

ESC-GAN: Extending Spatial Coverage of Physical Sensors

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Outline

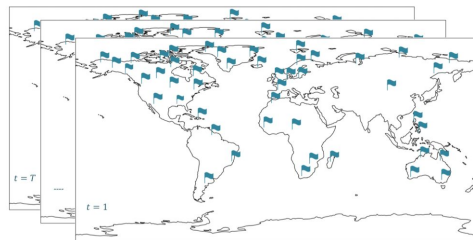
- Motivation
- Method
- Experiments
- Conclusion

Outline

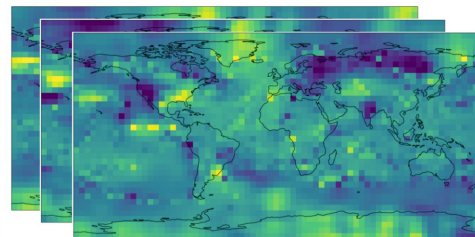
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Background

- Geo-sensors help monitor our ecosystem
 - Global warming, flood forecasting, agriculture
- However, geo-sensors are sparsely deployed!
 - Physical constraints, economic costs
- **Extend the Spatial Coverage of sensory data without deploying additional sensors**



(a) Original Station Data



(b) Extended Data

Challenges & Opportunities

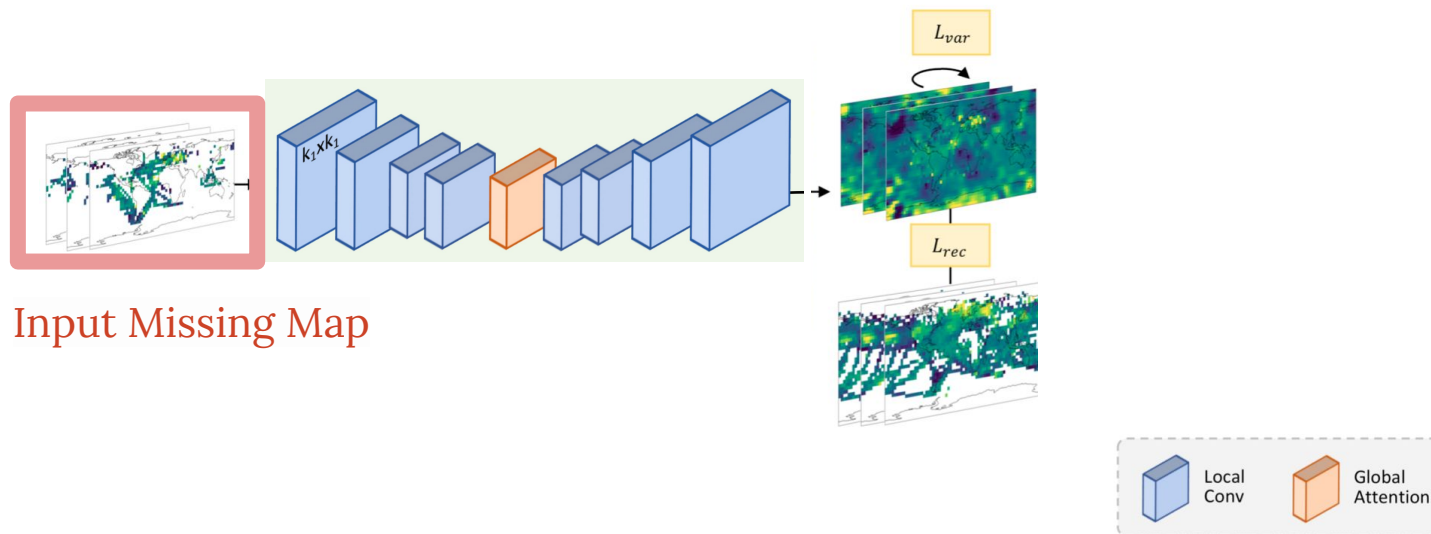
- Complete miss of temporal information
 - Fundamentally different from traditional imputation task
- Existence of local and global context
- Multi-scale structure
 - Fine-grained data for accurate local patterns
 - Coarse-grained data for “macro” view

