

## Motivation

Numerical Weather Prediction (NWP) post-processing based precipitation forecasting poses several challenges:

- Absence of a unified benchmark hindering cross-model evaluation.
- Uncertainty of atmospheric variable selection.
- The existing significant data imbalance.

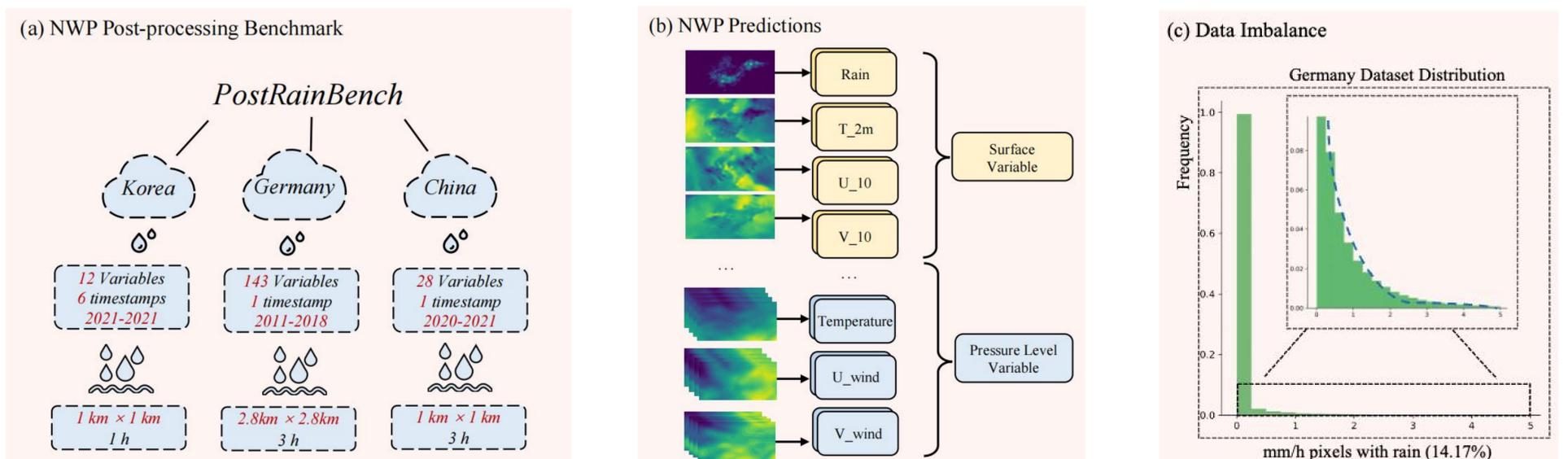
## Statistics

Dataset	Rain rate (mm/h)	Proportion (%)	Rainfall Level
KoMet	[0.0, 0.1)	87.24	No Rain
	[0.1, 10.0)	11.57	Rain
	[10.0, $\infty$ )	1.19	Heavy Rain
Germany	[0.0, $10^{-5}$ )	85.10	No Rain
	[ $10^{-5}$ , 2.0)	13.80	Rain
	[2.0, $\infty$ )	1.10	Heavy Rain
China	[0.0, 0.1)	91.75	No Rain
	[0.1, 2.0)	3.81	Rain
	[2.0, $\infty$ )	4.44	Heavy Rain

