Response to Referee 2:

Review of Impact of Multiple Radar Wind Profilers Data Assimilation on Convective Scale Short-Term Rainfall Forecasts: OSSE Studies over the Beijing-Tianjin-Hebei region

General Comments:

The study investigates the benefits of using radar wind profiler (RWP) observations for forecasting convective initiation (CI) in small-scale boundary layer convergence zones. The research employed the Weather Research and Forecasting (WRF) model along with the NSSL3DVAR data assimilation (DA) system. Synthetic RWP data, generated through Observing System Simulation Experiments (OSSE), were assimilated for three summer heavy rainfall events in the Beijing-Tianjin-Hebei region. The results indicated that assimilating RWP observations improved model initial conditions and enhanced short-term severe weather forecasts. Notably, improved forecasting outcomes were observed when combining operational, foothill, and ridge RWP data. Multiple sensitivity experiments were conducted to evaluate the impact of vertical resolution and maximum detection heights. The study identified optimal configurations for future real-time RWP data assimilation.

The research and results of the study are both interesting and significant. The manuscript is well-structured and clearly presented, offering a thorough analysis using the OSSE method. It is well-written and will be ready for publication after a few minor revisions and responses to my questions.

Response: The authors appreciate the referee's insightful comments and constructive suggestions, which helped us significantly improve the quality of this manuscript. For clarity purpose, here we have listed the reviewers' comments in black font, followed by our response in blue font.

Comments:

1. In lines 144-145, 'so we did not use the ensemble derived background error covariance, which is also incorporated in the variational framework'. What method is used to compute the background error statistics? What control variables are utilized to calculate the B-matrix? Is the covariance matrix a day or wet matrix. Write a few details about the calculation of the B-matrix.

   Response: Thanks! This is a very good suggestion. This has been added in lines 164-172: "The background error covariance matrix used in this study is constructed as the product of a diagonal matrix representing the standard deviations of background errors and a spatial recursive filter (Gao et al., 2004, 2013). The standard deviations for the pressure, potential temperature, relative humidity, zonal and meridional wind components are derived from the statistics of the Rapid Update Cycle (RUC, Benjamin et al., 2004) 3-hour forecasts over several years (Fierro et al., 2019b; Pan et al., 2021). The background error correlations are modeled by the recursive filter described by Purser et al. (2003a, b). The recursive filter can be applied in multiple passes (or outer loops), using different correlation length scales tailored to the scale of the weather systems represented by the assimilated observations."

2. Line 135, 'total precipitable water' are the products or sources of observations used for assimilating total precipitable water? The author needs to include appropriate references for each observation.

   Response: Thanks for pointing out this. The total precipitable water (TPW) is the satellite-retrieved product, such as GOES-16 TPW product, which contains water vapor information (Pan et al., 2018). The claims on lines 150-155 have been reworded as follows: "The NSSL3DVAR system assimilates multi-sensor high-resolution observations like radar radial velocity and reflectivity (Gao et al., 2013, 2016), sounding and surface data (Hu et al., 2021), and multiple satellite-retrieved products, such as cloud water path (Pan et al., 2021), total precipitable water (Jones et al., 2018; Pan et al., 2018), atmospheric motion vectors (Mallick and Jones, 2020; Zhao et al., 2021b, 2022), and Geostationary Lightning Mapper (GLM)-derived water vapor (Fierro et al., 2019a; Hu et al., 2020)."

3. Authors need to include additional information about the NSSL3DVAR assimilation system. This should encompass the minimization cost function, control variables, and the calculation of the B-matrix.