Outline

- Motivation
- **Method**
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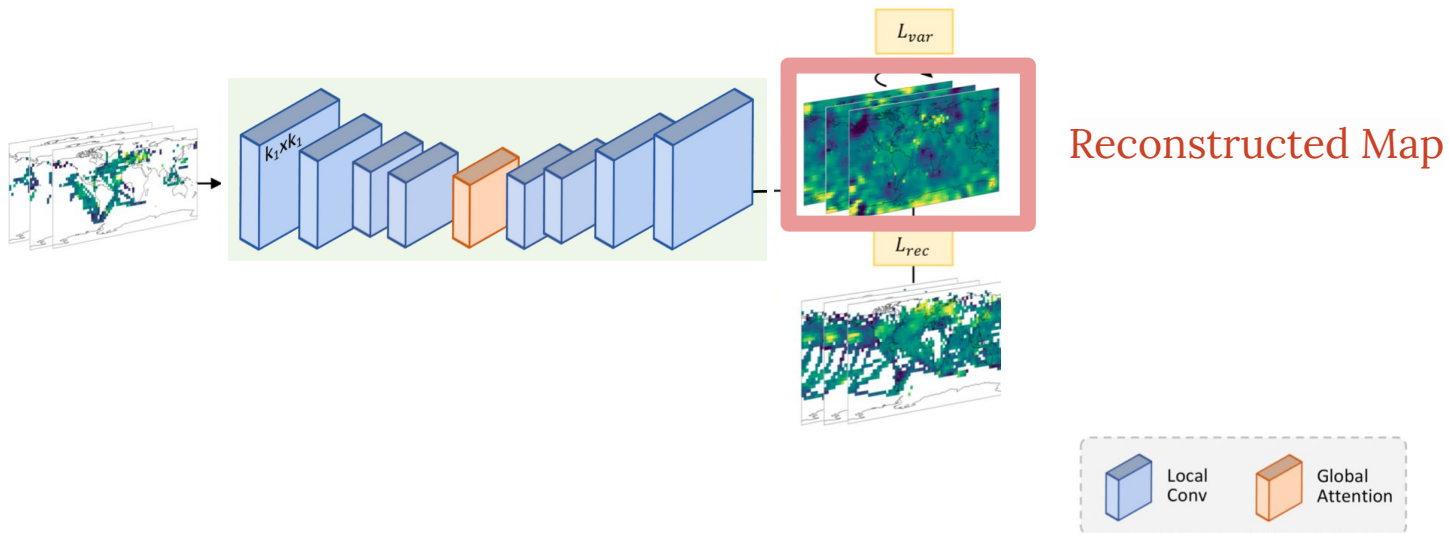
Model

