Physics-Guided Learning of Meteorological Dynamics for Weather Downscaling and Forecasting

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Prob: Unavailable Physical Terms

Deep learning models do not incorporate established physical laws (e.g., fluid dynamics, thermodynamics) to ensure that the model prediction is consistent with these laws.

However, incorporating physical laws requires a complete library of involved physical terms. Some terms are unavailable in typical weather datasets such as ERA5.

For instance, the PDE governing temperature evolution (from the 3D convection-diffusion equation for heat transfer)

$$\frac{\partial T}{\partial t} = \underbrace{-U\frac{\partial T}{\partial x} - V\frac{\partial T}{\partial y} - W\frac{\partial T}{\partial z}}_{\text{Advection}} + \underbrace{k\frac{\partial^2 T}{\partial z^2}}_{\text{Diffusion}} + \underbrace{H}_{\text{Source}}$$

Advection: movement of heat due to fluid flow, where vertical component is estimated.
Diffusion: spread of heat due to thermal diffusivity, where the diffusivity needs to be estimated.
Heat source: radiative heating, sensible heat fluxes, etc., which needs to be estimated.

Terms like thermal diffusivity k are unavailable in the data and must be estimated through parameterizations and assimilation.

Other instances include but are not limited to:

(1) Wind Velocity Components

$$\frac{\partial U}{\partial t} = -U\frac{\partial U}{\partial x} - V\frac{\partial U}{\partial y} - W\frac{\partial U}{\partial z} - \frac{1}{\rho}\frac{\partial p}{\partial x} + \nu\Delta\mathbf{u} + F_{f_x}$$

(2) Surface Pressure

$$\frac{\partial^2 p}{\partial t^2} = \frac{\partial^2 p}{\partial x^2} + \frac{\partial^2 p}{\partial y^2} + \frac{\partial^2 p}{\partial z^2}$$

(3) Humidity

$$\frac{\partial q}{\partial t} = -U\frac{\partial q}{\partial x} - V\frac{\partial q}{\partial y} - W\frac{\partial q}{\partial z} + \nabla(K_q\nabla q) + S_q$$

Sol: Meteorology with Latent Force

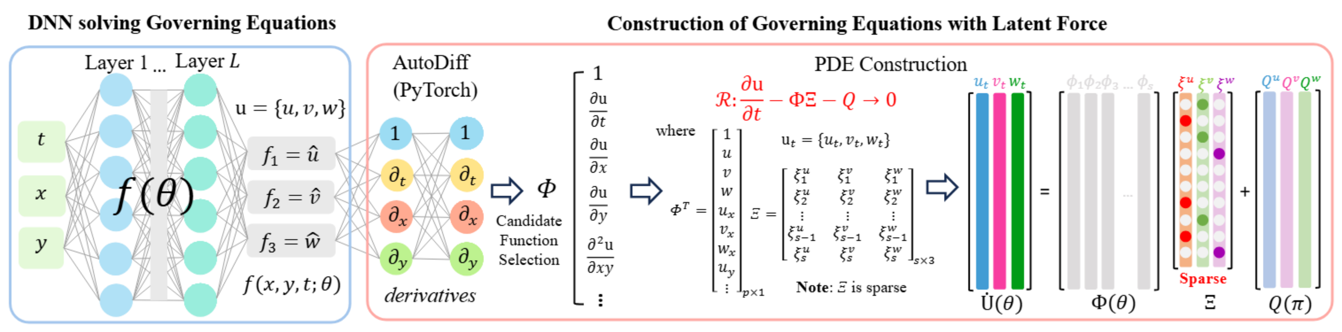


Figure 1: Schematic diagram of *PhyDL-NWP* for downscaling. First, given a continuous input coordinate (x, y, t), the surrogate model f_θ approximates the weather data. Then, based on PyTorch's auto-differentiation and the existing meteorology theory, we calculate the derivatives for the construction of physical mechanisms driven by PDE. Last, based on linear regression, we learn the PDE that fits the weather data well to provide physical guidance.

Governing equation can be parameterized:

$$\frac{\partial \mathrm{u}}{\partial t} = \underbrace{Q_\pi(x,y,t)}_{\text{Latent force}} + \underbrace{\Phi(\mathrm{u})\Xi}_{\text{Explicit terms}} = Q_\pi(x,y,t) + \sum_{i=1}^{p}\phi(\mathrm{u})_i\xi_i,$$

Latent force: terms unavailable from the data, and to be estimated by neural networks.
Explicit terms: terms derivable/calculable from the data directly.