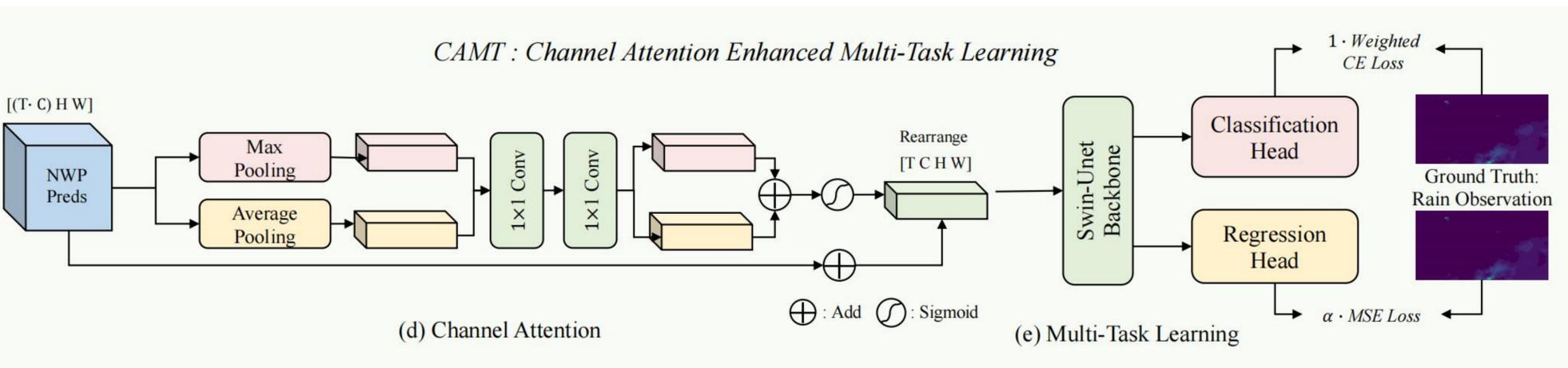
## Contribution

- We introduce a comprehensive multi-variable benchmark.
- We propose CAMT, a simple yet effective Channel Attention Enhanced Multi-task Learning framework with weighted loss function.
- On the proposed benchmark, our model outperforms state-of-the-art methods in rain Critical Success Index(CSI) on three datasets and shows significant improvement in heavy rain events.

## PostRainBench



## Method



## Conclusion

We introduce a comprehensive benchmark, **PostRainBench** and a new method, **CAMT** framework. Our approach demonstrates outstanding performance improvements compared to baseline models and NWP method. In conclusion, our research provides novel insights into the challenging domain of highly imbalanced precipitation forecasting tasks. We believe our benchmark could help advance the model development of the research community.



Code and Data Available!