- Local 3D Convolution paired with Global Attention Module



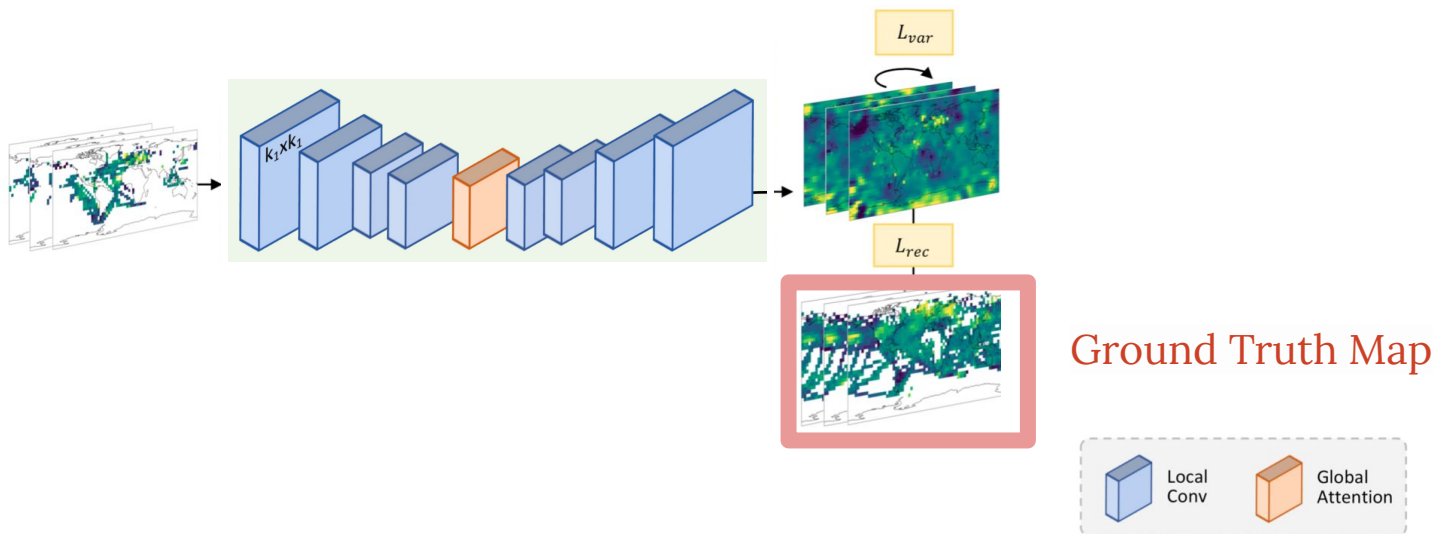
Model

- Local 3D Convolution paired with Global Attention Module



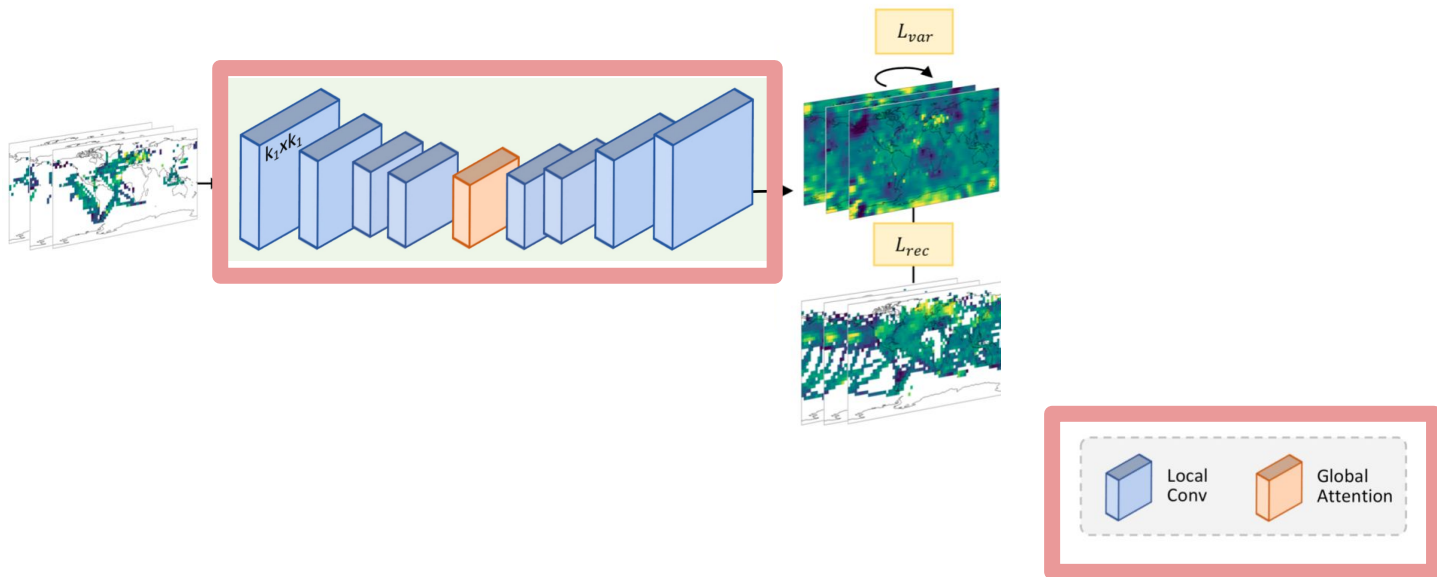
Model

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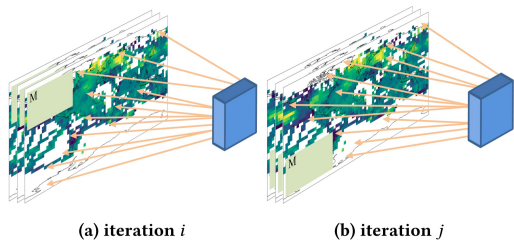
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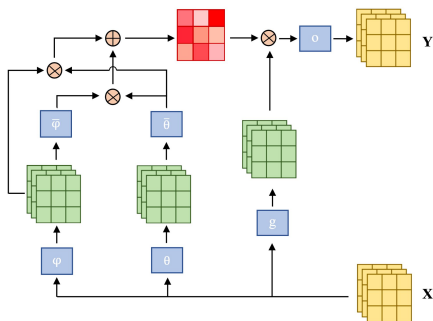
Model

- Local 3D Partial Convolution



$$Y = \begin{cases} \mathbf{W}^T (\mathbf{X} \odot \mathbf{M}) \frac{\mathbf{1}_1}{|\mathbf{M}|_1} + b, & \text{if } |\mathbf{M}|_1 > 0 \\ 0, & \text{otherwise.} \end{cases}$$