Weather variables can be predicted via a surrogate model:

$$\hat{\mathrm{u}} = f_\theta(x, y, t)$$

u: the actual weather variable values in the dataset.
f: the latent model that solves the governing equation to approximate the actual weather u.
All the equation terms can be approximated by automatic differentiation on f, instead of u.

Weather Downscaling in Arbitrary Coordinate

$f(x,y,t)$: **continuous** function over **any spatiotemporal coordinate**
(1) **Arbitrary-resolution** inference
(2) Without coarse-resolution inputs
(3) Without pre-defined grid structures

Model performance (RMSE) is new current state-of-the-art:

Model	100m Wind (U)		10m Wind (U)		Temperature		Surface Pressure		Average	
	2x	4x	2x	4x	2x	4x	2x	4x	2x	4x
Bicubic	1.687	1.765	1.215	1.272	1.714	1.848	0.818	1.220	1.515	1.654
EDSR	1.145	1.176	1.020	1.113	1.217	1.275	0.460	0.552	1.068	1.156
ResDeepD	1.092	1.111	1.003	1.079	1.182	1.204	0.301	0.317	1.010	1.043
RCAN	1.169	1.199	0.808	1.038	1.219	1.259	0.572	0.609	1.092	1.144
FSRCNN	1.197	1.202	1.090	1.126	1.198	1.233	0.430	0.560	1.093	1.149
YNet	1.116	1.125	0.947	1.103	1.192	1.226	0.467	0.575	1.062	1.125
DeepSD	1.205	1.216	1.020	1.117	1.218	1.265	0.454	0.591	1.087	1.149
GINE	1.126	1.285	0.875	1.069	1.166	1.235	0.350	0.363	1.036	1.101
PhyDL-NWP	**0.973**	**0.970**	**0.696**	**0.693**	**0.905**	**0.904**	**0.211**	**0.216**	**0.794**	**0.789**
Improv	10.9%	12.7%	13.9%	33.2%	22.4%	24.9%	29.9%	31.9%	20.1%	24.6%

Guiding Weather Forecasting Models

PhyDL-NWP is **a light-weighted plug-and-play module** that can be to finetune a large-scale weather forecasting foundation model.

Table 1: Comparison of the number of model parameters and running speed for weather forecasting on WeatherBench dataset. *PhyDL-NWP* is a light-weighted and efficient plug-and-play module, while others are standalone models. *PhyDL-NWP* is about 55~170 times faster and 10~3600 times lighter than a standalone model.

Model/Module	PhyDL-NWP	BiLSTM	Hybrid-CBA	ConvLSTM	AFNO	MTGNN	MegaCRN	ClimaX	FourcastNet	GraphCast
Number of parameters	**55K**	171M	198M	678K	520K	1.6M	580K	107M	73M	36M
Time cost per epoch	**7.8s**	11.9min	15.6min	7.1min	9.4min	9.9min	8.5min	22.2min	16.5min	13.6min

Challenge:
f_θ alone does not exhibit strong extrapolation/forecasting performance, as f_θ is only trained on historical weather data, while anywhere outside the bounds of where the model was trained is completely unknown.

However, the learned governing equation with latent force is universal, and can still help guide the optimization of weather forecasting.

PhyDL-NWP can adjust data resolution to adapt any weather forecasting model, using the weather downscaling. Then, calculate the governing equation and use it as a physical regularization to guide the forecasting.

