Impacts of terminal velocity on precipitation prediction and the error representation of terminal velocity in ensemble forecasts

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1 INTRODUCTION

The microphysical parameterization has been reported as a large source of model uncertainty for convective scale prediction (Snook and Xue, 2008). One uncertainty in the parameterization is the terminal velocity of hydrometeor which is a drop-size distribution associated variable. Many studies have shown the great impact of terminal velocity on rainfall prediction with respect to the intensity (Parodi and Emanuel, 2009), coverage (Bryan and Morrison, 2012), and duration (Singh and O’Gorman, 2014). In a bulk microphysics scheme, the mass-weighted mean terminal velocity is often used such that it depends on the mean drop size and the particle density at a grid point (Gilmore et al., 2004). Although the terminal velocity uncertainty has not yet been well determined, recent studies have shown that the plausible terminal velocity could be half of or as twice large as the model predicted terminal velocity value (Forbes and Clark, 2003; Morales et al., 2018; Stanford et al., 2019). Stanford et al. (2019) allowed for the terminal velocity uncertainty in small size ensembles and obtained variety in precipitation prediction. However, even though different species (liquid and ice) differ in terminal velocities, only the constant fall speeds for all hydrometeors (Singh and O’Gorman, 2014) and the ice species fall speed (Stanford et al., 2019) have been studied.
To extend previous studies, we investigated the sensitivities of precipitation intensity, coverage, and distribution to terminal velocities of different species in several scenarios differing in environments and mean drop sizes. How to use these sensitivities in ensemble forecasts was also concerned by this study. Stanford et al. (2019) have considered the terminal velocity uncertainty in precipitation ensemble forecasts, but only the ice species were involved. As a supplement to their work, we involved perturbations for both liquid and ice species.

2 | MODEL AND EXPERIMENTAL DESIGN

The Advanced Regional Prediction System (ARPS, Xue et al., 2000; Xue et al., 2001) was used. The abilities of this prediction model in convective-scale forecasts has been demonstrated by many studies (Schumacher et al., 2013; Pan et al., 2016; Snook et al., 2016; Wang et al., 2016). To avoid the impact of initial condition error, an idealized squall line case was employed, which was created in an environment generated using the sounding (Case 1) extracted from the Weather Research and Forecast model (Skamarock et al., 2008) package. This is an environmental sounding of Weisman and Klemp (1984) with the convective available potential energy (CAPE) and 0–2 km above ground level (AGL) shear of the above sounding being approximately 1800 J·kg⁻¹ and 11 m·s⁻¹, respectively. Two variants of this sounding were created to simulate drier or moister environments by decreasing the water vapor mixing ratio by 2.5% at all levels (Case 2) or increasing the mixing ratio by the same magnitude (Case 3). The value of 2.5% is not large, but it caused large precipitation rate difference. The number of grids with precipitation rate greater than 5 mm per 10 min in Case 3 is twice as large as that in Case 2. The grid mesh is 2 km in both X and Y direction; the domain size is 103 × 103 × 53, using a stretching vertical-grid with an mean grid spacing of 400 m and minimum spacing of 20 m near surface. Four thermal bubbles with horizontal and vertical radii of 20 km and 1.5 km, respectively, were uniformly placed from Y = 80 km to Y = 140 km along X = 40 km and vertically located at 1.5 km AGL. A 5 hr simulation was performed.

