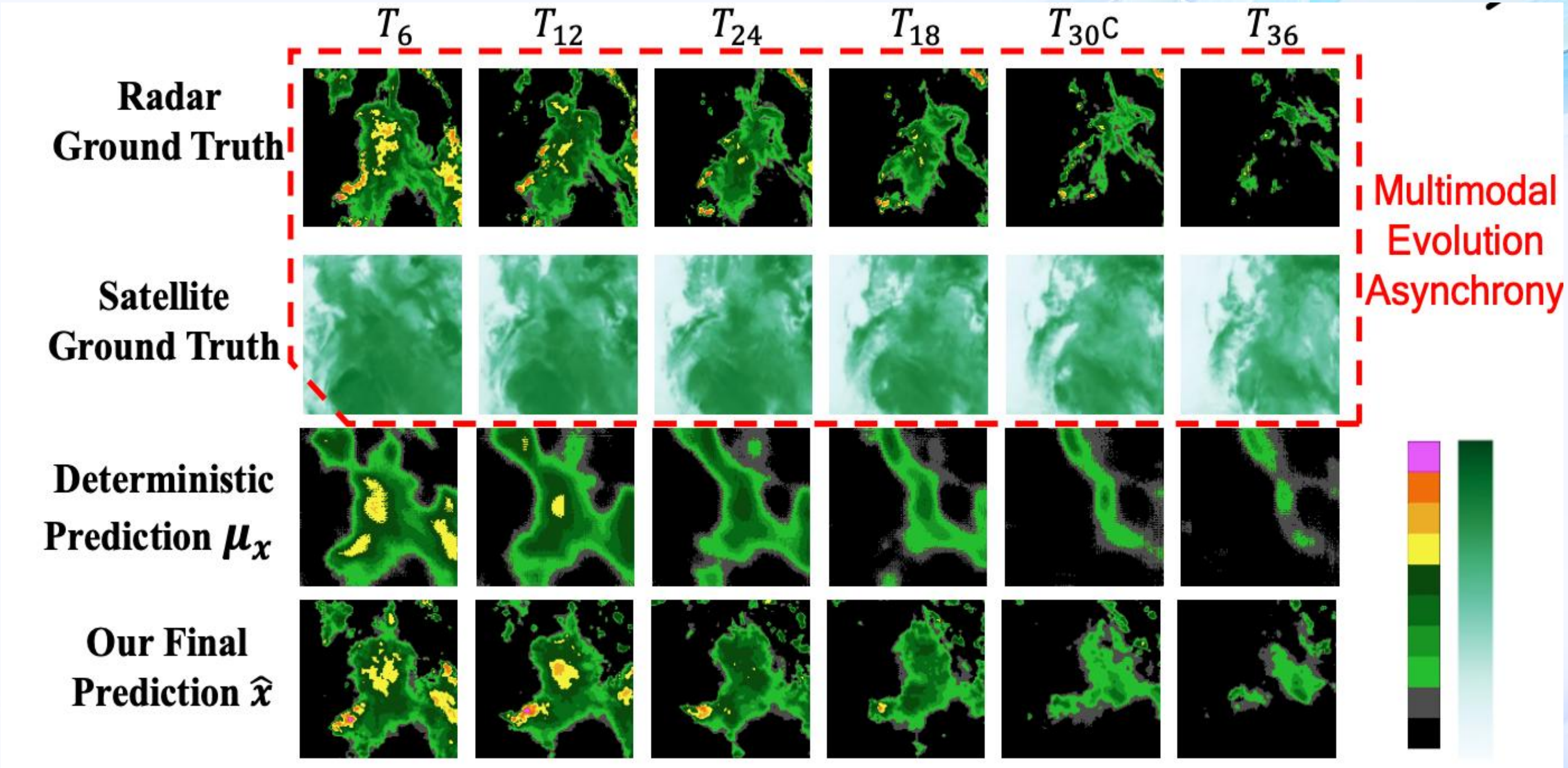


Experiment Results

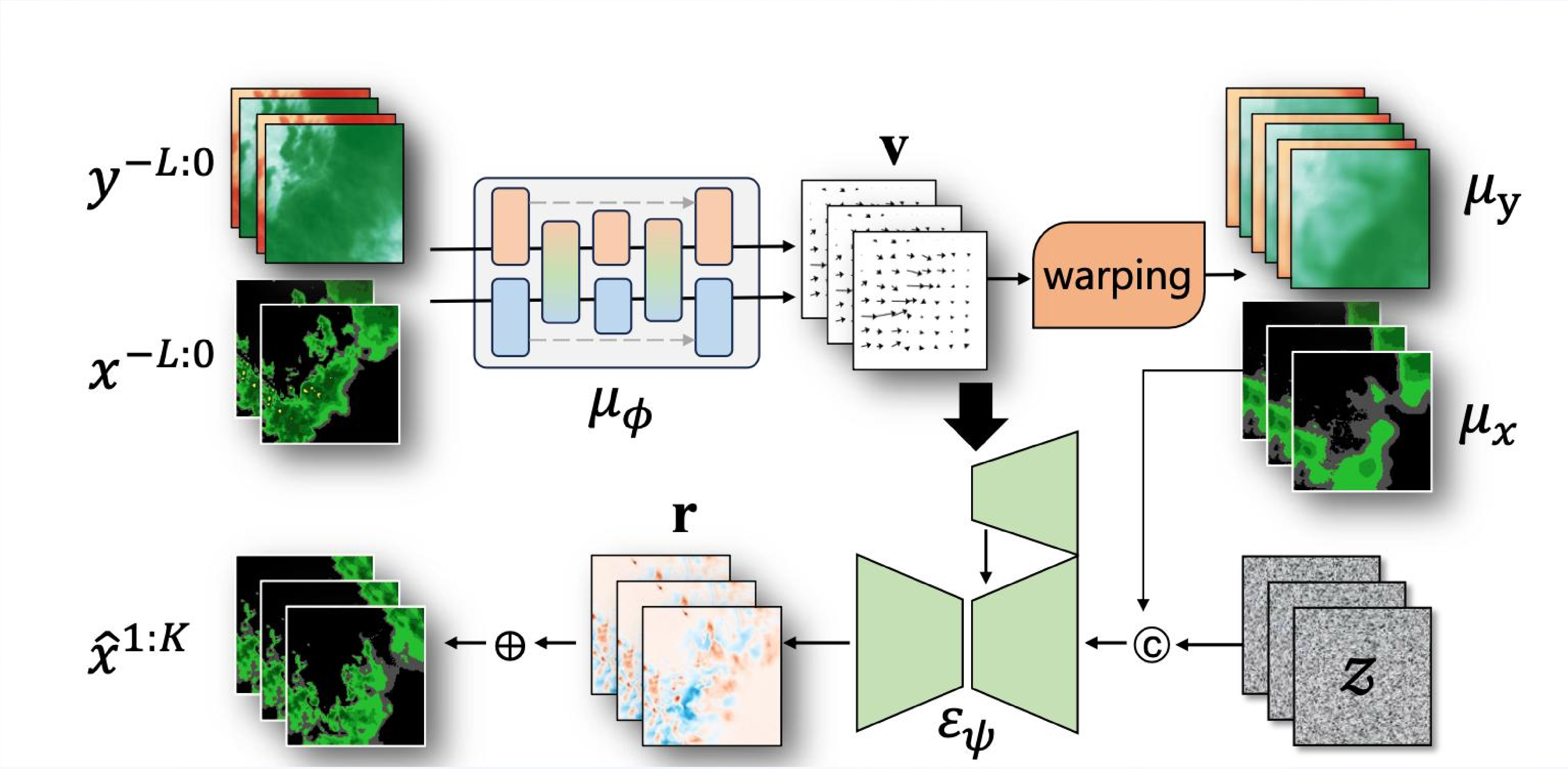


Physics-Mechanism-Guided Multi-Source Precipitation Forecasting Model

- **Challenges**:
  - How to incorporate the physical mechanism?
  - How to align the multi-model features?
  - How to robustly achieve the long-term prediction?



