<u>RESPONSE LETTER</u>

We would like to thank the Topic editor and reviewers for the valuable suggestions on our manuscript once again. The suggestions made by the Topic editor and reviewers further improved our manuscript.

Comments from Topic editor:

Comment 1: *The authors have carefully revised their manuscript following the reviewers' comments and suggestions. However, as the reviewer suggested, please discuss the performance of very short-term nowcasting (0-30min) of GAN-argcPredNet v2.0 among all schemes.*

Response: Thanks for your suggestion. In comparison experiments, we add the average 0-30 min forecast lead-time scores and analyze the performance of each model from 0-30 min, 30-60 min forecast lead-time. The results show that GAN-argcPredNet v2.0 most effectively curbs echo attenuation and has a more competitive overall performance. (Page 12-13, Figure 8-9; Page 11-12, Line 258-275; Page 13, Line 284-298).

Comment 2: *Page 19, Line 351: This is because in the input sequence, the other strong echoes have a smaller range, making them more susceptible to attenuation during extrapolation. -> Did the authors mean the strong echoes have a smaller scale? Or, a smaller intensity range? Please clarify it.*

Response: Thanks for your suggestion. We modify it to "This is because in the input sequence, the other strong echoes have a smaller spatial range, making them more susceptible to attenuation during extrapolation." (Page 19, Line 361-362).

Comment 3: *Does this imply that the scheme learns only the main features and is less capable of tracking the minor features with rapid growth? If yes, please address this issue in the summary.*

Response: Thanks for your suggestion. We add the following description: "In Figs. 10-11, GAN-argcPredNet v2.0 has a clear advantage for out-of-center region curb the attenuation compared to other deep learning models. And there are fewer incorrect predictions compared to the optical flow. This indicates that GAN-argcPredNet v2.0 focuses on the main features and also pays more attention to the minor features with rapid growth than other models. Overall, GAN-argcPredNet v2.0 is capable of curbing echo attenuation, the center region is more significant, and the overall performance is more competitive." (Page 19, Line 362-366).

Comments from Reviewer 1:

Comment 1: *Page 1, line 17, "Aim to the problem,": This phrase sounds somewhat strange to me. Please consider rephrasing.*

Response: Thanks for your suggestion. We modify to "To solve this issue" (Page 1, Line 17).

Comment 2: *Page 3, line 85 and page 18, line 338: "more severe" -> "severer".*

Response: Thanks for your suggestion. We modify to "severer" (Page 3, Line 85; Page 18, Line 348).

Comment 3: The description of STIC is repeated too many times. I would recommend reducing them because this is redundant.

Page 3, line 91-92, "The purpose of the generator is to curb echo attenuation by suppressing the blurring effect of rain distribution and reducing the negative bias."

Page 4, line 111-112, "The STIC-Prediction generator is designed to reduce echo attenuation by suppressing the blurring effect and reducing the negative bias."

Page 5, line 118-119, "The purpose is to better maintain spatiotemporal features during information transmission within the model. After passing through STIC Attention, the features are fed to the lower layers, aiming to avoid blurring or to maintain the intensity during extrapolation."

Page 7, line 147-148, " The module calculates the importance of evolutionary information, which aims to suppress the blurring effect and reduce the negative bias."

In my opinion, the description in page 5 is sufficient. Please be concise.

Response: Thanks for your suggestion. We revise this description:

"The purpose of the generator is to more accurately forecast future precipitation distributions by curbing echo attenuation." (Page 3, Line 91-92).

"The STIC-Prediction generator is designed to reduce echo attenuation and consists of the argcPredNet and the STIC Attention module (Fig. 3)." (Page 4, Line 110-111).

"The module calculates the importance of evolutionary information." (Page 6, Line 147).

Comment 4: Figure 3, caption: The description here is somewhat confusing. Please consider rephrasing.

Response: Thanks for your suggestion. We have revised this description "The STIC-Prediction structure at time T with four layers (l=0, 1, 2, 3). The STIC Attention is located between the second layer (l=1) and the third layer (l=2). During prediction, R_{l+1}^{T} forms the sequence

$R_{l+1}^{0}: R_{l+1}^{T}$ with R_{l+1} prior to the moment T. Then, the sequence fed into the STIC module, which captures the correlation between the sequences and adjusts R_{l+1}^{T}. Finally, the new R_{l+1}^{T} is output. See Section 2.2 for further explanation." (Page 6, Line 138-141).

Comment 5: *Page 12, line 250: "Pysteps" -> "pySTEPS"*

Response: Thanks for your suggestion. We revise to "pySTEPS"(Page 11, Line 248).

Comment 6: *In pySTEPS, what algorithm did you actually use? The pySTEPS has different options for motion vector computation. There must be also parameters for them.*

Response: Thanks for your suggestion. We add information about optical flow: "The first one is a traditional method, and the code comes from the pySTEPS library (Pulkkinen et al., 2019), which we performed using a local tracking approach (Lucas-Kanade)." (Page 11, Line 248-249).

Comment 7: *Regarding conventional spatiotemporal extrapolation methods, prediction accuracy can be largely improved by adopting data assimilation (you can find some previous studies). Although you do not need to perform additional experiments, it would be better to mention that in the discussion section. A fair comparison is always difficult; all the participating models must be well-tuned.*

Response: Thanks for your suggestion. We add an insight into data assimilation in the discussion section. "Given the proven efficacy of data assimilation in numerous fields, exploring the integration of data assimilation techniques with other meteorological variables, such as temperature, to study multi-modal models represents a crucial direction for precipitation nowcasting." (Page 20, Line 387-389).

Comments from Reviewer 2:

Comment 1: *About Fig.1 and Fig.2, since they both present the structure of GAN-argcPredNet v1.0 and v2.0 , it will be nice for the readers if authors arrange the same boxes、arrows、items in the same directions and positions. In that way, readers will be easier to recognize the differences between v1.0 and v2.0.*

Response: Thanks for your suggestion. We redrew Figures 1 and 2 (Page 4, Figure 1; Page 5, Figure 2).

Comment 2: *lines 281-285: please put the descriptions of Fig. 10 and Fig. 11 in the same paragraph as Fig. 9.*

Response: Thanks for your suggestion. We put together the descriptions of Figures 9,10,11. (Page 13, Line 284-298).

Comment 3: About the anlaysis of the results: so far, authors showed Figs. 9-11 as different cases to demonstrate different evolution of the events, and display the average scores in Fig. 8 (all events and 0-60 forecast leadtime) to illustrate that GAN-argcPredNet v2.0 outperform all other systems. However, by examining the performance of 0-30 min forecast lead-time (Figs. 9,10,11), it is also noticed that GAN-argcPredNet v2.0 may not always outperform other systems. For disaster prevention, it is very important to examine the performance of nowcast in a short period of time, and Fig. 8 somehow only reflects 1-h accumulated results. I think it is necessary to show and explain (or discuss) the results/performance between 0-30 min and 30-60 min forecast lead-time of the nowcasting systems. It also corresponds to the future work in the conclusion.

Response: Thanks for your suggestion. In comparison experiments, we add the average 0-30 min forecast lead-time scores and analyze the performance of each model from 0-30 min, and 30-60 min forecast lead-time. The results show that GAN-argcPredNet v2.0 most effectively curbs echo attenuation and has a more competitive overall performance. (Page 12-13, Figure 8-9; Page 11-12, Line 258-275; Page 13, Line 284-298).