Impact of FORMOSAT-3/COSMIC GPS Radio Occultation and Drop-windsonde Data on WRF Simulations

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1. Introduction

The Southwest Monsoon Experiment/Terrain-influenced Monsoon Rainfall Experiment (SoW-MEX/TiMREX) is an international collaborative field experiment that collects special observations over the western plain and mountain slope region of southern Taiwan in the 2008 Mei-yu season. A pilot experiment of this project was conducted in the 2007 Mei-yu season. During a heavy rain event that occurred in central and southern Taiwan in 5-10 June 2007 (Fig. 1a), dropwindsonde observations were undertaken over the Taiwan Strait and the northern South China Sea. In this study, we take advantage of dropwindsonde observations, together with the FORMOSAT-3/COSMIC GPS RO data, to examine their impact on regional weather predictions during an 11-day period from 5 to 15 June 2007.

2. Model results

The model configuration includes two domains with 45- and 15-km horizontal grid spacing and 31 vertical levels. The physics used in the simulation included Kain-Fritsch cumulus parameterization scheme, WSM-5 class microphysics scheme, and the YSU PBL scheme. Four experiments are conducted for this study. The control experiment (CON) uses the conventional (surface and sounding) observation data in the WRF-Var data assimilation. Three sensitivity experiments are carried out. The GRO and DWS experiments are the same as the CON experiment except that the data from FORMOSAT-3/COSMIC GPS RO and dropwindsonde observations, respectively, are added in the data assimilation. The ALL experiment ingests all the aforementioned data in the data assimilation. Figures 1b, c present an example of the locations of observations from each observing platform at 0000 UTC 6 June 2007. The average amount of GPS RO data was about 10-20 at each time. The dropsonde data, however, were only available at 6 times (0000 UTC, 5-10 June). While the GPS RO data were distributed in a widespread area, the dropwindsonde data were mostly collected over the ocean to the southwest of Taiwan.

Each of the four experiments contains 22 runs of 72-h WRF simulations. These runs were initialized twice daily from 0000 UTC 5 June to 1200 UTC 15 June 2007. The initial data (first guess) of the first run at 0000 UTC 5 June 2007 were obtained from the NCEP GFS, while those of the other 21 runs were from the 12-h forecast of their previous WRF runs (i.e., 12-h update cycling).

The verification was done by comparing the geopotential height (H), temperature (T), relative humidity (RH), and east-west- and north-south-wind components (U and V) with those of the analyses from the NCEP GFS plus mesoscale data assimilation of traditional surface and upper-air observations. The root-mean square error (RMSE) and skill score (SS) are calculated by using data from all the grid points in domain 2 from all the 22 runs during the 11-day period. Skill score is defined as the percentage improvement of RMSE of a particular experiment (e.g., GRO or DWS) over the reference forecasts (CON). It can clearly demonstrate the improvement or worsening of the particular experiment over CON.

Figure 2a shows SS of GRO against CON. At 300 hPa, GRO shows positive SSs for geopotential height at all time periods, and the SS is the largest (~9%) at 24 h. The other variables do not have large improvement like geopotential height, but they still exhibit a trend of increasing SS at the longer integration time. At 72 h, the SSs are positive for all variables.

At 500 and 850 hPa, GRO still shows, for almost all the variables, the tendency of improving forecast skill at the longer forecast time. Geopotential height has consistently the largest SSs after 48 h of
integration at these two levels. Combining the result at 300 hPa, it is clear that the GPS data provide useful information of height fields such that the forecast of geopotential height can be greatly improved, especially after longer integration. The 500-hPa temperature forecasts of GRO also improve over CON, but the SSs are relatively small (<4%). At 850 hPa, their SSs are close to zero. Relative humidity has positive SSs at 500 hPa, but negative SSs at 850 hPa. There are several possible reasons for this. First, the moisture analysis contains considerable uncertainties, and does not serve as a good verification for the prediction. There is negative refractivity bias in the GPS RO soundings (Rokcen et al. 1997) that affects the accuracy of moisture analysis. Third, over region with significant moisture variability, such as near a Mei-yu front, a more sophisticated nonlocal observation operator should be used (e.g., Sokolovskyi et al. 2006) for the assimilation of GPS RO data.