   Response: Thanks for pointing out this. Descriptions of cost function, control variables, and the calculation of the B-matrix have been added in the manuscript as follows:

   1) Lines 138-149: "In the NSSL3DVAR system, the analysis is derived by minimizing the cost function defined as the background term J_b and the observation term J_o plus the constraint term J_c:

$$J = J_b + J_o + J_c = \frac{1}{2}(\mathbf{x}-\mathbf{x}_\mathrm{b})^\mathrm{T}\mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}_\mathrm{b}) + \frac{1}{2}(H(\mathbf{x})-\mathbf{y_o})^\mathrm{T}\mathbf{R}^{-1}(H(\mathbf{x})-\mathbf{y_o}) + J_c, \quad (1)$$

   where $\mathbf{x}$ and $\mathbf{x}_\mathrm{b}$ are the analysis and background state vectors, respectively; H is the observation operator projecting analysis into the observational space; and $\mathbf{y}_\mathrm{o}$ is the observation vector. $\mathbf{B}$ is the background error covariance matrix, and $\mathbf{R}$ is the observation error covariance matrix. J_c represents weak constraints which include elastic mass continuity equation and diagnostic pressure equation constraints suitable for convective-scale data assimilation (Gao et al., 2004; Ge et al., 2012). Analysis variables include the three-dimensional wind fields, air pressure, potential temperature, water vapor mixing ratio, and the hydrometeors containing the mass mixing ratios for cloud water, rainwater, ice, snow, and graupel (Gao and Stensrud, 2012).

2) Lines 164-172: “The background error covariance matrix used in this study is constructed as the product of a diagonal matrix representing the standard deviations of background errors and a spatial recursive filter (Gao et al., 2004, 2013). The standard deviations for the pressure, potential temperature, relative humidity, zonal and meridional wind components are derived from the statistics of the Rapid Update Cycle (RUC, Benjamin et al., 2004) 3-hour forecasts over several years (Fierro et al., 2019b; Pan et al., 2021). The background error correlations are modeled by the recursive filter described by Purser et al. (2003a, b). The recursive filter can be applied in multiple passes (or outer loops), using different correlation length scales tailored to the scale of the weather systems represented by the assimilated observations.”

4. Line 132: Add a few references after the phrase water path, total precipitable water, and atmospheric motion vector. Jones, T. A., Wang, X., Skinner, P., Johnson, A., & Wang, Y. (2018). Assimilation of GOES-13 imager clear-sky water vapor (6.5 μm) radiances into a warn-on-forecast system. Monthly Weather Review, 146(4), 1077–1107. https://doi.org/10.1175/MWR-D-17-0280.1 Mallick, S., & Jones, T. A. (2020). Assimilation of GOES-16 satellite derived winds into the warn-on-forecast system. Atmospheric Research, 245, 105131. https://doi.org/10.1016/j.atmosres.2020.105131

   Response: Thank you so much for your suggestion and for providing the references. They have been added in lines 152-154: “multiple satellite-retrieved products, such as cloud water path (Pan et al., 2021), total precipitable water (Jones et al., 2018; Pan et al., 2018), atmospheric motion vectors (Mallick and Jones, 2020; Zhao et al., 2021b, 2022)”.

5. Did the authors use any additional conventional observations or satellite observations in their assimilation system?

   Response: No, we only assimilate RWP observations without incorporating additional conventional or satellite observations in this study. This exclusion simplifies the analysis by isolating the impact of RWPs but may inflate their relative importance. We will evaluate the impact of RWP networks by assimilating RWPs together with more diverse observation types to enhance realism and provide broader operational insights in future studies. The corresponding claims have been added in the manuscript as follows:

   1) Lines 252-256: “As our focus is to assess the impacts of assimilating wind observations from various RWP network layouts on convective-scale analysis and short-term severe weather prediction, only synthetic RWP data are assimilated in this study, excluding conventional observations such as radiosondes, surface stations, and satellite observations. This exclusion simplifies the analysis by isolating the impact of RWPs but may inflate their relative importance (Hoffman and Atlas, 2016).”

