Response to Reviewer #2

REVIEWER # 2

We must thank Reviewer #2 for providing us with useful comments to improve this article. We have gone through the comments and made revisions accordingly.

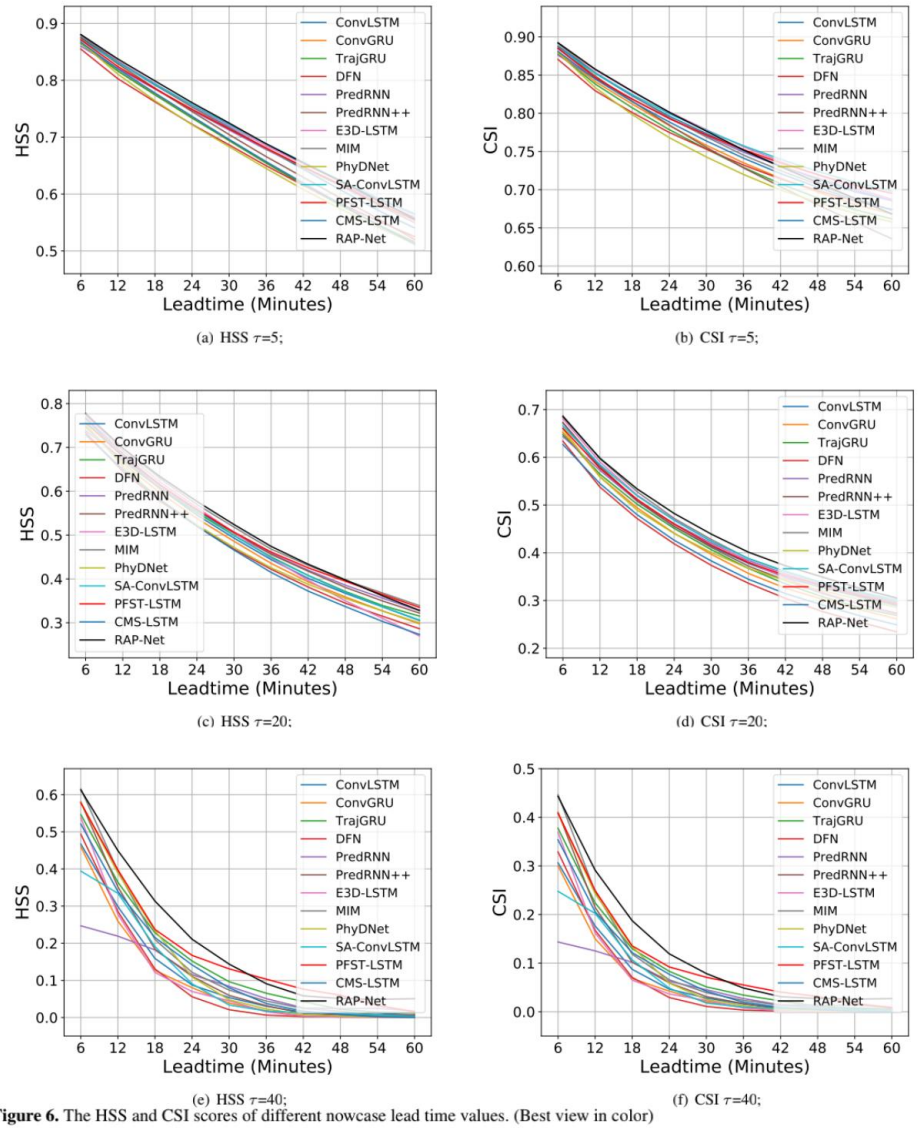
Comments to the Author

The paper describes a RAP-Net network that can be used for radar echo extrapolation. Experiments demonstrate the effectiveness of this method. The authors are suggested to supplement the experimental comparison of high-intensity echoes.

Reply: Thanks for your advice. The performance of RAP-Net in high-intensity echoes can be represented from three aspects. Firstly, from the evaluation metrics in Table 2, the HSS and CSI of RAP-Net in the highest thresholds (40dBZ) are higher than other models. Secondly, from Figures 6 (e) and (f), the predictions of RAP-Net keep the best HSS and CSI in 40 dBZ under most of the lead time. Especially, in the last prediction, the HSS and CSI of RAP-Net are obviously higher than other models. Finally, from Figure 7, we can see that only the RAP-Net model predicts color regions. It implies that the proposed model predicts better than other models in heavy rainfall areas. The above three observations jointly confirm that our model is better in high thresholds. The table 2, Figure 6, and Figure 7 can be respectively shown as follows:

