

PostCast: Generalizable Postprocessing for Precipitation Nowcasting via Unsupervised Blurriness Modeling



Junchao Gong*, Siwei Tu*, WeidongYang*, Ben Fei[†], Kun Chen, Wenlong Zhang, Xiaokang Yang, Wanli Ouyang, Lei Bai

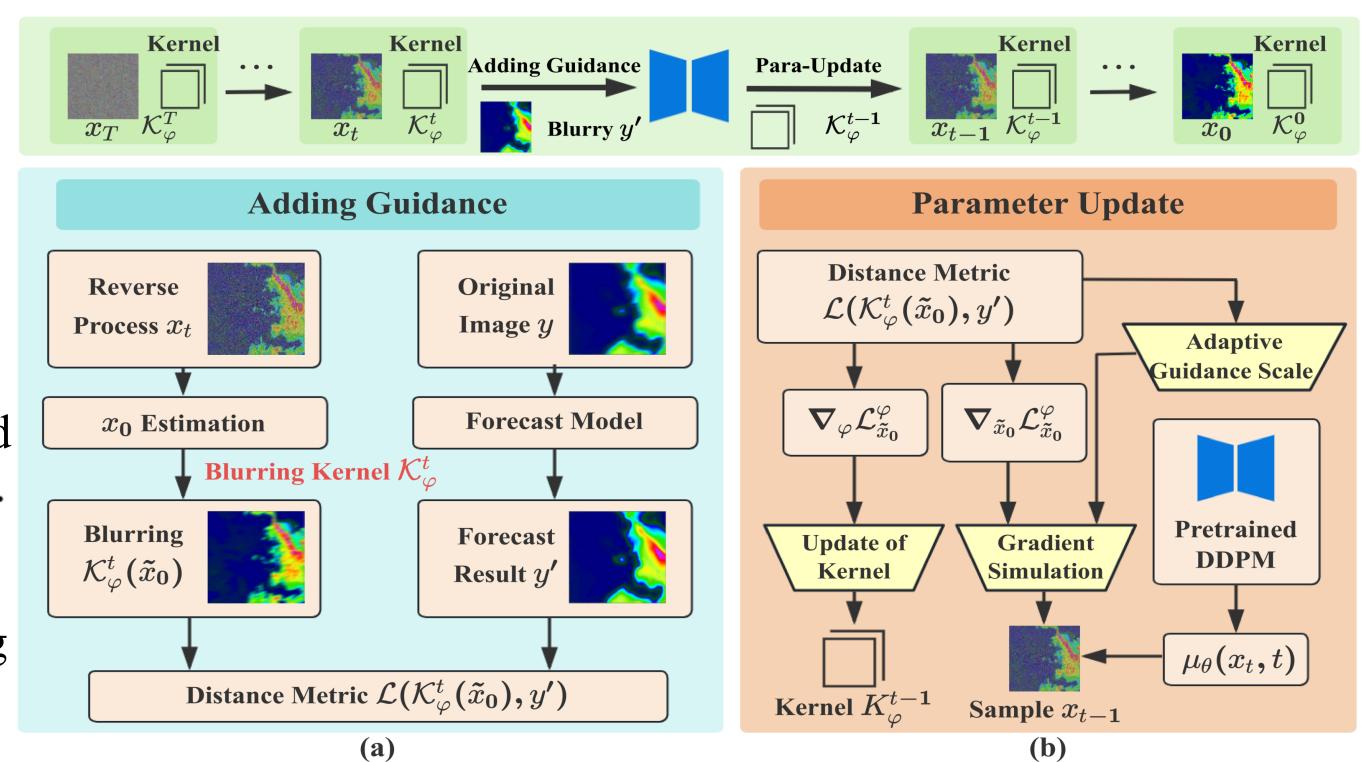
Motivation

- Deterministic models and probabilistic models are combined together for precipitation nowcasting with both accurate global trend and clear local pattern.
- However, previous combination methods suffers from limited generalization to various datasets, lead times, and deterministic models.
- Furthermore, to train the probabilistic component, the blurry predictions and the corresponding ground truth are required to be provided in advance, making the training process of the probabilistic part exhausting.