- Global Attention Module

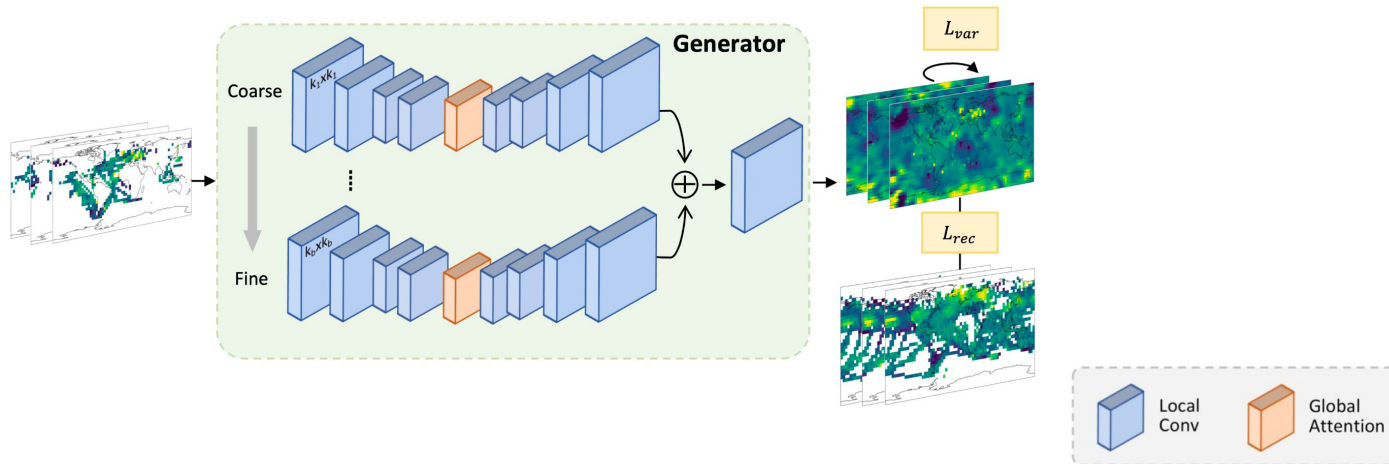


$$f(\mathbf{X}, \mathbf{X}') = \frac{e^{(\theta(\mathbf{X}) - \mu_\theta)^T (\phi(\mathbf{X}') - \mu_\phi) + \mu_\theta^T \phi(\mathbf{X}')}}{\sum_{\mathbf{X}'} e^{(\theta(\mathbf{X}) - \mu_\theta)^T (\phi(\mathbf{X}') - \mu_\phi) + \mu_\theta^T \phi(\mathbf{X}')}}$$

$$O_{t,y,x} = \sum_{\forall t',y',x'} f(X_{t,y,x}, X_{t',y',x'}) g(X_{t',y',x'})$$