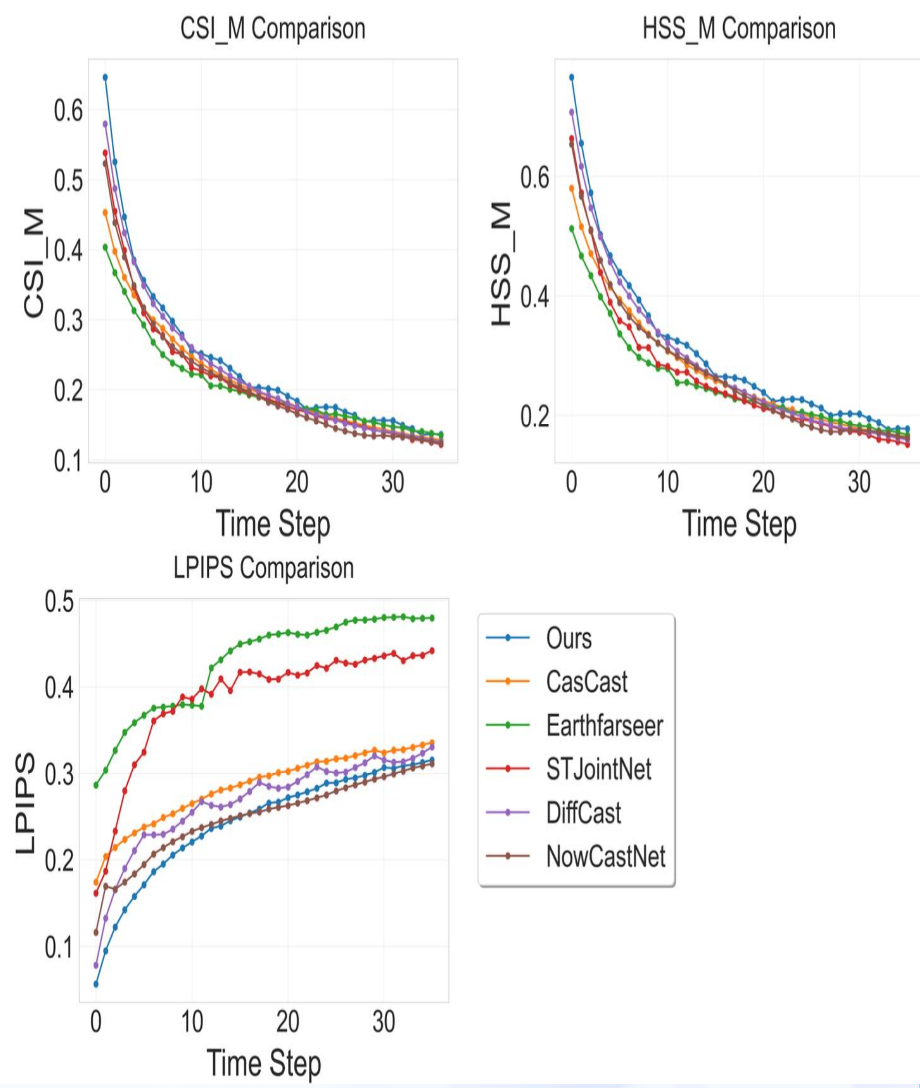
The architeture of PiMMNet



Deming Yu, Wenchuan Du, Kenghong Lin, Xutao Li, Yunming Ye, Chuyao Luo, Xunlai Chen. ***Introducing Multi-modal Precipitation Nowcasting Via a Physics-Informed Perspective*** ***. ACM MM***, 2025.