   2) Lines 721-728: “Furthermore, this study focuses exclusively on assimilating

RWP data, without incorporating conventional observations or satellite data. While this approach simplifies the analysis by isolating the impact of RWPs, it may inflate their relative importance. Future research directions include: (1) Expanding the study to other precipitation types and high-impact convective events under diverse weather scenarios. (2) Evaluating the impact of RWP networks by assimilating RWPs together with more diverse observation types and incorporating non-identical twin setups to enhance realism and provide broader operational insights."

6. Line 201, rewrite the line 'meridional wind components (u and v)' to 'meridional wind (u and v) components'.

   Response: Rephrased as suggested.

7. Line 217, 'The perturbations are assumed to be normally distributed Gaussian random errors with a mean of zero and a standard deviation of 2 m/s' , How do you calculate the observation error for each location?

   Response: Thank you for your question regarding the calculation of observation error. In this study, the observation errors at each location were modeled as normally distributed Gaussian random errors with a mean of zero and a standard deviation of 2 m/s. These errors were applied uniformly across all locations, assuming they reflect the typical uncertainties in RWP observations based on previous studies and operational experience (Hu et al., 2017; Zhang et al., 2016). The 2 m/s standard deviation represents a reasonable estimate of the observational error for RWP wind measurements. This value was chosen based on literatures on data quality assessment and data assimilation of wind profiles from the operational RWP network of China (Liu et al., 2020; Wang et al., 2020; Wang et al., 2023; Zhang et al., 2016; Zhang et al., 2017), ensuring consistency in evaluating the impact of different RWP network configurations.

8. In the summary section, write a few words on how incorporating flow-dependent background error covariances in data assimilation (DA) systems can enhance precipitation forecasting compared to the static background errors used in 3DVAR.

   Response: Thanks! This is a very good suggestion. This has been added in lines 729-736: "Moreover, future studies can address the limitations of static background errors in 3DVAR by incorporating flow-dependent background error covariances estimated from ensemble forecasts. As ensemble-based background error covariances can dynamically adapt to the evolving state of the atmosphere, the DA system will better represent the spatial and temporal variability of background errors, particularly in regions with complex topography or mesoscale features like convective systems. By leveraging flow-dependent background errors, the analysis can more accurately capture the initial atmospheric state, ultimately leading to more accurate precipitation predictions."

9. Based on OSSE results, what are the key considerations for designing and deploying optimal RWP networks in complex terrain regions?

Response: The OSSE results provide some insights into designing and deploying optimal RWP networks in complex terrain regions like the Taihang Mountains. Key considerations include:

a) **Station Placement in Key Terrain Areas**. The OSSE results consistently demonstrate that the FH_RD experiment, combining data from ridge, foothill, and operational wind profiler networks, delivers the most accurate short-term forecasts. Specifically, the assimilation of RWP data from ridge network significantly reduces wind errors in complex terrain, such as the Taihang Mountains upstream of Beijing. These regions are critical for convective initiation in Beijing and its surroundings. Therefore, RWP deployment in complex terrain should prioritize locations where terrain-driven meteorological processes are most pronounced, such as ridges, valleys, and foothills.

b) **Integrated Network Configuration**. The FH_RD experiment shows that combining ridge, foothill, and existing operational RWP networks delivers the most accurate short-term forecasts. This finding highlights the importance of integrating new RWP stations with existing observation resources to create a synergistic and complementary network, optimizing coverage and forecast accuracy.

c) **High Vertical Resolution and Detection Height**. Sensitivity experiments on vertical resolution and detection height further emphasize the importance of high vertical resolution and maximizing detection height in optimizing the RWP network for enhanced forecast accuracy. In complex terrain regions, where the lower atmosphere is strongly influenced by topography, accurate vertical wind profiles in the lower and mid-troposphere are essential for improving forecasts of convection and precipitation.

d) **Regional Adaptation to Terrain and Meteorological Characteristics.** Each complex terrain region has unique topographical and meteorological features. Tailored analyses are necessary to optimize station placement based on regional characteristics. For instance, in other mountainous regions, RWP networks might focus on capturing monsoon systems or localized storm development, requiring adjustments to station positioning accordingly.