General statement

We would like to thank the editor for coordinating the review of our work and the peer-reviewers for their valuable comments on our study. In the following, we will address the referees' comments and present our plans and ideas for revising the manuscript. For clarity, our responses are highlighted in red.

Referee comment #1

Ji et al. present a method combining a generative adversarial network (GAN) with a U-Net and recurrent LSTM cells as the generator, for a high spatio-temporal resolution prediction of precipitation up to two hours ahead. The CLGAN model introduced in this work is compared against a set of baseline models and competing deep-learning based models with a comprehensive set of evaluation criteria. The work is well presented and the evaluation appears comprehensive, and is good for the scope of GMD. I only have minor comments before recommending this manuscript for publication.

General comments:

1. The authors use an "ablation study" (as defined in the abstract), or more specifically a sensitivity analysis on the weight of the GAN component, to assess the importance of the newly added GAN component for generating forecasts that pass the visual test and are more skillful in capturing the statistical properties of observed precipitation. This is a very useful contribution, although I feel that too many different technical terms are used in different places of the manuscript for describing this process (L8-10; L53-57; L73-74; L331-L342). I recommend the authors start with more general terms (e.g., "weight of the GAN-component") then use the terms reconstruction loss and adversarial loss after they are introduced in L189 eq. (3). Using it too early in the introduction may confuse readers.

Thanks for the comment and we will give more explanations of the used terms in the manuscript. We will start with the general terms "weight of the GAN-component" as suggested and then use specific terms "reconstruction loss and adversarial loss" after being introduced. Specifically, the reconstruction loss refers to the L1 or L2 loss and the adversarial loss refers to the score on the model to distinguish between real and generated data which is subject to mini-max optimization. The revision will be traceable in the manuscript.

2. Through looking at the code archived on Zenodo there appears to be code from a Git repository. Besides providing the Zenodo DOI could you also provide the GitLab repository link as well? This way potential users can follow the developments of the code and look at the README and documentation easier.

Thanks for the hint. We will add the gitLab repository link in the section of "Code and data availability".

Specific comments:

1. L73-74: As in general comment 1, try to avoid terms like "adversarial loss" before introducing

it. I also suggest being more specific about "sheds light on the interaction between the generator and the discriminator", e.g., the role of the GAN-component in generating forecasts with closer statistical properties of the observed precipitation.

Thanks for the comment and we will rephrase the sentence, i.e. A sensitivity analysis is performed on the contribution of the GAN-component in generating forecasts with closer statistical properties of the observed precipitation.

3. L161-162: The authors apply stronger weighting on higher precipitation rates to optimize towards heavy precipitation events. How much of an effect (if any) does this have on the precipitation of lighter precipitation events?

Thanks for the question. We calculated CSI with multiple thresholds of precipitation rate (0.1, 1, 2, and 8 [mm/hour]) and found that the proposed CLGAN model was competitive with the advanced model PredRNN-v2 for the nowcasting of lighter precipitation events, while both outperformed the Persistence, DenseRotation and ConvLSTM. PredRNN-v2 is slightly superior for shorter lead times (the first 60 minutes), whereas CLGAN outperforms for the longer lead times. Since we were more interested in the heavy precipitation forecasting, we only gave the evaluation of the precipitation events exceeding 8 mm/hour in the manuscript.

4. L372-374: It is mentioned that CLGAN can provide probabilistic forecasting by adding random noises. There is also mention of using ensemble forecasts to quantify forecast uncertainty in the introduction (L49-51). Is this part of future work or shown in this work? It was not very clear and I had to look if probabilistic forecasts were made in this work.

Thanks for pointing it out and sorry for the confusion. We didn't deploy a probabilistic forecasting framework in this study. This is mentioned in Line 372-374. However, it is correct that the proposed CLGAN can be used for probabilistic forecasting, by adding the noise as additional input. We acknowledge that a probabilistic nowcasting system is appealing due to the strong inherent uncertainties in the dynamics of precipitation patterns. This is especially true for small-scale convective precipitation systems which may produce extreme events. In this study, we focused on proving that a GAN-based approach is capable to circumvent the issue of forecasting too smooth precipitation patterns and investigate its sensitivity to the weighting terms in the loss function. The capacity of CLGAN to generate probabilistic forecasts will however be investigated in future studies.

4. Figure 1c. Is L^G supposed to be L^GAN here, to be consistent with text?

Thanks for pointing it out and we will revise it in Figure 1c.

5. Figure 6. For ease to read please label the subfigures (a)-(e) with subtitles (Observation, Persistence, DenseRotation, …)

Thanks for the comment and we will add the labels in Figure 6.