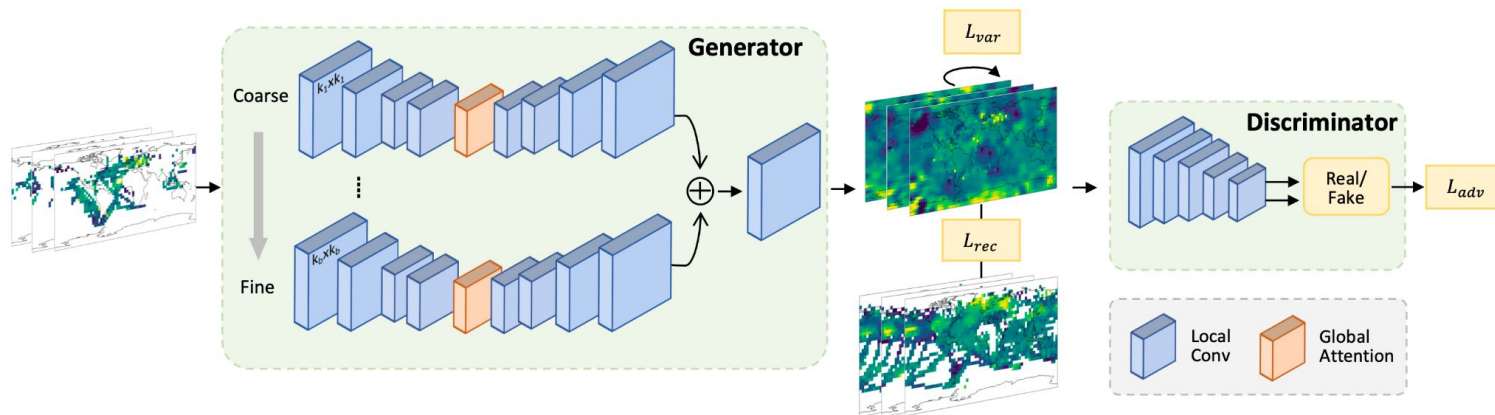
Model

- Multi-scale Structure



Model

- Irregular and stochastic forms, high variations
- Generative Adversarial Network (GAN)
- Generator, Discriminator, adversarial training



Optimization

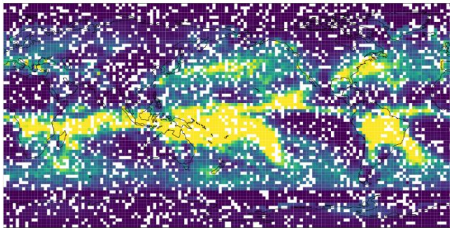
- Reconstruction Loss $L_{rec} = \frac{1}{N_{masked}} \sum_t \sum_y \sum_x (1 - M_{t,y,x}) (Z_{t,y,x} - X_{t,y,x})^2$
- Variation Loss
$$L_{var} = \frac{1}{N} \left(\sum_{(y,x) \in R, (y+1,x) \in R} \|\tilde{X}_{t,y+1,x} - \tilde{X}_{t,y,x}\|_1 \right. \\ \left. + \sum_{(y,x) \in R, (y,x+1) \in R} \|\tilde{X}_{t,y,x+1} - \tilde{X}_{t,y,x}\|_1 \right)$$
- Adversarial Loss $L_D = \mathbb{E}_{\mathbf{x} \sim P_X(\mathbf{x})} [RELU(1 - D(\mathbf{x}))] + \mathbb{E}_{\mathbf{z} \sim P_Z(\mathbf{z})} [RELU(1 + D(\mathbf{z}))]$
 $L_{adv} = L_G = -\mathbb{E}_{\mathbf{z} \sim P_Z(\mathbf{z})} [D(\mathbf{z})]$
- Objective $L = L_{rec} + \lambda_{var} L_{var} + \lambda_{adv} L_{adv}$

Outline

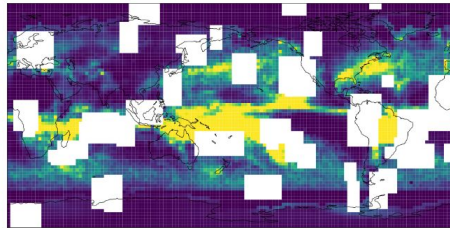
- Motivation
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Dataset

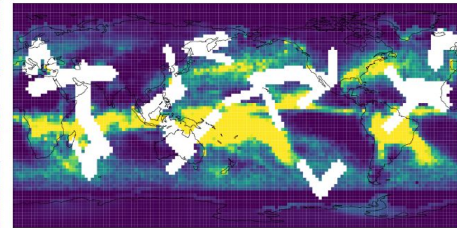
Dataset	Lat	Lon	Time	Granularity	#Grid Cells
HadCRUT	36	72	2004	$5^{\circ} \times 5^{\circ}$	5,194,368
CMAP	72	144	503	$2.5^{\circ} \times 2.5^{\circ}$	5,215,104
KDD CUP 2018	6	8	8736	$0.0167^{\circ} \times 0.0175^{\circ}$	96096