## Experiments

		Rain				Heavy Rain			
		CSI $\uparrow$		HSS $\uparrow$		CSI $\uparrow$		HSS $\uparrow$	
		Mean(Std)	Best	Mean(Std)	Best	Mean(Std)	Best	Mean(Std)	Best
Korea	NWP	0.263( $\pm 0.000$ )			*	0.045( $\pm 0.000$ )			*
	U-Net	0.300 ( $\pm 0.025$ )	0.322	0.384( $\pm 0.025$ )	0.408	0.006( $\pm 0.005$ )	0.010	0.011( $\pm 0.009$ )	0.018
	ConvLSTM	0.302 ( $\pm 0.009$ )	0.312	0.384( $\pm 0.009$ )	0.395	0.009( $\pm 0.007$ )	0.015	0.016( $\pm 0.012$ )	0.026
	MetNet	0.298 ( $\pm 0.012$ )	0.307	0.375( $\pm 0.014$ )	0.384	0.005( $\pm 0.007$ )	0.012	0.009( $\pm 0.012$ )	0.023
	<b>Ours</b>	<b>0.321</b> ( $\pm 0.005$ )	<b>0.326</b>	<b>0.384</b> ( $\pm 0.007$ )	0.389	<b>0.052</b> ( $\pm 0.010$ )	<b>0.058</b>	<b>0.089</b> ( $\pm 0.017$ )	<b>0.097</b>
	<b>Ours <math>\Delta</math></b>	+6.3%		+0%		+15.6%		+456.3%	
Germany	NWP	0.338( $\pm 0.000$ )		0.252( $\pm 0.000$ )		0.178( $\pm 0.000$ )		0.173( $\pm 0.000$ )	
	U-Net	0.491 ( $\pm 0.007$ )	0.495	0.601( $\pm 0.006$ )	0.605	0.082( $\pm 0.028$ )	0.107	0.148( $\pm 0.048$ )	0.189
	ConvLSTM	0.477 ( $\pm 0.026$ )	0.478	0.587( $\pm 0.004$ )	0.590	0.091( $\pm 0.041$ )	0.121	0.162( $\pm 0.068$ )	0.212
	MetNet	0.485 ( $\pm 0.002$ )	0.487	0.595( $\pm 0.005$ )	0.599	0.027( $\pm 0.016$ )	0.094	0.147( $\pm 0.027$ )	0.168
	<b>Ours</b>	<b>0.514</b> ( $\pm 0.003$ )	<b>0.518</b>	<b>0.609</b> ( $\pm 0.006$ )	<b>0.616</b>	<b>0.209</b> ( $\pm 0.014$ )	<b>0.224</b>	<b>0.339</b> ( $\pm 0.020$ )	<b>0.359</b>
	<b>Ours <math>\Delta</math></b>	+4.7%		+1.3%		+17.4%		+96.0%	
China	NWP	0.164( $\pm 0.000$ )		0.123( $\pm 0.000$ )		0.110 ( $\pm 0.000$ )		0.089( $\pm 0.000$ )	
	U-Net	0.065 ( $\pm 0.007$ )	0.073	0.093( $\pm 0.009$ )	0.103	0.058( $\pm 0.014$ )	0.070	0.089( $\pm 0.024$ )	0.110
	ConvLSTM	0.054 ( $\pm 0.011$ )	0.066	0.079( $\pm 0.009$ )	0.088	0.065( $\pm 0.003$ )	0.068	0.104( $\pm 0.010$ )	0.114
	MetNet	0.064 ( $\pm 0.019$ )	0.078	0.061( $\pm 0.047$ )	0.106	0.057( $\pm 0.017$ )	0.076	0.069( $\pm 0.057$ )	0.118
	<b>Ours</b>	<b>0.208</b> ( $\pm 0.007$ )	<b>0.216</b>	<b>0.274</b> ( $\pm 0.014$ )	<b>0.289</b>	<b>0.145</b> ( $\pm 0.015$ )	<b>0.163</b>	<b>0.225</b> ( $\pm 0.019$ )	<b>0.246</b>
	<b>Ours <math>\Delta</math></b>	+26.8%		+122.8%		+31.8%		+116.3%	

Our method outperforms sota by **6.3%**, **4.7%**, and **26.8%** in rain CSI and improvements of **15.6%**, **17.4%**, and **31.8%** over NWP predictions in heavy rain CSI on respective datasets.

## Ablation Study

	Weighted Loss	Multi-Task Learning	CAM	Rain		Heavy Rain	
				CSI $\uparrow$	HSS $\uparrow$	CSI $\uparrow$	HSS $\uparrow$
(a)	✓	✓	✓	0.514	0.609	0.209	0.339
(b)	✗	✓	✓	0.517 (+0.6%)	0.625 (+2.6%)	0.042 (-97.6%)	0.008 (-11.1%)
(c)	✓	✗	✓	0.495 (-3.7%)	0.588 (-3.4%)	0.192 (-8.1%)	0.317 (-6.5%)
(d)	✓	✓	✗	0.505 (-1.8%)	0.602 (-1.1%)	0.183 (-11.1%)	0.305 (-11.1%)
(e)	✗	✗	✗	0.521	0.628	0.000	0.000
(f)	✓	✗	✗	0.490 (-6.0%)	0.580 (-7.6%)	0.188 $\uparrow\uparrow$	0.307 $\uparrow\uparrow$
(g)	✗	✓	✗	0.516 (-0.1%)	0.629 (+0.2%)	0.067 $\uparrow$	0.007 $\uparrow$
(h)	✗	✗	✓	0.513 (-1.5%)	0.624 (-0.6%)	0.115 $\uparrow$	0.204 $\uparrow$