The two-moment microphysics scheme (MY2) proposed by Milbrandt and Yau (2005), was used as the truth. The one-moment Lin scheme (Lin et al., 1983) served as an imperfect microphysical parameterization. The one-moment scheme is still widely used in recent studies (e.g., Dahl and Xue, 2016; Supinie et al., 2016) and operation centers (e.g., Federico, 2016; Nuissier et al., 2016). The above two schemes differ in many respects not just in terminal velocity; this is true in the real world so that we can investigate to what extent perturbing terminal velocity influences the precipitation prediction performance. Four intercept parameters groups (IntcptGrp) of rain (NOr) and hail (Nh) were set (Table 1) to simulate scenarios that the mean drop sizes were overestimated or underestimated. The snow intercept parameter was not involved because its impact on precipitation is relatively small (Snook and Xue, 2008); the Lin scheme in ARPS only predicts hail so that discussion on graupel was excluded. Note that varying intercept parameters simultaneously change terminal velocities, which is undesired for isolating terminal velocity uncertainty. However, intercept parameters differ in previous studies, which raises the necessity to evaluate if multiplicative perturbations are effective in different cases. Considering that ice-species density also influences the terminal velocity, in addition to the default values (100 kg·m⁻³ and 913 kg·m⁻³ for snow and hail, respectively), four combinations of snow and hail densities, namely 20 kg·m⁻³ (snow) and 200 kg·m⁻³ (hail), 40 kg·m⁻³ (snow) and 400 kg·m⁻³ (hail), 60 kg·m⁻³ (snow) and 600 kg·m⁻³ (hail), and 80 kg·m⁻³ (snow) and 800 kg·m⁻³ (hail), respectively, were empirically determined to simulate the variety of ice-phase terminal velocity. The hail density of 200 kg·m⁻³ serves as an extreme case because the particle with this density is more like graupel. The sensitivity of precipitation to terminal velocities of rainwater, snow, and hail were examined by varying the multiplicative factors of terminal velocities. The factors were 0.4, 0.6, 0.8, 1.0, 1.2, 1.4, and 1.6 for seven sensitivity simulations, but the same factor was used for rainwater, snow, and hail in each simulation. Note that raindrop fall speed uncertainty may be smaller than that of ice species, implying that using the same factor may not be reasonable. Here, factors like 0.4 and 1.6 only serve as extreme

| IntcptGrp 1 | IntcptGrp 2 | IntcptGrp 3 | IntcptGrp 4 |
|------------|-------------|-------------|-------------|
| NOr (m⁻⁴)  | 8 × 10⁶     | 1 × 10⁶     | 8 × 10⁵     | 4 × 10⁵     |
| Nh (m⁻⁴)   | 4 × 10⁴     | 9 × 10³     | 4 × 10³     | 2 × 10³     |
| Characteristics | Relatively small particle size | Plausibly proper particle size | Plausibly proper particle size | Large particle size |
scenarios that provide relatively comprehensive view of forecast response to terminal velocity bias.

Considering that the true terminal velocities are known in idealized cases, we calculated four sets of multiplicative factors, \( \alpha \), for each intercept parameter group according to \( \left( S / S_t + M / M_t \right) / \left( S_t^2 + M_t^2 \right) \), where \( M \) and \( S \) denote the mean and standard deviation of the three-dimensional terminal velocity, respectively, and the subscripts \( f \) and \( t \) represent the forecast and truth, respectively. These factors were calculated using default densities and were designed to minimize the difference between forecast and truth in terms of the frequencies of the terminal velocities of rainwater, snow, and hail. Our further examination indicated that involving the terminal velocities of rainwater, snow, and hail. Our further examination indicated that involving S did not push the factor to 1.0. The time-averaged results showed that \( \alpha \) for rainwater ranged from 1.35 to 0.86 and decreased with increasing intercept parameters, which is consistent with previous studies (Gilmore et al., 2004; Snook and Xue, 2008) that small raindrops resulted in the underestimation of terminal velocity and vice versa. For snow and hail, the factors approximately range from 0.4 to 0.5 in 5-hr simulation. For each intercept parameter group, averaging the factors over three cases and 5-hr simulation, we obtained case-averaged factors of 1.35 (rainwater), 0.40 (snow), and 0.50 (hail) for IntcptGrp 1, 0.98 (rainwater), 0.41 (snow), and 0.47 (hail) for IntcptGrp 2, 0.97 (rainwater), 0.41 (snow), and 0.44 (hail) for IntcptGrp 3, and 0.89 (rainwater), 0.42 (snow), and 0.44 (hail) for IntcptGrp 4, respectively. For brevity, these factors are referred as diagnostic factors. The above result also indicates that the raindrop fall speed uncertainty is not as large as that of ice species. Notably, the above factors have to be determined with fall speed observations in real cases.