(a) Scatter



(b) Regular Cluster



(c) Irregular Cluster

Main Results

Method	HadCRUT						CMAP					
	Scatter		Reg Cluster		Irr Cluster		Scatter		Reg Cluster		Irr Cluster	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Zero	1.0396	0.6638	0.8551	0.5983	0.7446	0.5879	1.0290	0.6830	1.2861	0.7620	1.2869	0.7390
Mean	0.9697	0.6375	0.7985	0.5744	0.6971	0.5677	1.0272	0.6804	1.3294	0.7548	1.2969	0.7364
sKNN	0.3756	0.3991	0.4645	0.4649	0.3791	0.4210	0.1120	0.1785	0.7159	0.4863	0.4888	0.3960
IDW	<u>0.3524</u>	<u>0.3868</u>	0.4440	0.4535	0.3596	0.4087	0.1042	0.1719	0.7036	0.4792	0.4658	0.3839
Kriging	0.9517	0.6308	0.7995	0.5767	0.6906	0.5703	0.8838	0.5863	0.9709	0.6279	1.1257	0.6545
MF	0.6181	0.5216	0.7669	0.5782	0.6111	0.5390	0.1721	0.2395	0.8583	0.5753	0.5942	0.4974
BTF	0.5867	0.5225	0.6798	0.5553	0.5764	0.5332	0.2474	0.3137	0.9423	0.6237	0.5723	0.5154
ST-MVL	0.3648	0.3964	0.4710	0.4655	<u>0.3581</u>	0.4084	0.1162	0.1832	0.7202	0.4919	0.5039	0.4177
IGKNN	0.7214	0.5492	0.7212	0.5501	0.6405	0.5491	0.8474	0.6132	1.1710	0.7285	1.1254	0.7170
NAOMI	1.0391	0.6637	0.8550	0.5983	0.7442	0.5877	1.0288	0.6833	1.2859	0.7620	1.2863	0.7396
PConv	0.3908	0.4211	0.4759	0.4784	0.4122	0.4494	<u>0.1008</u>	<u>0.1704</u>	0.6469	0.4492	0.2969	<u>0.3024</u>
3DGated	0.3610	0.3907	<u>0.4265</u>	<u>0.4454</u>	<u>0.3581</u>	0.4066	0.1400	0.2071	<u>0.5532</u>	<u>0.4381</u>	0.2952	0.3033
ESC-GAN	0.3354	0.3800	0.4097	0.4295	0.3418	0.3971	0.0802	0.1531	0.5441	0.4308	0.2739	0.3017

Main Results

Method	HadCRUT						CMAP					
	Scatter		Reg Cluster		Irr Cluster		Scatter		Reg Cluster		Irr Cluster	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Zero	1.0396	0.6638	0.8551	0.5983	0.7446	0.5879	1.0290	0.6830	1.2861	0.7620	1.2869	0.7390
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sKNN	0.3756	0.3991	0.4645	0.4649	0.3791	0.4210	0.1120	0.1785	0.7159	0.4863	0.4888	0.3960
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Kriging	0.9517	0.6308	0.7995	0.5767	0.6906	0.5703	0.8838	0.5863	0.9709	0.6279	1.1257	0.6545
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IGKNN	0.7214	0.5492	0.7212	0.5501	0.6405	0.5491	0.8474	0.6132	1.1710	0.7285	1.1254	0.7170
NAOMI	1.0391	0.6637	0.8550	0.5983	0.7442	0.5877	1.0288	0.6833	1.2859	0.7620	1.2863	0.7396
PConv	0.3908	0.4211	0.4759	0.4784	0.4122	0.4494	<u>0.1008</u>	<u>0.1704</u>	0.6469	0.4492	0.2969	<u>0.3024</u>
3DGated	0.3610	0.3907	<u>0.4265</u>	<u>0.4454</u>	<u>0.3581</u>	0.4066	0.1400	0.2071	<u>0.5532</u>	<u>0.4381</u>	0.2952	0.3033
ESC-GAN	0.3354	0.3800	0.4097	0.4295	0.3418	0.3971	0.0802	0.1531	0.5441	0.4308	0.2739	0.3017