We propose a new pipeline composed of explicitly blurriness modeling with conv kernel and deblurring with an unconditional diffusion model guided by fuzzy prediction.

Blurriness modelling: blur modes in precipitation nowcasting with a unified formulation: $y' = conv(\mathcal{K}_{S,T,M}, y)$.

Unsupervised deblurring: fuzzy predictions could be tackled by solving the fuzzy inverse problem. This process is achieved by our Zero-shot blur estimation. Specifically, in each reverse diffusion step, we implement Adding Guidance and Parameter Update to guide the diffusion model generate radar images same as the fuzzy predictions after blur while estimate the parameters of blur kernel step by step. Besides, we propose an auto-scale gradient guidance strategy to adaptively set the guidance scale for each blurry mode.



Algorithm 1 Guided diffusion model with the guidance of blurry prediction y'. An unconditional diffusion model $\epsilon_{\theta}(x_t, t)$ fine-tuned on 5 datasets is given.

Input: Blurry prediction y', optimized blur kernel \mathcal{K} with parameters φ , learning rate l, guidance scale s, distance metric \mathcal{L} .

Output: Deblurred prediction x_0 conditioned on y'. Sample x_T from $\mathcal{N}(0, I)$

- 1: **for all** t from T to $\frac{1}{\sqrt{1-\bar{\alpha}_t}} \epsilon_{\theta}(x_t)$
- 2: $\tilde{x}_0 = \frac{x_t}{\sqrt{\bar{\alpha}_t}} \frac{\sqrt{1-\bar{\alpha}_t}\epsilon_{\theta}(x_t,t)}{\sqrt{\bar{\alpha}_t}}$ 3: $\mathcal{L}_{\varphi,\tilde{x}_0} = \mathcal{L}(y',\mathcal{K}_{\varphi}^t(\tilde{x}_0))$
- 4: $s = -\frac{(x_t \mu)^T g + C}{C(Kt)(\tilde{c})}$
- 5: $\tilde{x}_0 \leftarrow \tilde{x}_0 \frac{s(1-\bar{\alpha}_t)}{\sqrt{\bar{\alpha}_{t-1}}\beta_t} \nabla_{\tilde{x}_0} \mathcal{L}_{\varphi,\tilde{x}_0}$
- 6: $\tilde{\mu}_t = \frac{\sqrt{\bar{\alpha}_{t-1}}\beta_t}{1-\bar{\alpha}_t}\tilde{x}_0 + \frac{\sqrt{\bar{\alpha}_t}(1-\bar{\alpha}_{t-1})}{1-\bar{\alpha}_t}x_t$
- 7: $\tilde{\beta}_t = \frac{1 \bar{\alpha}_{t-1}}{1 \bar{\alpha}_t} \beta_t$
- 8: Sample x_{t-1} from $\mathcal{N}(\tilde{\mu}_t, \tilde{\beta}_t I)$ 9: $\varphi \leftarrow \varphi - l \nabla_{\varphi} \mathcal{L}_{\varphi, \tilde{x}_0}$
- 10: **end for**
- 11: **return** x_0

Experimental results

Improved precipitation nowcasting skill

Model	SEVIR				HKO7						TAASRAD19					
1120402	P1	P4	P16	HSS↑	POD↑	P1	P4	P16	HSS↑	POD↑	P1	P4	P16	HSS↑	POD↑	
TAU +ours	1				0.372 0.438	1					1					
PredRNN +ours	1				0.358 0.432	1					1					
SimVP +ours	ı				0.385 0.462	1					1					
EarthFormer +ours	1				0.357 0.427	1					1					
DiffCast CasCast	0.039	0.067	0.156	0.335		0.054	0.108	0.235	0.343	0.375 0.454 0.182	0.040	0.064	0.174 0.128 0.120	0.221	0.260	
DGMR STRPM			0.062 0.060		0.233	1					1				0.091 0.138	
DGP	0.020	0.042	0.070	0.372	0.355	0.039	0.083	0.187	0.372	0.328	0.018	0.041	0.094	0.238	0.196	