Two types of ensembles were designed. One type (Ens_uniform) contained seven members with each member using the same factor for rainwater, snow, and hail; the factors were 0.4, 0.6, 0.8, 1.0, 1.2, 1.4, and 1.6 for members 1 to 7, which is based on the above sensitivity experiments. The other type (Ens_diag) also had 7 members but factors differed in species, according to the diagnostic factors mentioned above. For rainwater, the factor was uniformly distributed between 0.75 and 1.25 for members; for snow and hail, the corresponding ranges were 0.25 and 0.45, and 0.30 and 0.50, respectively. The first type represents the scenario that the bias difference among species is ignored, while the second type simulated the scenario that bias difference has been approximately estimated. The ensemble size is not large, but our further examination indicated that enlarging the ensemble sizes of Ens_uniform and Eng_diag to 20 did not significantly change the result as long as the perturbation ranges were not changed.

3 | RESULTS

3.1 | The impact of terminal velocity on precipitation forecasts

The precipitation intensity was represented by the maximum grid point precipitation over the computational domain; the precipitation coverage was denoted by the number of grid points with precipitation greater than 5 mm per 10 min. Considering that precipitation amounts substantially differed across cases, the precipitation maxima and precipitation coverage were investigated in terms of the ratio between simulations using the Lin scheme and MY2 scheme. The cold pool was defined within the coverage of precipitation greater than 1 mm per 10 min and its intensity was represented by the averaged potential temperature subtracted from domain mean value. For brevity, the average results (over cases and intercept parameter groups) are discussed.

Figure 1 shows the results averaged over all cases and intercept parameter groups. For example, Lin_diag is the averaged results of 12 experiments using diagnostic factors (three cases with four intercept parameter groups in each case). On average, the precipitation maximum increases with terminal velocity factor (Figure 1a), consistent with previous studies (Gilmore et al., 2004; Singh and O’Gorman, 2014). The results also show that the precipitation maximum is more sensitive to terminal velocity factors smaller than 1.0. Further increasing factors did not result in much larger precipitation maxima than simulations using factor of 1.0. Further examination (not shown) indicates that the above result did not substantially change among cases and intercept parameter groups, except the scenario that the intercept parameters were extremely underestimated, which will be discussed later. By contrast, reducing the snow and hail densities have less impact on the precipitation maxima, although small-density combination produced small precipitation maximum (Figure 1b), which is consistent with Gilmore et al. (2004). The difference between Figure 1a,b implies that rainwater terminal velocity has more impact on the precipitation maximum such that only considering the uncertainty of ice-species terminal velocity may be insufficient to estimate the precipitation maximum uncertainty. Additionally, using the diagnostic factors produced precipitation maximum close to the truth, which implies that precipitation prediction could be improved by perturbing terminal velocity.
FIGURE 1  The average (over all cases and intercept parameter groups) ratios of (a, b) precipitation maximum and (c, d) precipitation coverage between the MY2 simulation and Lin simulations using (a, c) multiplicative factors of terminal velocity and (b, d) different snow and hail densities. The multiplicative factors are shown in legend where suffix “diag” denotes the use of diagnostic factors. The hail density values are also shown in legends as suffix. (e, f) As in (a, b), except for the cold pool intensity of Lin and MY2 simulations. (g, h) The average (over all cases and intercept parameter groups throughout the simulation) mixing ratio profiles of rainwater (red), snow (green), and hail (blue).
The results of precipitation coverage (Figure 1c,d) are consistent with other studies (Gilmore et al., 2004; Snook and Xue, 2008; Singh and O’Gorman, 2014) that slower terminal velocity results in larger precipitation coverage and vice versa. Varying ice-species densities produced larger variation of precipitation coverage (Figure 1d) than varying rainwater, snow, and hail terminal velocities (Figure 1c), implying that ice-species terminal velocities primarily contribute to precipitation coverage variety because the fall speed in the Lin scheme increases with increasing density. Further increasing the terminal velocity (factor greater than 1.0) did not further reduce the precipitation coverage much. On average, using the diagnostic factors did not produce much better precipitation coverage prediction, but perturbing terminal velocity in a broad range is likely to envelope the truth.

For cold pool intensity, the results demonstrated that the terminal velocity of rainwater has greater impact than the ice-species counterparts because the variety of cold pool intensity in Figure 1e is larger than that in Figure 1f. The simulations using diagnostic factors (yellow curve) producing cold pool close to those with factor of 1.0 (black curve) indicates that the rainwater terminal velocity mainly contributes to the cold pool variety in this idealized case because the diagnostic factors of rainwater is close to 1.0 while those of ice-species are approximately 0.5. Overall, slower terminal velocity of rainwater resulted in stronger cold pool because rainwater has more time for evaporation (Dawson et al., 2010), except in the early stage that slower velocity caused weaker cold pool due to lighter rainfall. Note that the stronger cold pool also contributes to the large precipitation coverage. The above results imply that perturbing only ice-species densities cannot effectively envelop the true cold pool intensity.

