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# DAWP: A framework for global observation forecasting via Data Assimilation and Weather Prediction in satellite observation space

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Anonymous Author(s)

Affiliation

Address

email

## 1 More experiment results

Table 1: More results on spatiotemporal methods. MAE error of forecasting during 3 lead time periods (0-12h, 12-24h, and 24-36h) for different channels of the satellite data. We use the unit of  $1e-5$  for AMSU-A,  $1e-4$  for MHS, and  $1e-0$  for both ATMS and HIRS.

Methods	Lead time	AMSU-A		ATMS		HIRS		MHS	
		ch0	ch1	ch0	ch1	ch9	ch10	ch0	ch1
Persistence [1]	0-12h	5.86	9.15	14.37	11.69	12.43	2.21	7.01	14.74
ConvLSTM [2]		127.82	208.90	73.21	78.44	77.40	11.05	62.27	158.57
PredRNN [3]		2.95	4.96	6.99	6.21	9.26	1.42	4.11	10.20
RainFormer [4]		3.95	6.52	9.08	8.05	10.41	1.63	4.98	11.69
EarthFormer [1]		18.97	33.94	37.33	38.75	22.49	3.62	18.00	55.04
SimVP [5]		3.61	6.02	7.29	6.61	9.84	1.53	4.68	11.35
TAU [6]		3.84	6.31	7.70	6.86	9.94	1.58	4.87	11.42
EarthNet [7]		2.93	4.89	6.96	6.14	9.15	1.39	3.96	9.65
Transformer-DOP [8]		2.67	4.48	6.40	5.61	9.22	1.42	3.91	9.48
Ours		1.92	3.39	3.36	3.27	7.70	1.12	3.07	7.91
Persistence [1]	12-24h	4.35	6.94	10.40	8.86	13.58	2.30	6.07	15.09
ConvLSTM [2]		128.13	211.14	81.22	82.60	71.64	9.98	59.26	145.44
PredRNN [3]		3.85	6.26	11.14	8.82	10.92	1.84	5.48	13.16
RainFormer [4]		11.46	15.72	19.43	17.76	18.75	3.28	11.74	32.10
EarthFormer [1]		18.98	33.96	37.33	38.76	22.50	3.62	18.01	55.03
SimVP [5]		4.83	7.74	11.48	9.10	11.49	2.02	6.43	14.20
TAU [6]		4.46	7.21	11.46	9.06	11.65	2.04	6.24	13.94
EarthNet [7]		4.12	6.65	11.25	9.00	11.14	1.98	5.46	13.11
Transformer-DOP [8]		3.84	6.14	10.04	8.04	11.08	1.95	5.19	12.65
Ours [1]		3.11	5.12	7.35	6.35	9.57	1.54	4.51	10.54
Persistence [1]	24-36h	6.39	9.84	15.37	12.52	14.61	2.61	8.00	17.86
ConvLSTM [2]		128.42	211.83	82.03	85.17	72.62	10.15	60.44	148.62
PredRNN [3]		4.58	7.23	12.18	9.69	12.03	2.08	6.24	15.04
RainFormer [4]		24.89	32.34	35.49	36.54	30.78	4.92	21.51	69.68
EarthFormer [1]		18.98	33.96	37.34	38.77	22.51	3.63	18.02	55.04
SimVP [5]		5.72	8.91	12.93	10.33	12.71	2.32	73.95	15.99
TAU [6]		5.61	8.76	13.23	10.53	12.98	2.34	7.15	15.85
EarthNet [7]		5.17	8.14	12.52	10.08	12.37	2.36	6.41	15.08
Transformer-DOP [8]		4.91	7.54	11.35	9.07	12.39	2.27	6.22	14.70
Ours		3.66	5.80	7.84	6.81	10.71	1.79	5.15	12.22

As shown in Table 1, we compare DAWP with more spatiotemporal methods including RNN-based ( [2], [3]), CNN-based ( [5], [6]), and transformer-based ( [4], [1]). Our DAWP maintains a

4 significant advantage over these methods, demonstrating the effectiveness of our AIDA module in  
5 improving the roll-out and efficiency of AIWP.

## 6 **2 Detailed dynamic visualization**

7 We provide videos of the predictions in the form of .gif. These results exhibit that our DAWP  
8 successfully simulates the long-term trend of observations, while other methods fail to capture the  
9 long-term trend.

10 Lastly, it is worth noting that the ground-truth magnitudes appear slightly weaker than the predictions.  
11 This discrepancy arises because the ground-truth data are sparse, and `ax.imshow()` fills in the gaps by  
12 interpolating using the background value.

## References

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