Compared with GRO, DWS has lower SSs (<5%) and it does not show the trend of improvement over time (Fig. 2b). Instead, the SSs are in general higher at the earlier time and they decrease as the integration time increases. The assimilation of drop-windsonde data helps to improve the simulation for most of the variables at 300 and 500 hPa, but it barely shows forecast improvement at 850 hPa.

With both the GPS RO and the dropwindsonde data assimilated together in the model, ALL (Fig. 3a) shows even higher SSs than either GRO or DWS. The most notable is the forecast of geopotential height. Its SSs are relatively high, for example, they are up to 15% at 850 hPa in the 60- and 72-h forecasts. The tendency of SSs for each variable is very similar to that of GRO, except with some minor differences. This is because the drop-windsonde data are available only in 6 out of the 22 runs. Their overall impact is relatively small compared with that of the GPS data.

Because the GPS data were provided continuously in time, the 12-h cycling data assimilation setting may not be good enough to take advantage of all the available observations. Therefore, it would be interesting to compare the result with that from the 6-h cycling experiments. The dropwindsonde data, however, are only available in every 24 h from 0000 UTC 5 June to 0000 UTC 10 June 2007. The 6-h cycling strategy, compared with the 12-h cycling, does not provide further improvement to the forecast (not shown).

For brevity, only the SSs from the 6-h cycling GRO experiment that are calculated against the CON experiment of the same cycling group are presented here for comparison (Fig. 3b). It is found that the SSs of the 6-h cycling runs overall are lower than those of the 12-h cycling runs of GRO (Fig. 2a) at the earlier forecast time, but they become slightly higher as the integration time increases. For most variables, the tendency of SS change with time is quite similar to that of the 12-h cycling runs. This result suggests that the 6-h cycling strategy does help to take advantage of the continuous GPS RO data because the 6-h cycling GRO experiment obtains more improvement than that of the 12-h cycling at the longer integration time when the data start to show a positive impact. At the earlier time, because the 6-h cycling CON has lower RMSEs than the 12-h cycling CON by assimilating more surface observation in a 6-h interval, it is difficult for the 6-h cycling GRO to present higher SSs than the 12-h cycling GRO.

Figure 4 presents the ETS and bias of the 12-h rainfall forecasts of the four experiments verified against the 390 rain gauge observations in Taiwan. For brevity, only the results between 12 and 60 h in the simulation are shown. At 12-24 h (Fig. 4a), the ETSs of CON (#1 curve) are slightly below 0.3 for rain thresholds smaller than 35 mm and drop to below 0.2 at the 50-mm threshold. The corresponding biases are very good, around 1 for all thresholds. Compared with CON, there is nearly no improvement in terms of ETS for either GRO (#2 curve) or DWS (#3 curve). DWS even produces much lower ETSs at thresholds between 10 and 35 mm. ALL (#4 curve) is the worst among all the experiments at small thresholds, but it becomes better at large thresholds.

At 24-36 h (Fig. 4b), the ETSs show that both GRO and DWS predict better rainfall than CON at small thresholds (≤5 mm), but do worse than CON at large thresholds (≥35 mm). In a similar manner, ALL has the highest ETSs at those small thresholds and the lowest ETSs at those large thresholds. Bi-
ases of all the experiments are still very good at this forecast time period.

The ETSs of the rainfall forecast at 36-48 h (Fig. 4c) present that GRO produces the highest ETS at almost all the rainfall thresholds. The reason is that the model starts to over-predict rainfall at this time period and the biases increase with increasing rainfall thresholds, but GRO appears to have this over-prediction problem reduced. On the contrary, DWS has the highest biases, and its ETSs are the worst among the four experiments at thresholds larger than 10 mm. The ETSs of ALL are nearly the same as CON, except at small thresholds where the ETSs of ALL are slightly higher.

At 48-60 h (Fig. 4d), GRO still has the highest ETSs, except at large thresholds where the ETSs are low and the biases are high. The biases of DWS are not too bad (closest to 1) and its ETSs become better at this time period. ALL overall does not perform well at this time period.