Main Results

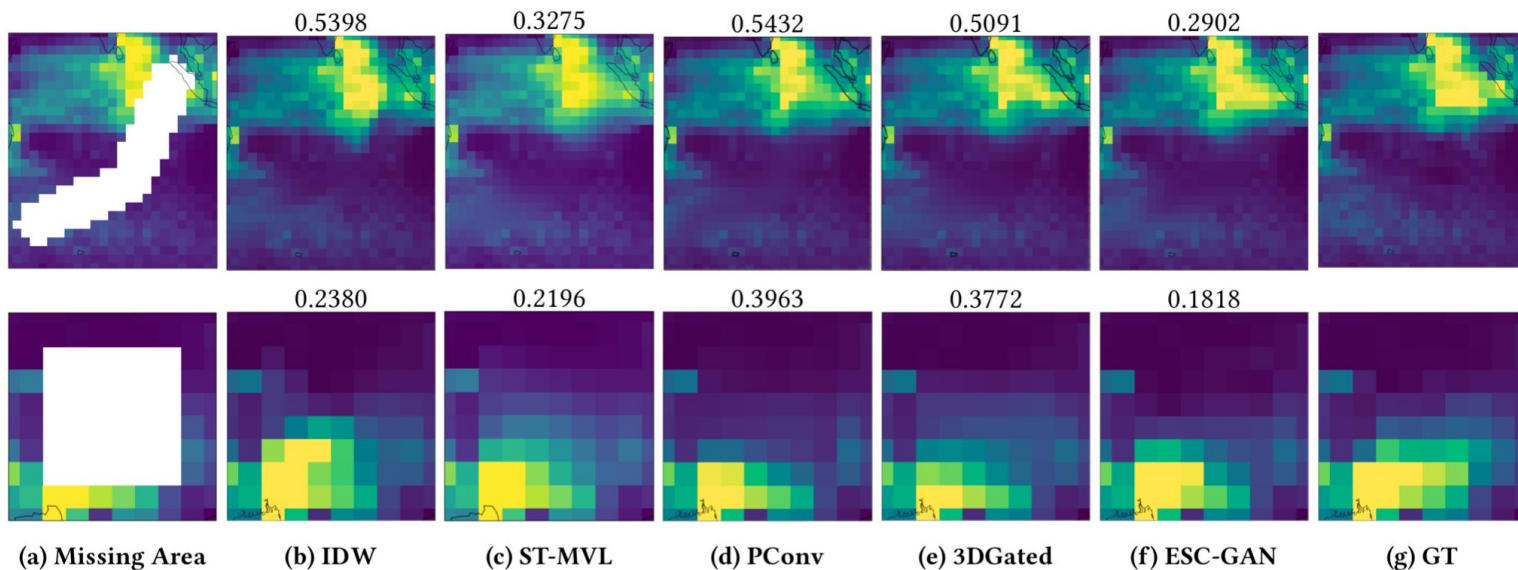
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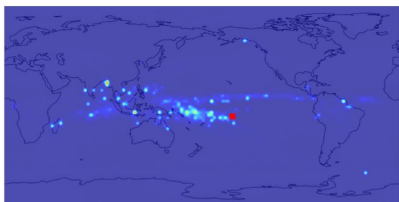
Qualitative Results

Numbers above figures are Mean Square Errors

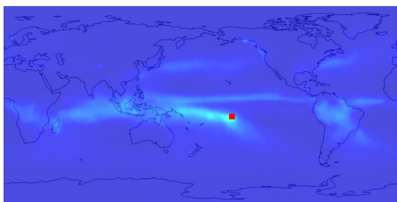


Ablation & Visualization

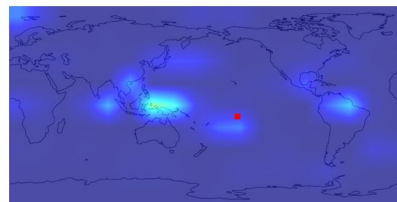
Method	Scatter		Reg Cluster		Irr Cluster	
	MSE	MAE	MSE	MAE	MSE	MAE
ESC-GAN-vanilla	0.0825	0.1557	0.5874	0.4433	0.2900	0.3099
ESC-GAN-local	0.0818	0.1545	0.5848	0.4362	0.2785	0.3032
ESC-GAN-single	0.0842	0.1588	0.5814	0.4388	0.2880	0.3107
ESC-GAN	0.0802	0.1531	0.5441	0.4308	0.2739	0.3017



(a) Dot Product GT

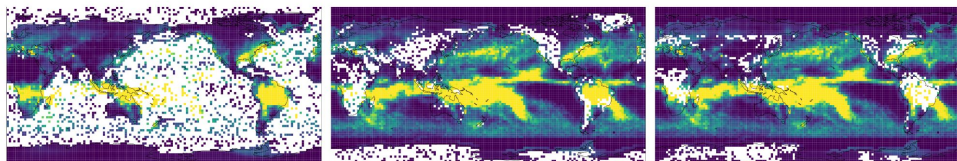


(b) Cosine GT



(c) ESC-GAN

Robustness to Missing Patterns



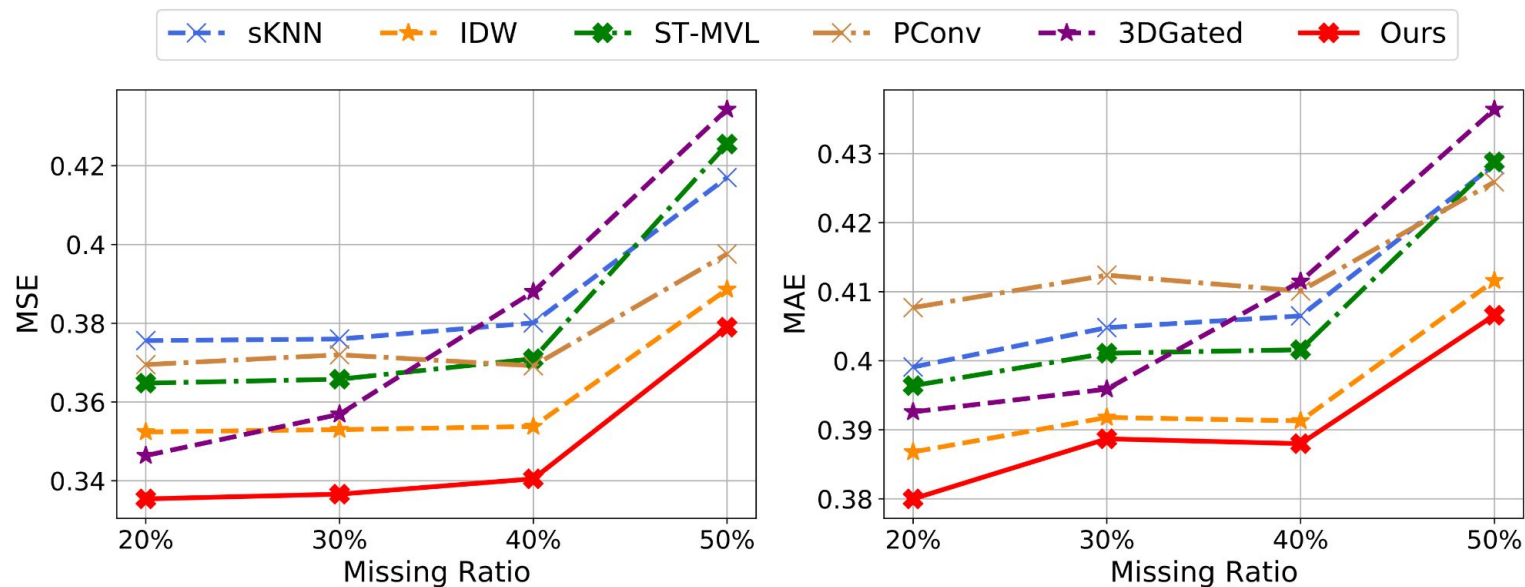
(a) Ocean

(b) High-altitude

(c) High-vegetation

Method	Ocean		High-altitude		High-vegetation	
	MSE	MAE	MSE	MAE	MSE	MAE
sKNN	0.3162	0.3160	0.0865	0.1428	0.1857	0.2178
IDW	0.2738	0.2929	0.0786	0.1335	0.1687	0.2060
ST-MVL	0.2855	0.2972	0.0784	0.1347	0.1710	0.2061
PConv	0.2174	0.2517	0.0743	0.1303	0.1588	0.2004
3DGated	0.2989	0.3093	0.1231	0.1878	0.2254	0.2644
ESC-GAN	0.1929	0.2512	0.0663	0.1234	0.1399	0.1911

Robustness to Missing Ratios



Generalization to Random Missing

%Missing	20%	30%	40%	50%	60%	70%	80%	90%
Last	1.073	0.894	0.901	0.990	1.040	1.236	1.689	2.870
Mean	0.916	0.907	0.914	0.923	0.973	0.935	0.937	1.002
KNN	0.892	0.803	0.776	0.798	0.856	0.852	0.873	1.243
MF	0.850	0.785	0.787	0.772	0.834	0.805	0.860	1.196
MTSI	0.844	0.780	0.753	0.743	0.803	0.780	0.837	1.018
BRITS	0.455	0.421	0.372	0.409	0.440	0.482	0.648	0.725
DCRNN	0.579	0.565	0.449	0.506	0.589	0.622	0.720	0.861
CDSA	0.373	0.393	0.287	0.291	0.387	0.495	0.521	0.631
ESC-GAN	0.207	0.229	0.232	0.231	0.274	0.299	0.326	0.434

Outline

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- **Conclusion**

Conclusion

- Extending Spatial Coverage (ESC) of sensory data to locations without historical values
- How to address challenges in ESC task?
 - Local and global context
 - Structure across multiple scales
 - Adversarial training
- Extensive experiments on geo-sensory datasets demonstrate state-of-the-art performance^{1, 2}

1. https://xiyuanzh.github.io/assets/publications/WSDM22_ESC_GAN.pdf
2. <https://github.com/xiyuanzh/ESC-GAN>

Thanks!

Q & A