Zero-shot generalization on other datasets

Model	SCWDS CAP30						S	CWDS C	R		MeteoNet					
	P1	P4	P16	HSS	POD	P1	P4	P16	HSS	POD	P1	P4	P16	HSS	POD	
TAU	0.038	0.042	0.064	0.312	0.280	0.082	0.075	0.082	0.413	0.384	0.001	0.003	0.016	0.272	0.240	
+CasCast	0.067	0.102	0.224	0.306	0.315	0.101	0.145	0.258	0.380	0.377	0.029	0.067	0.128	0.271	0.294	
+DiffCast	0.023	0.050	0.166	0.157	0.235	0.051	0.101	0.245	0.232	0.554	0.006	0.015	0.063	0.079	0.065	
+ours	0.075	0.126	0.269	0.345	0.428	0.143	0.214	0.338	0.444	0.549	0.024	0.059	0.182	0.288	0.344	
PredRNN	0.003	0.004	0.008	0.239	0.203	0.040	0.043	0.066	0.351	0.323	0.000	0.000	0.002	0.230	0.190	
+CasCast	0.035	0.056	0.129	0.252	0.231	0.086	0.139	0.283	0.337	0.390	0.010	0.030	0.101	0.249	0.238	
+DiffCast	0.017	0.035	0.102	0.157	0.235	0.066	0.105	0.230	0.349	0.341	0.006	0.019	0.076	0.241	0.215	
+ours	0.060	0.126	0.267	0.331	0.351	0.140	0.206	0.315	0.405	0.485	0.022	0.050	0.148	0.283	0.298	
SimVP	0.025	0.026	0.035	0.312	0.276	0.056	0.046	0.041	0.410	0.373	0.000	0.000	0.002	0.281	0.245	
+CasCast	0.069	0.111	0.226	0.314	0.319	0.098	0.134	0.242	0.382	0.364	0.030	0.053	0.149	0.282	0.305	
+DiffCast	0.024	0.044	0.129	0.224	0.201	0.047	0.071	0.169	0.295	0.280	0.017	0.037	0.105	0.240	0.216	
+ours	0.085	0.136	0.255	0.367	0.436	0.140	0.205	0.296	0.459	0.545	0.025	0.054	0.147	0.316	0.391	
EarthFormer	0.021	0.024	0.036	0.298	0.258	0.072	0.065	0.063	0.417	0.406	0.000	0.003	0.008	0.259	0.219	
+CasCast	0.050	0.089	0.190	0.296	0.287	0.100	0.130	0.223	0.381	0.383	0.019	0.055	0.159	0.266	0.265	
+DiffCast	0.041	0.071	0.175	0.299	0.278	0.101	0.144	0.268	0.407	0.417	0.009	0.029	0.096	0.263	0.243	
+ours	0.070	0.117	0.241	0.350	0.404	0.141	0.211	0.326	0.444	0.570	0.019	0.058	0.164	0.287	0.320	
DGMR	0.018	0.048	0.160	0.161	0.153	0.039	0.090	0.240	0.207	0.208	0.019	0.057	0.192	0.123	0.131	
STRPM	0.014	0.049	0.160	0.234	0.197	0.029	0.080	0.201	0.296	0.264	0.014	0.046	0.145	0.192	0.155	
DGP	0.027	0.059	0.111	0.294	0.258	0.071	0.083	0.099	0.409	0.397	0.037	0.082	0.186	0.250	0.218	

Visualization with different lead times and datasets