Figure 1g shows that the hydrometeor amount increases with the decrease of terminal velocity. The altitudes of peak snow and hail become higher as terminal velocity decreases, which is consistent with Gilmore et al. (2004). The above variations of snow and hail profiles are approximately repeated when the snow and hail densities were perturbed (Figure 1h). This result implies that perturbing terminal velocity and the corresponding densities are qualitatively equivalent in terms of representing the terminal velocity uncertainties of snow and hail. However, only perturbing ice-species densities produced less variety for low-level rainwater than scenarios that rainwater terminal velocity was perturbed, which is likely due to the indirect influence of perturbing ice-species densities on low-level rainwater amount. The distribution of rainwater curves approximately follows the above rule that slower fall speed causes more rainwater in the air. The results also indicate that it is difficult to envelop the true hydrometeor profiles by perturbing terminal velocity or density. Fortunately, in the examined squall line cases, the true rain profile at low levels is enveloped by using Lin scheme with different factors.

Although the precipitation intensity often increases with terminal velocity, there are scenarios where faster terminal velocity may result in weaker precipitation. Figure 2 shows a part of precipitation simulations for Case 2. In this case, the MY2 simulation created a linear precipitation band (Figure 2a) that was missed in the simulation (Figure 2b) using Lin scheme with small intercept parameters (IntcptGrp 4). By using diagnostic factors for IntcptGrp 4, the linear precipitation structure was rebuilt (Figure 2c) with its leading edge approximately matching the MY2 results. Considering that all diagnostic factors for IntcptGrp 4 are smaller than 1.0, the different results between two Lin simulations indicate the overestimation of terminal velocities when IntcptGrp 4 parameters were used. Hydrometeors falling too fast formed a cold pool that is too weak for a linear precipitation system developing from thermal bubbles. This result partly explains why large multiplicative factors (>1.0) did not further increase the precipitation maximum in this idealized case. By contrast, with IntcptGrp 1 parameters, the Lin scheme simulation produced a stronger cold pool and a linear precipitation band (Figure 2g) which, however, moved faster than the MY2 counterpart. The faster moving precipitation band is partly attributable to the cold pool stronger than the truth. With multiplicative factor of rainwater greater than 1.0 (diagnostic value for IntcptGrp 1), the precipitation band is closer to the truth (Figure 2h).

Overall, the above results demonstrate that precipitation prediction is sensitive to terminal velocities and perturbing terminal velocities may produce precipitation maxima, coverage, and cold pool intensity closer to the truth, implying the potential benefit of involving terminal velocity uncertainty in ensemble forecasts.

### 3.2 The representation of terminal velocity uncertainty

The fractions skill score (FSS, Roberts and Lean, 2008), the coverage under the relative operating characteristic curve (AUC, Stanski et al., 1989), and the reliability diagram (Wilks, 2011) were used to evaluate ensemble forecasts. To remove precipitation bias, the percentile of precipitation over the computational domain was used for FSS calculation. The FSSs were aggregated over three cases, all members, and 5-hr simulation for each intercept parameter group. The FSSs of members with a factor...
FIGURE 2  The 10 min precipitation (shaded), potential temperature (blue contours) and reflectivity (red contours) at the third model level for (a, d) MY2 runs, (b, e, g, i) Lin runs with no terminal velocity perturbation, and (c, f, h, j) Lin runs with diagnostic multiplicative factors.
of 1.0 served as baselines. The resampling approach (Hamill, 1999) with 1,000 resamples was used to determine the significance of FSSs. To highlight the spatial distribution error, we used grid-scale probability for calculating AUC and the reliability diagrams. The reliability diagrams were calculated over three cases and 5-hr simulation for each intercept parameter group.