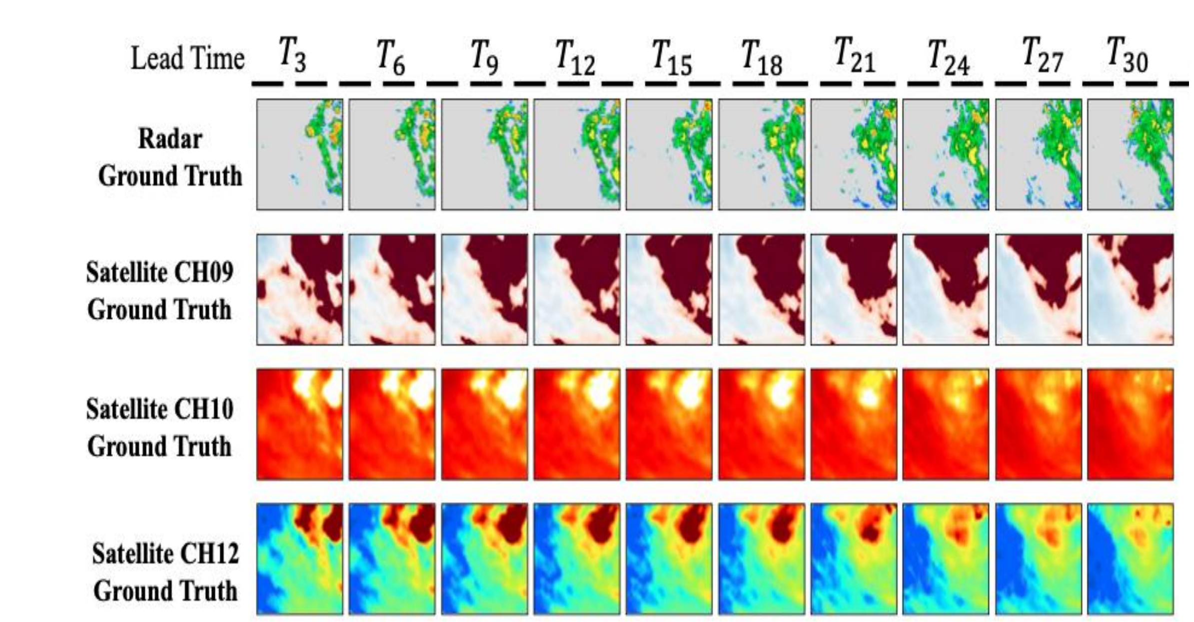
Experiment results

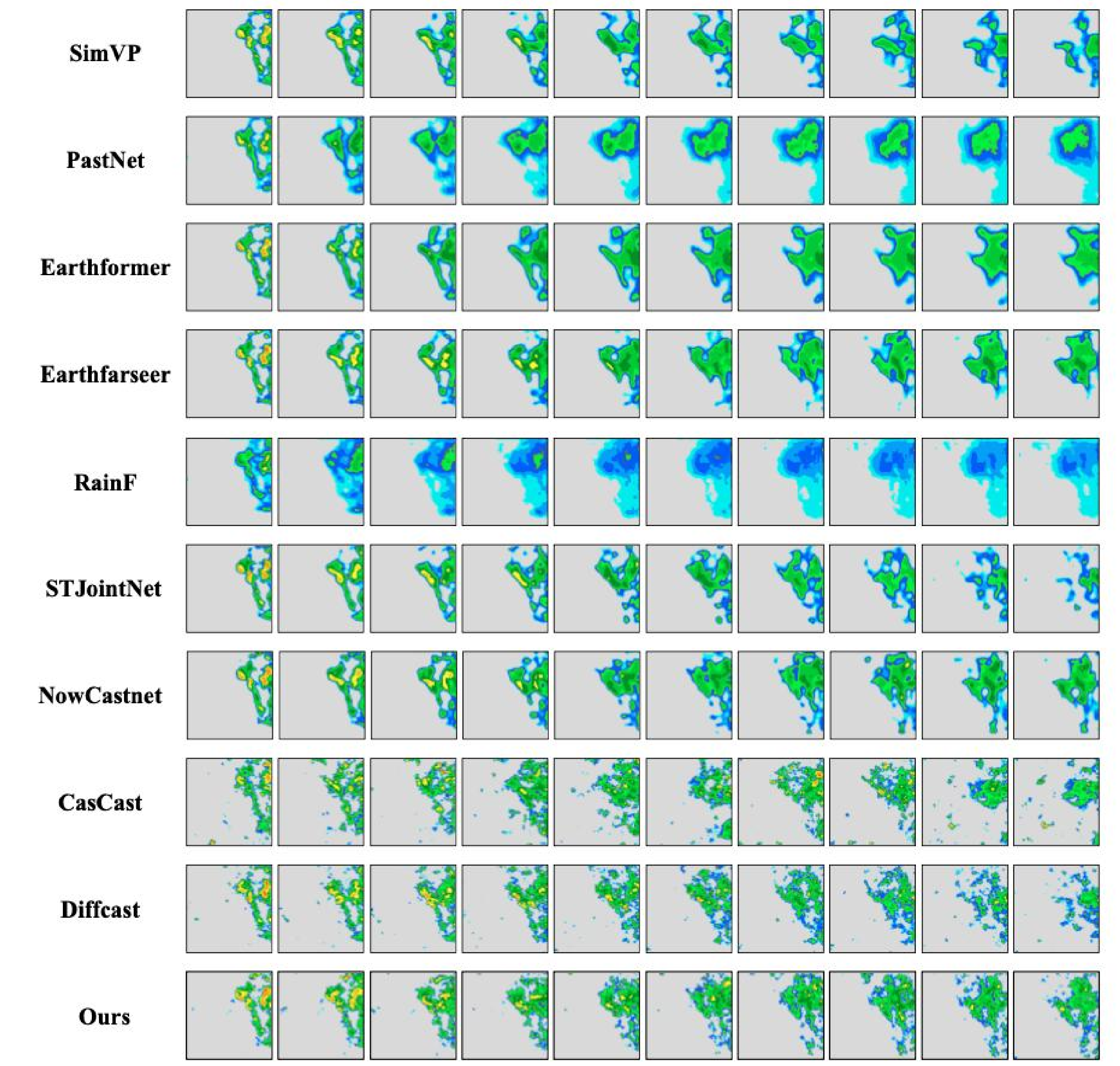
Dataset	Type	Model	Precipitation Skill HSS-m↑	CSI-m↑	CSI_4-m↑	CSI_{16}-m↑	CSI-th_{1st}↑	CSI-th_{2nd}↑	Pixel Skill LPIPS↓
SEVIR	Deterministic	SimVP	0.2403	0.1896	0.1913	0.2057	0.1198	0.0009	0.4398
		Earthformer	0.2559	0.2045	0.2113	0.2282	0.1540	0.0032	0.4276
		PastNet	0.2571	0.2053	0.2120	0.2147	0.1035	0.0047	0.4245
		Earthfarsser	0.2638	0.2078	0.2070	0.2192	0.1343	0.0069	0.4385
	Multi-modal	Rain-F	0.2481	0.2014	0.2097	0.2234	0.1150	0.0106	0.4154
		STJointNet	0.2657	0.2133	0.2291	0.2529	0.1438	0.0110	0.3858
	Generative	Nowcastnet	0.2760	0.2106	0.2549	0.3370	0.1598	0.0234	0.2487
		CasCast	0.2750	0.2134	0.2515	0.3498	0.1451	0.0287	0.2850
		DiffCast	0.2893	0.2259	0.2691	0.3601	0.1579	0.0286	0.2666
		Ours	**0.3078**	**0.2380**	**0.2838**	**0.3946**	**0.1862**	**0.0374**	**0.2428**
MMGD	Deterministic	SimVP	0.2651	0.1941	0.2089	0.2671	0.2183	0.0495	0.4534
		Earthformer	0.2569	0.1888	0.1985	0.2196	0.2137	0.0486	0.4424
		PastNet	0.2467	0.1922	0.2064	0.2277	0.2137	0.0440	0.4658
		Earthfarsser	0.2451	0.1789	0.1858	0.2227	0.1964	0.0446	0.4551
	Multi-modal	Rarin-F	0.2583	0.1861	0.1979	0.2202	0.2047	0.0523	0.5214
		STJointNet	0.2483	0.1805	0.1936	0.2266	0.2072	0.0376	0.5071
	Generative	Nowcastnet	0.2773	0.2114	**0.2801**	0.4174	0.2335	0.0802	0.2673
		CasCast	0.2631	0.1968	0.2636	**0.4559**	0.2162	0.0738	0.2765
		DiffCast	0.2790	0.2029	0.2701	0.4267	0.2231	0.0737	0.2897
		Ours	**0.2904**	**0.2230**	0.2771	0.4222	**0.2529**	**0.0808**	**0.2662**