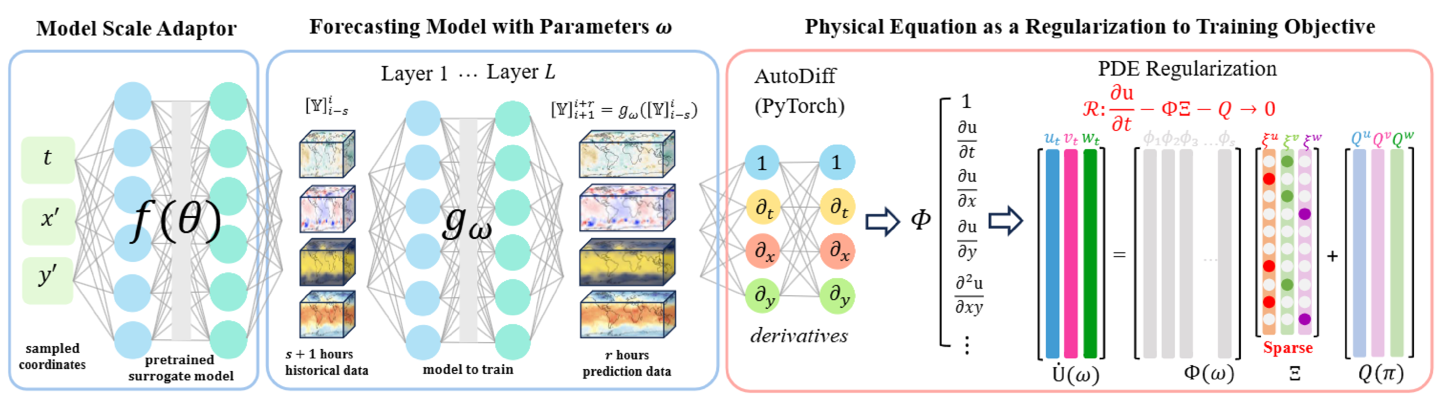
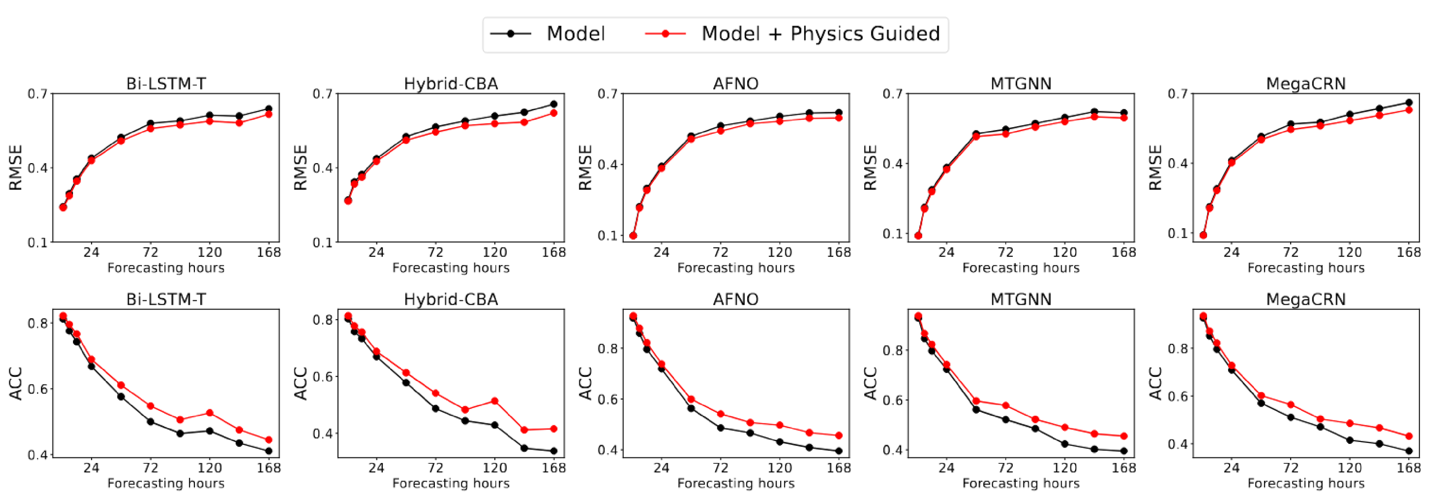


Figure 2: Schematic diagram of *PhyDL-NWP* for forecasting. We first use pre-trained surrogate model for weather downscaling to perform data augmentation, which is a necessity for aligning weather data resolution in the forecasting model. Then, we take the augmented historical data and use a pre-trained state-of-the-art forecasting model to predict future data. Based on the spatio-temporal coordinates of the predicted data, we add a physics loss to recover the previously learned PDE.