The FSS results indicate that the Ens_uniform ensemble produced significantly better result at the threshold of 0.98 for most radii when large (Figure 3a) or substantially small parameters (Figure 3d) were used. However, with IntcptGrp 2 and 3 parameters (Figure 3b,c), less improvements were made at the 98th percentile threshold by adopting the Ens_uniform ensemble. For smaller threshold, improvements were obtained when IntcptGrp 3 and 4 were employed. Further examination (not shown) indicates that the low FSSs of the Ens_uniform ensemble (Figure 3a,b) at small thresholds were attributable to large spatial distribution error, similar to the scenarios shown in Figure 2g;i; this is logical because some members with small factors (<1.0) may pronouncedly underestimate the terminal velocity when large intercept parameters were used (IntcptGrp 1 and 2), and thus produces small and slow falling raindrops that substantially intensify the evaporation and lead to stronger cold pool and larger spatial distribution error.

For Ens_diag ensemble, significant outperformances are observed in more scenarios (Figure 3e–h), especially for small radius of influence, which is consistent with results shown in Figure 2 that using diagnostic factors resulted in smaller spatial distribution error. The above results indicate that considering terminal velocity uncertainty could benefit the FSSs, especially when the terminal velocity bias difference among species was approximately estimated.

When IntcptGrp 1 was used, the AUCs of Ens_uniform ensemble (Figure 4a–c) were low. Further examination (not shown) indicated that these low AUCs were associated with false alarms corresponding to large spatial distribution errors that were caused by cold pool stronger than the truth, consistent with FSS results and previous studies (Snook and Xue, 2008; Dawson II et al., 2010) that the default intercept parameters of Lin scheme tend to produce strong cold pool. Although the Ens_diag ensemble also suffered the above issue with IntcptGrp 1 parameters, this ensemble obtained higher AUC throughout 1 hr to 4 hr, consistent with results in Figure 3e. For other intercept parameter groups, qualitatively similar differences can be seen between the Ens_diag ensemble and Ens_uniform ensemble, although the difference is smaller. The reliability diagram also demonstrates the superiority of using the Ens_diag ensemble (Figure 4d) that produced forecast probabilities closer to the observation frequency than the Ens_uniform ensemble for all intercept parameter groups. Considering that the multiplicative factors used in the Ens_diag ensemble are distributed around the diagnostic values calculated in section 2, the above results agree with Palmer (2019) that the performance of an ensemble relies on the performance of individual members. Overall, the results in Figure 4 demonstrate that the

![Figure 3](image-url)

**FIGURE 3** The FSSs of 10 min precipitation as functions of radius of influence for the (a, b, c, d) Ens_uniform and (e, f, g, h) Ens_diag ensemble, where dots near the bottom represent the FSSs of ensemble forecasts are significantly higher than those of Lin_1.0 (lines without markers), crosses denotes significantly lower. The intercept parameters are shown in plots.
Ens_diag ensemble worked in more scenarios and it is better to consider the terminal velocity uncertainty for different hydrometeors.

4 | CONCLUSIONS

Our results show that the terminal velocities of hydrometeors have great impacts on precipitation prediction with respect to precipitation maxima, coverage, and spatial distribution. Most of our results are consistent with previous studies (e.g., Gilmore et al., 2004; Snook and Xue, 2008; Singh and O’Gorman, 2014) that precipitation maxima approximately increase with increasing terminal velocity. However, we found that extremely fast velocity could lead to a cold pool too weak to support the development of precipitation system and weaken the precipitation maximum. The new finding is that the precipitation prediction could be improved when the biases of terminal velocities of different species are approximately estimated.

The ensemble forecast results demonstrated that considering the terminal velocity uncertainty could benefit the forecast skill, especially with respect to spatial distribution. The results also show that uniformly perturbing terminal velocity mainly benefits the scenario when mean drop sizes are substantially overestimated, while creating perturbations based on the biases of different species improves the forecast skill in more scenarios. This result highlights the necessity to separately consider the terminal velocity error for different species.

Although this work shows the potential benefit of considering terminal velocity uncertainty in ensemble forecast, our results have limitations. The ensemble size is small, although it is sufficient in this work. The precipitation types are limited, although the used

![AUC curves](image_url)
soundings resulted in pronouncedly different precipitation distribution in Lin scheme simulations. In addition, considering that the surface temperature is approximately 300 K, the results of this work may not be valid in cold season. Applying fixed multiplicative factors for whole domain and throughout the simulation may not be representative, so stochastic perturbations (e.g., Romine et al., 2014) should be considered in the future.

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CONFLICT OF INTEREST

The authors have no conflict of interest to declare.

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