Experiment results

- **Prediction Results**



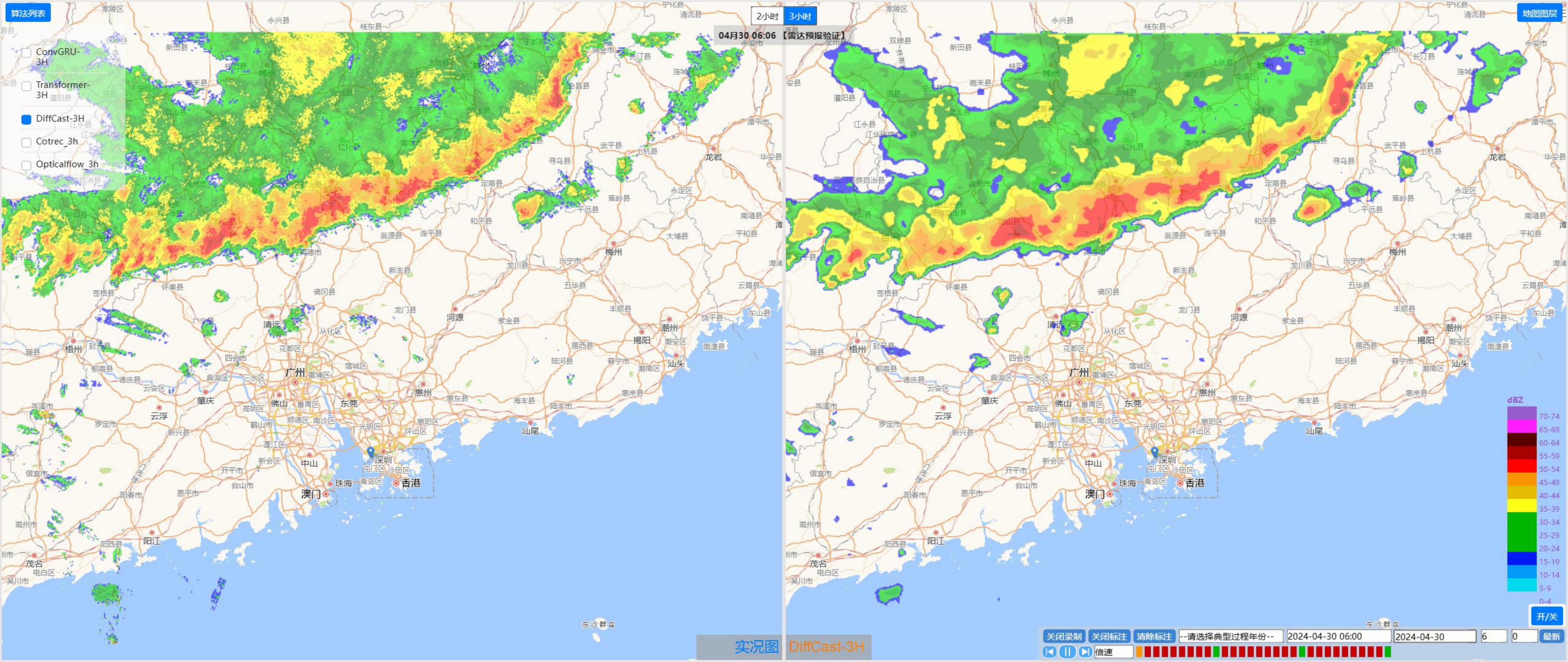


A nowcasting system on radar data

雷达检验

起报时间: 04月30 06:00

预报时间: 04月30 06:06



Thanks a lot!