3. Summary

The assimilation of the GPS RO data can help to improve the WRF forecast at the longer forecast time (e.g., > 36 h). The forecast of geopotential height, among the five meteorological variables, receives the largest impact from the GPS data. All the variables at all levels more or less show a positive impact, except relative humidity which has negative SSs at 850 hPa at all time. The improvement of assimilating the dropwindsonde data is in general positive at the earlier forecast time and its impact decreases over time. However, this improvement only shows up at high levels like 300 and 500 hPa. At 850 hPa, the dropwindsonde data in general do not improve forecasts. Because there are usually very few GPS RO observations located in the fine domain, it takes time for the influence to propagate from the coarse domain into the region where the verification is done. In other words, the large-scale simulation is first improved due to the GPS RO observations, and the change can have a positive impact on the mesoscale at the later time. The dropwindsonde observations, however, were taken inside the fine domain such that their impact can be detected early in the simulation. This reflects the fact that GPS RO is primarily a large-scale observation (both in terms of its measurement characteristics and data distribution), while the dropsonde is primarily a mesoscale observation. With both the GPS RO and the dropwindsonde data assimilated, the model receives even more positive impact. It is also found that a 6-h update cycling strategy can further help the forecast by assimilating more GPS RO data into the model, but the difference is not very significant.

The GPS and dropwindsonde data start to help the rainfall forecast only after 24 h. At 36-60 h, the GPS RO data significantly help to improve the rainfall prediction because the over-prediction problem of the model is reduced. Compared with the verification of the five meteorological fields, this suggests that when the model simulates better basic fields with the GPS RO data, the rainfall is better predicted because the dynamics and physics processes are better reproduced. One exception for this, however, is the simulation of low-level (850 hPa) moisture, because with the GPS RO data assimilation the moisture simulation was not improved. Since low-level moisture is very important in determining the accuracy of precipitation, the inconsistent result leads us toward a possible explanation that the moisture analysis we used does not serve as a good verification for the prediction. This is often the case because the moisture analysis usually contains considerable uncertainties at low levels. The other possibility is that there is negative refractivity bias in the GPS RO soundings that affects the accuracy of moisture analysis. In addition, over region with significant moisture variability, such as near a Mei-yu front, a more sophisticated nonlocal observation operator or directly assimilation of bending angle should be considered. The dropwindsonde data also provide a positive impact on rainfall forecasts, but it is not as significant as the GPS RO data. It should be noted, however, that the above result is based on the current data availability of dropwindsonde observation in the field program. If dropwindsonde data were available at more times, the impact would probably be larger. However, since they are usually distributed in a limited area, their impact should be less than that of the GPS RO data when the large-scale weather system is more dominant.
Fig. 1: (a) The 12-h accumulated rainfall observation in Taiwan in May and June 2007. The rainfall amount (mm) shown here is an average of all the 390 rain gauge stations over Taiwan. (b) The locations of observation data within domain 1 from traditional sounding plus dropwindsonde at 0000 UTC 6 June 2007. (c) Same as b, but for synoptic surface stations plus GPS RO. There were 155 soundings (circle), 13 dropwindsondes (black dot), 877 surface data points (cross), and 10 GPS RO observations (black dot). Box in b denotes the location of domain 2.

Fig. 2: Skill score (%) for (a) GRO and (b) DWS against CON at 300, 500, and 850 hPa. The abscissa denotes time into the simulation (h). Color curves in green, blue, red, magenta, and cyan represent results for H, T, RH, U, and V, respectively.
Fig. 3: Same as Fig. 2, but for (a) ALL and (b) 6-h GRO.

Fig. 4: The ETS (left) and bias (right) of 12-h precipitation forecasts from CON (black, #1), GRO (red, #2), DWS (blue, #3), and ALL (green, #4). The abscissa is the rainfall thresholds (mm). Time periods of the 12-h rainfall verified include (a) 12-24 h, (b) 24-36 h, (c) 36-48 h, and (d) 48-60 h.