Guiding Weather Forecasting Models

Model performance on regional real measurement data:

Model	100m wind		10m wind		Humidity		Temperature		Average	
	RMSE↓	ACC↑	RMSE↓	ACC↑	RMSE↓	ACC↑	RMSE↓	ACC↑	RMSE↓	ACC↑
NWP	0.892	0.606	0.875	0.581	0.932	**0.699**	0.422	0.910	0.868	**0.587**
PINN	**0.622**	0.520	**0.605**	0.489	0.835	0.443	0.657	0.727	0.652	0.427
PINO	0.640	0.504	0.602	0.516	0.609	0.538	0.477	0.838	0.626	0.452
Bi-LSTM-T	0.666	0.588	0.704	0.562	0.576	0.597	0.472	0.876	0.601	0.443
Bi-LSTM-T+	0.635	**0.649**	0.664	0.621	0.550	0.672	0.442	0.903	0.571	0.485
Improv	4.65%	10.4%	5.68%	10.5%	4.51%	12.6%	6.36%	3.08%	5.00%	9.48%
Hybrid-CBA	0.674	0.568	0.717	0.550	0.590	0.595	0.460	0.865	0.617	0.431
Hybrid-CBA+	0.641	0.637	0.680	0.609	0.572	0.657	0.411	0.906	0.586	0.474
Improv	4.90%	12.1%	5.16%	10.7%	3.05%	10.4%	10.7%	4.74%	5.02%	9.98%
ConvLSTM	0.701	0.524	0.732	0.535	0.572	0.602	0.489	0.858	0.636	0.418
ConvLSTM+	0.658	0.587	0.699	0.607	0.550	0.671	0.454	0.891	0.596	0.463
Improv	6.13%	12.0%	4.51%	13.5%	3.85%	11.5%	7.16%	3.85%	5.97%	10.8%
AFNO	0.659	0.592	0.710	0.546	0.528	0.584	0.429	0.894	0.599	0.465
AFNO+	0.625	0.648	0.669	**0.630**	0.500	0.695	0.397	**0.929**	0.556	0.530
Improv	5.16%	9.46%	5.78%	15.4%	5.30%	19.0%	7.46%	3.91%	7.18%	14.0%
MTGNN	0.685	0.566	0.720	0.538	0.521	0.589	0.434	0.887	0.597	0.457
MTGNN+	0.657	0.629	0.672	0.613	**0.489**	0.679	**0.388**	0.918	**0.555**	0.514
Improv	4.09%	11.1%	6.67%	13.9%	6.14%	15.3%	10.6%	3.49%	7.04%	12.5%
MegaCRN	0.698	0.520	0.734	0.535	0.544	0.595	0.492	0.866	0.621	0.426
MegaCRN+	0.667	0.591	0.684	0.600	0.521	0.666	0.458	0.907	0.590	0.477
Improv	4.44%	13.7%	6.81%	12.1%	4.23%	11.9%	6.91%	4.73%	5.00%	12.0%

Model performance on regional re-analysis data:

Model	100m wind(U)		10m wind(U)		Temperature		Surface pressure		Average	
	RMSE↓	ACC↑	RMSE↓	ACC↑	RMSE↓	ACC↑	RMSE↓	ACC↑	RMSE↓	ACC↑
NWP	0.968	0.521	0.933	0.514	**0.319**	**0.844**	0.325	0.961	0.901	**0.526**
PINN	**0.697**	0.470	**0.681**	0.437	0.635	0.654	0.494	0.904	0.666	0.387
Bi-LSTM-T	0.822	0.502	0.804	0.485	0.583	0.525	0.160	0.961	0.638	0.411
Bi-LSTM-T+	0.798	**0.545**	0.777	0.520	0.560	0.584	0.156	0.965	0.616	0.445
Improv	2.92%	8.57%	3.36%	7.22%	4.28%	11.2%	2.50%	0.42%	3.45%	8.27%
Hybrid-CBA	0.842	0.456	0.819	0.445	0.652	0.430	0.150	0.964	0.657	0.338
Hybrid-CBA+	0.801	0.536	0.790	0.509	0.563	0.589	**0.149**	**0.966**	0.621	0.416
Improv	4.87%	17.5%	3.54%	14.4%	13.7%	37.0%	0.67%	0.21%	5.48%	18.8%
ConvLSTM	0.865	0.429	0.848	0.408	0.592	0.499	0.175	0.959	0.656	0.364
ConvLSTM+	0.826	0.477	0.814	0.472	0.520	0.619	0.170	0.955	0.622	0.419
Improv	4.51%	11.2%	4.01%	15.7%	12.2%	24.0%	2.86%	-0.42%	5.18%	15.1%
AFNO	0.856	0.436	0.838	0.421	0.501	0.571	0.153	0.962	0.619	0.395
AFNO+	0.823	0.505	0.808	0.498	0.466	0.693	0.153	0.956	0.596	0.456
Improv	3.86%	15.8%	3.58%	18.3%	6.99%	17.9%	0.00%	-0.31%	3.72%	15.4%
MTGNN	0.835	0.484	0.820	0.465	0.502	0.526	0.162	0.958	0.617	0.395
MTGNN+	0.810	0.525	0.792	**0.521**	0.469	0.677	0.160	0.959	**0.595**	0.455
Improv	2.99%	8.47%	3.41%	12.0%	6.57%	28.7%	1.96%	0.10%	3.57%	15.2%
MegaCRN	0.840	0.455	0.824	0.432	0.646	0.487	0.188	0.958	0.661	0.370
MegaCRN+	0.809	0.510	0.793	0.485	0.598	0.600	0.183	0.954	0.629	0.432
Improv	4.64%	12.1%	3.76%	12.3%	7.43%	23.2%	2.66%	-0.42%	4.84%	16.8%