Table 2. Comparison results on RadarCIKM in terms of HSS, CSI, SSIM, and MAE

Methods	HSS ↑				CSI ↑				MAE ↓	SSIM ↑
	5dBZ	20dBZ	40dBZ	avg	5dBZ	20dBZ	40dBZ	avg		
ConvLSTM Xingjian et al. (2015)	0.7031	0.4857	0.1470	0.4453	0.7663	0.4092	0.0801	0.4186	5.97	0.6334
ConvGRU Shi et al. (2017)	0.6816	0.4827	0.1225	0.4289	0.7522	0.3952	0.0657	0.4043	6.00	0.6338
TrajGRU Shi et al. (2017)	0.6809	0.4945	0.1907	0.4553	0.7466	0.4028	0.1061	0.4185	5.90	0.6424
DFN Jia et al. (2016)	0.6772	0.4719	0.1306	0.4266	0.7489	0.3771	0.0704	0.3988	6.03	0.6268
PredRNN Wang et al. (2017)	0.7082	0.4915	0.1639	0.4606	0.7692	0.4051	0.0901	0.4215	5.42	0.6887
PredRNN++ Wang et al. (2018a)	0.7061	0.5047	0.1710	0.4548	0.7642	0.4176	0.0940	0.4253	5.44	0.6851
E3D-LSTM Wang et al. (2018b)	0.7111	0.4810	0.1361	0.4427	0.7720	0.4060	0.0734	0.4171	5.51	0.6958
MIM Wang et al. (2019)	0.7052	0.5166	0.1858	0.4692	0.7628	0.4279	0.1034	0.4313	5.47	0.6796
PhyDNet Guen and Thome (2020)	0.6741	0.4709	0.1832	0.4427	0.7402	0.4003	0.1017	0.4141	6.25	0.6443
SA-ConvLSTM Lin et al. (2020)	**0.7118**	0.4861	0.1582	0.4520	**0.7725**	0.4161	0.0870	0.4252	5.71	0.6709
PFST-LSTM Luo et al. (2020)	0.7045	0.5071	0.2218	0.4778	0.7680	0.4175	0.1257	0.4371	5.82	0.6367
CMS-LSTM Chai et al. (2021)	0.6835	0.4605	0.1720	0.4387	0.7567	0.3788	0.0948	0.4101	5.95	0.6496
RAP-Net	0.7117	**0.5116**	**0.2293**	**0.4842**	0.7666	**0.4305**	**0.1307**	**0.4426**	**5.37**	**0.7019**



(a) HSS τ=5; (b) CSI τ=5;

(c) HSS τ=20; (d) CSI τ=20;

(e) HSS τ=40; (f) CSI τ=40;

Figure 6. The HSS and CSI scores of different nowcase lead time values. (Best view in color)

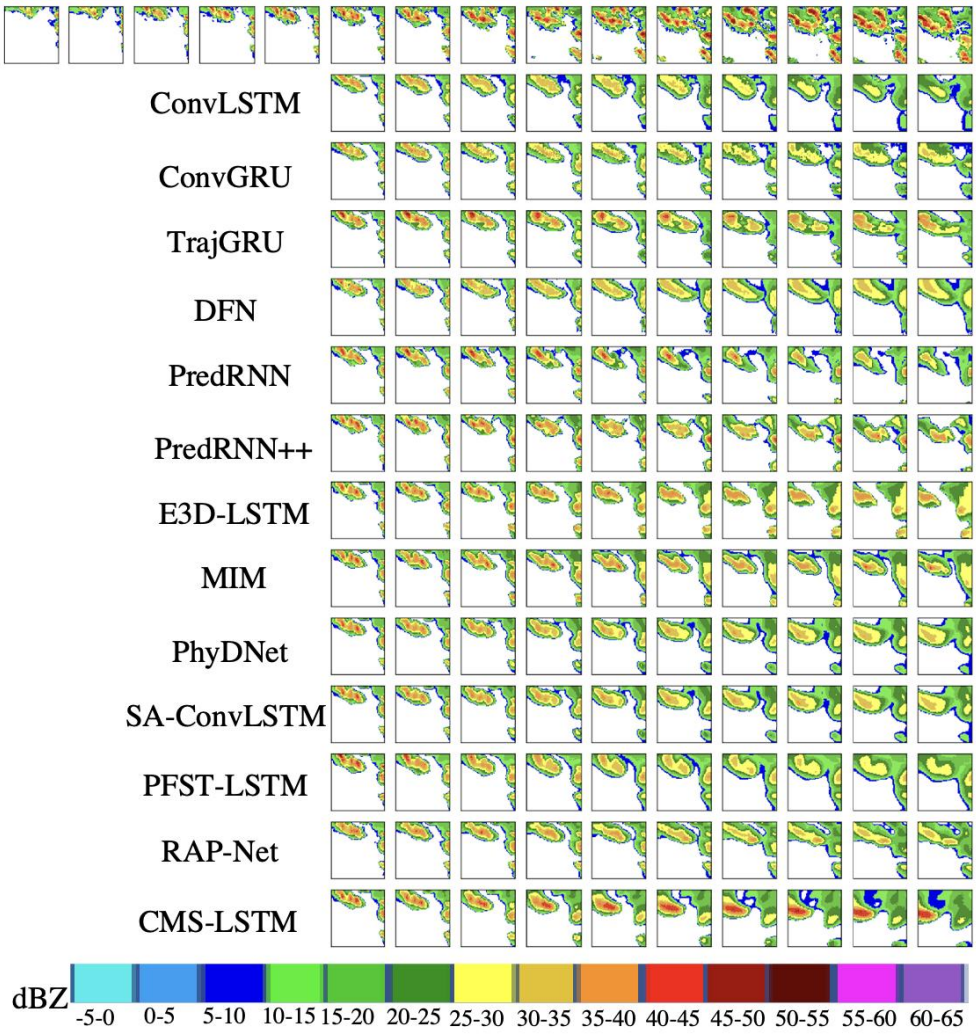


Figure 7. The first row is the reflectivity of ground truth and reminders are the predicted reflectivity of various methods on an example from the RadarCIKM dataset (Best view in color)