Model performance on global re-analysis data:

Variable	Hours	ClimaX		ClimaX+		FourcastNet		FourcastNet+		GraphCast		GraphCast+	
		RMSE↓	ACC↑	RMSE↓	ACC↑	RMSE↓	ACC↑	RMSE↓	ACC↑	RMSE↓	ACC↑	RMSE↓	ACC↑
t2m	6	1.46	0.92	1.13	0.98	1.27	0.99	1.01	0.99	0.40	0.99	0.39	0.99
	12	1.58	0.91	1.25	0.96	1.48	0.98	1.12	0.99	0.47	0.99	0.46	0.99
	18	1.75	0.90	1.42	0.95	1.63	0.98	1.27	0.99	0.52	0.99	0.50	0.99
	24	1.90	0.88	1.58	0.94	1.69	0.96	1.40	0.98	0.59	0.99	0.56	0.99
	48	2.80	0.84	2.34	0.92	2.26	0.94	1.90	0.97	0.74	0.98	0.72	0.99
t	6	1.32	0.95	1.02	0.98	1.15	0.99	0.99	0.99	0.39	0.99	0.39	0.99
	12	1.66	0.94	1.28	0.98	1.36	0.99	1.17	0.99	0.46	0.99	0.45	0.99
	18	1.87	0.92	1.48	0.97	1.53	0.99	1.35	0.99	0.53	0.99	0.51	0.99
	24	2.16	0.91	1.66	0.96	1.66	0.98	1.52	0.99	0.59	0.99	0.57	0.99
	48	2.94	0.86	2.11	0.95	1.94	0.97	1.70	0.99	0.80	0.99	0.77	0.99
z	6	207.6	0.93	128.5	0.97	142.3	0.96	100.8	0.99	44.1	0.99	44.0	0.99
	12	222.3	0.90	159.9	0.96	217.2	0.89	126.6	0.99	47.6	0.99	47.2	0.99
	18	268.7	0.87	197.6	0.95	255.0	0.74	166.2	0.98	50.6	0.99	49.5	0.99
	24	305.5	0.84	224.1	0.94	304.2	0.71	203.2	0.97	78.4	0.98	75.7	0.99
	48	497.2	0.77	292.4	0.92	477.6	0.62	278.0	0.95	118.6	0.98	112.5	0.98
u10	6	1.56	0.90	1.28	0.94	1.39	0.93	1.12	0.95	0.50	0.98	0.50	0.98
	12	1.98	0.89	1.73	0.94	1.88	0.92	1.69	0.94	0.53	0.98	0.53	0.98
	18	2.20	0.89	1.94	0.93	2.10	0.90	1.88	0.93	0.57	0.98	0.56	0.98
	24	2.46	0.85	2.15	0.92	2.36	0.89	2.09	0.92	0.75	0.97	0.73	0.98
	48	2.91	0.78	2.46	0.88	2.79	0.88	2.36	0.90	1.24	0.96	1.16	0.97
v10	6	1.78	0.88	1.37	0.94	1.55	0.94	1.22	0.94	0.52	0.98	0.52	0.98
	12	1.99	0.86	1.52	0.93	1.81	0.90	1.39	0.93	0.55	0.98	0.55	0.98
	18	2.35	0.85	1.74	0.92	2.11	0.88	1.63	0.92	0.58	0.98	0.57	0.98
	24	2.66	0.83	2.08	0.90	2.40	0.85	1.96	0.91	0.79	0.97	0.76	0.98
	48	3.74	0.70	2.49	0.87	3.06	0.80	2.25	0.89	1.36	0.96	1.24	0.97

Comparison of 7-day weather forecast w/o *PhyDL-NWP*: