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IMPROVING CLOUD PREDICTION IN WRF THROUGH THE USE OF GOES SATELLITE ASSIMILATION

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1. INTRODUCTION

Clouds directly modulate the radiation budget over their area of influence. Changes in cloud cover, therefore, can have pronounced effects on the meteorological conditions of a given area. In turn, changes in meteorological conditions greatly affect chemical processes in the atmosphere. Unfortunately, numerical weather prediction (NWP) models fall short of accurately producing clouds at the correct time and location with respect to observations. This results in an inaccurate representation of the atmospheric state throughout the model domain. These errors inhibit the model's ability to accurately predict variables such as temperature and radiation, and lead to a misrepresentation of vertical mixing and inaccurate development of the boundary layer. These errors then impact chemistry by modifying photodissociation reaction rates, biogenic emission rates, wet removal, and vertical mixing of pollutants. Reducing the errors in these fields is highly advantageous for improving the meteorological inputs into air quality models, especially for State Implementation Plan (SIP) modeling. Through assimilation of Geostationary Operational Environmental Satellite (GOES) derived cloud fields within the Weather Research and Forecasting (WRF) model, cloud placement in time and space within the model can be improved.

While many studies focus on improving NWP models for forecasting applications, the focus of this study is to improve the simulation of clouds in space and time in order to better represent the physical atmosphere for air quality studies. More specifically, the goal is to improve model simulations for SIP modeling. Improving cloud forecasts, including non-precipitating clouds which are important for atmospheric chemistry, is difficult due to the lack of available observations at the necessary spatial and temporal scales. Standard weather service observations are not dense enough to be used for cloud specification, and the NWS WSR-88D radar network is not designed to be sensitive enough to retrieve cloud droplet information. Therefore, geostationary satellites remain the only dataset which provides sufficient spatial and temporal resolutions to quantify cloud fields. The GOES Imager has a spatial resolution of 1-km over the visible channel and 4-km resolution over the infrared channel for timescales down to an hour or less. From this data, a cloud albedo can be retrieved from the visible channel, while the infrared channel is used to estimate the cloud top heights. The GOES satellite retrieval of cloud albedo is described in Haines et al. (2004) and is based on an implementation of the Gautier et al. (1980) method with the improvements from Diak and Gautier (1983). These satellite derived fields are used to define the location of clouds within the atmosphere.

Since these simulations are conducted retrospectively, a wide array of observational and model analysis data is available throughout the simulation time period. This allows the Four Dimensional Data Assimilation (FDDA) technique, based on Newtonian Relaxation or "nudging", to be used throughout the simulation time period. Nudging works by adding artificial forcing terms to the governing equations to force the model towards an observed state (Stauffer and Seaman, 1990). In this work, analysis nudging, which entails nudging to a gridded analysis field of meteorological variables at each grid point, is used to assimilate GOES derived clouds into WRF to improve cloud performance in retrospective modeling simulations.

2. METHODOLOGY

The assimilation technique is based on creating a dynamic environment that is supportive of cloud formation or removal through the use of GOES cloud information. The basic approach is

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to create positive vertical motion within the model to produce clouds, and negative vertical motion to dissipate clouds, based on GOES cloud fields. The use of FDDA allows for the assimilation of horizontal wind fields into the model domain at specified times. Thus, the developed technique calculates the necessary vertical velocity needed to create or dissipate clouds within WRF, and then derives the corresponding horizontal wind field needed to produce the vertical motion. This new horizontal wind field can then be assimilated into the model through a FDDA field.

First, the locations where the model cloud fields and GOES clouds fields disagree are determined. In order to compare model cloud fields with GOES derived cloud albedo, a model cloud albedo was derived. This was done by completing a model simulation without microphysics and cumulus parameterization schemes enabled to determine the max insolation predicted by the model's radiation scheme at every grid point across the domain. The ratio in the insolation fields from the model simulation with cloud fields, and without, allows the model cloud albedo to be determined. Using a ten percent albedo threshold to identify if a model or GOES grid is flagged as cloudy, areas of disagreement between the two can be determined. The disagreement areas are split into two categories: underprediction and overprediction of clouds by the model. Underprediction locations are where the model is clear (cloud albedo less than 10%), and GOES is cloudy (cloud albedo greater than 10%). Overprediction areas are locations where the model is cloudy when the satellite is clear. Because the GOES cloud albedo is retrieved from the visible GOES channel, the assimilation window is limited to the daytime. With the modeling domain covering the Contiguous United States (CONUS) region, the assimilation window was chosen as 14-23 UTC to ensure that the solar zenith angle was as small as possible over the model domain. This reduces the error in the calculation of both the model and the satellite derived cloud albedos.

Once the disagreement areas between the model and satellite are known, an analytical method for determining vertical velocities necessary to create or remove clouds within the model is applied. In order to create the derived vertical motion within the model, a one-dimensional variational technique based on O'Brien (1970) is used to determine the divergence fields. The derived divergent component of the wind is then blended back into the horizontal wind field. The variational technique requires four inputs which are effectively the boundary conditions. These inputs are: the target vertical velocity, the target height, the bottom adjustment height, and the top adjustment height. These inputs are derived for both the underprediction and overprediction cases.

2.1 Underprediction

Underprediction by the model is characterized by locations where the model fails to produce clouds in locations where GOES is cloudy. In these locations the goal is to produce a cloud within the model that is comparable to the satellite field. Using GOES infrared temperature and cloud albedo estimates, the observed cloud top and bottom is estimated based on the model column's vertical profile. The observed cloud top height is determined by calculating the height at which the model column temperature is equal to the derived infrared temperature of the observed cloud. With the cloud top height known, the cloud thickness is estimated based on the GOES cloud albedo. This is done by assuming that an increase in cloud albedo indicates an increase in cloud thickness and that there is only one cloud layer. Based on the cloud thickness, it is possible to determine the maximum height at which saturation must occur within the model to produce an equivalently thick cloud below the column tropopause. Next, the lifted condensation level of each model vertical layer is determined. The layer which has to be lifted the smallest distance to become saturated and can achieve saturation before the determined maximum height is used to calculate the maximum vertical motion. The target vertical velocity is calculated by taking the distance the layer has to rise to reach saturation divided by 45 minutes. Forty-five minutes is selected because GOES assimilation occurs on an hourly time scale, and thus, it is necessary to create the cloud within an hour, indicating that saturation must occur before an hour of time. The target height is then defined as the height at which the target model layer reaches its lifted condensation level. The top adjustment height is set to be the target height plus the estimated GOES cloud thickness. Finally, the bottom adjustment height is defined to be the target model layer minus one kilometer. However, for the bottom adjustment height, thresholds are set to ensure that this level does not reach the surface. This is done to ensure the assimilated nudged winds minimally affect the surface layer of the model.

2.1 Overprediction

Overprediction by the model is characterized by locations where the model produced clouds in locations where GOES was clear. First, the locations of clouds within the model column are determined. The presence of clouds is determined by the total cloud liquid water (CLW) in each vertical layer. The CLW is the sum of the liquid and ice water within each layer. The layer with the maximum amount of CLW is used to calculate the downward displacement necessary to sufficiently warm the air parcels in order to evaporate the cloud. The distance is calculated as the vertical distance that a parcel must sink and result in a relative humidity that is less than sixty percent. The calculated distance divided by 45 minutes then yields the target vertical velocity. The target height is set to the height of the layer with the maximum CLW. The cloud top and cloud base is then determined by setting a $1.0\ x\ 10^{-6}\ kg\ kg^{-1}$ CLW threshold to indicate a cloud. The top adjustment height is then calculated as the model cloud top height plus one kilometer or the column troposphere height, whichever height is less. The bottom adjustment height is calculated as the height at which the layer containing the maximum CLW will evaporate minus one kilometer, or the determined model column cloud base minus a quarter of the distance between this point and the surface, whichever height is less. Similar to the underprediction case, a minimum threshold height is set to ensure the bottom adjustment height does not reach the surface.

3. MODEL CONFIGURATION

The WRF-ARW version 3.6.1 was used to conduct model simulations over the August 2006 and 2013 time periods. For each time period, two different simulations were conducted. The first is the baseline simulation (Control) in which no satellite data is assimilated, and the second simulation includes satellite assimilation (Cloud Assimilation). The simulations were performed on a parent 36-km domain covering the CONUS area, a nested 12-km domain covering the South/Southeastern U.S., and a nested 4-km domain covering Eastern Texas. While the domains between the 2006 and 2013 simulations were similar, there were some slight east/west shifts in the 12- and 4-km domains. Important physics options for the August 2006 and 2013 model simulations are shown in Table 1.

Table 1. Physics options used for the WRF model simulations.

Physics	August 2006	August 2013
Shortwave Radiation	Dudhia (Dudhia, 1989)	RRTMG (Iacona et al., 2008)
Longwave Radiation	RRTM (Mlawer et al., 1997)	RRTMG (Iacona et al., 2008)
Land Surface Model	4-layer Unified Noah (Tewari et al., 2004)	4-layer Unified Noah (Tewari et al., 2004)
Planetary Boundary Layer	YSU (Hong et al., 2006)	YSU (Hong et al., 2006)
Cloud Microphysics	Lin (Lin et al., 1983)	Thompson (Thompson et al., 2008)
Cumulus Parameterization	Kain-Fritsch (Kain, 2004) with the moisture-advection trigger (Ma and Tan, 2009)	Kain-Fritsch (Kain, 2004) with the moisture-advection trigger (Ma and Tan, 2009)
Analysis Nudging	U, V, T, Q	U, V, T, Q

4. MODEL EVALUATION

To validate the assimilation technique, both the Control and Cloud Assimilation model simulations were compared to surface observations and GOES retrievals. The METSTAT package developed by Ramboll Environ was used to determine the model mean bias (MB) and root mean square error (RMSE) for wind speed, temperature and mixing ratio. For wind direction, MB and mean absolute gross error (MAGE) was calculated. Precipitation MB and RMSE were also calculated. Model predicted downwelling radiation was also evaluated against U. S. Climate Reference Network (USCRN) pyranometer measurements.

In order to determine how well each model simulation performed with respect to clouds, a cloud agreement index (AI) was developed to quantify the model cloud performance. The AI is calculated as the percentage of the total grids which agree with the satellite and is expressed as:

$$AI = \frac{A + D}{A + B + C + D} \qquad (1)$$

where A represents the number of grids where both the model and GOES indicates clouds, B represents the number of grids where GOES indicates clouds and the model is clear, C represents the number of grids where GOES is clear and the model is cloudy, and D represents the number of grids where both GOES and the model are clear. The grid cells were characterized as cloudy or clear based on the derived cloud albedos for the model and satellite using a ten percent albedo threshold to signify a cloudy cell.

5. RESULTS

5.1 Cloud Performance

In order to determine how well each model simulation performed with respect to clouds, the daily average AI was calculated. The daily average AI for August 2006 for the 36-km, 12-km, and 4-km domains are shown in Figure 1. Likewise, the August 2013 daily average AI is shown in Figure 2. The results in Figure 1 and 2 show that the assimilation technique improves the AI on every day of the simulation period for the 36-km and 12-km domains. At the 4-km domain, the improvement is not as significant, but on the majority of the days, the assimilation still improves the agreement with GOES. The variability in the AI for the 4-km domain can be attributed to the more transient nature of clouds within the smaller grid cell over a time period of one hour. The average daily percent change in the AI over the August 2006 time period was found to be positive 14.02%, 11.3%, and 5.12% for the 36-km, 12-km, and 4-km domains, respectively.

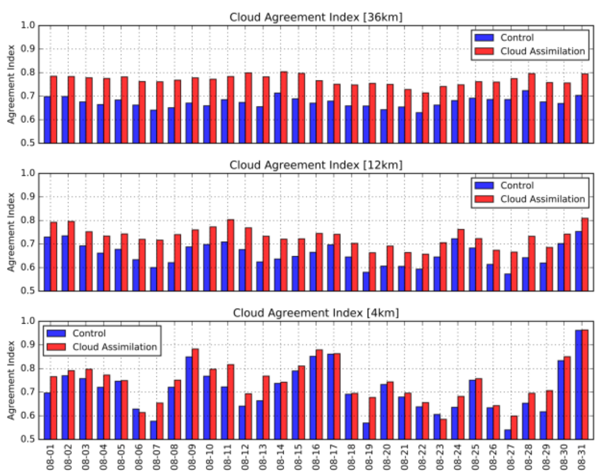

Figure 1. Daily average AI for the Control (Blue) and Cloud Assimilation (Red) simulation over August 2006. Top is the 36-km domain, middle is the 12-km domain, and bottom is the 4-km domain.

For the August 2013 time period, the average daily percent change in AI was found to be positive 13.26%, 10.06%, and 5.93% for the 36-km, 12-km, and 4-km domains, respectively. Comparing the two years, we find that the improvement in the cloud performance was consistent across years.

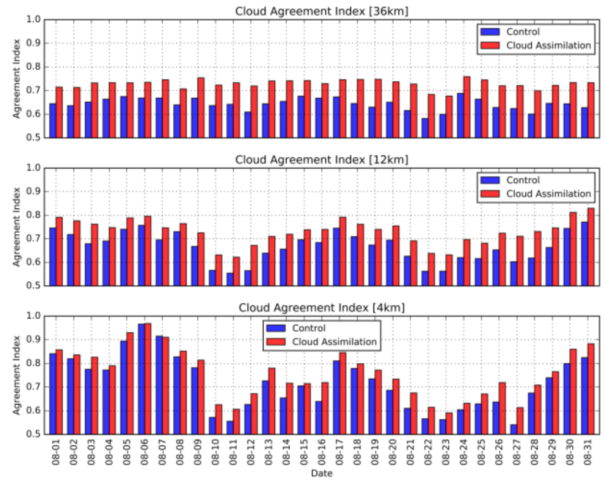

Figure 2. Daily average AI for the Control (Blue) and Cloud Assimilation (Red) simulation over August 2013. Top is the 36-km domain, middle is the 12-km domain, and bottom is the 4-km domain.

The spatial fields of model/GOES cloud agreement and cloud albedo reveals the overall effect of the assimilation technique. Figures 3 and 4 show spatial plots of AI at the 36-km and 12-km domains, respectively. From these figures, it is clear that the assimilation technique reduces the amount of under and overprediction by the model.

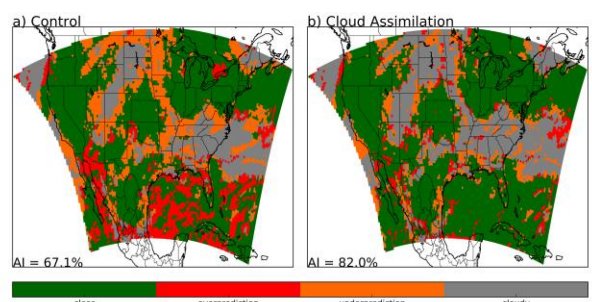

Figure 3. Spatial plot of AI on August 12, 2006 at 17 UTC for the 36-km domain. Green represents areas where the model and GOES is clear, red represents areas where the model is cloudy and GOES is clear, orange represents areas where the model is clear and GOES is cloudy, and gray represents areas where the model and GOES are cloudy.

Figure 5 shows how the assimilation technique improves the spatial distribution of clods in terms of cloud albedo. While the exact magnitude of the cloud albedo is different than GOES, the improvement in the spatial pattern of clouds with the use of cloud assimilation is clearly evident.

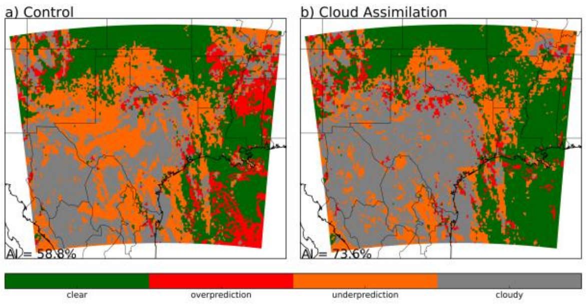

Figure 4. Spatial plot of AI on August 27, 2013 at 22 UTC for the 12-km domain. Green represents areas where the model and GOES is clear, red represents areas where the model is cloudy and GOES is clear, orange represents areas where the model is clear and GOES is cloudy, and gray represents areas where the model and GOES are cloudy.

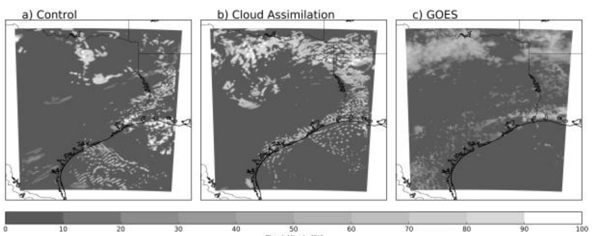

Figure 5. Spatial plot of cloud albedo at 17 UTC on August 12, 2006 over the 4-km domain.

5.2 Surface Statistics

The surface statistics with respect to wind speed and direction, temperature, mixing ratio, and precipitation were calculated.

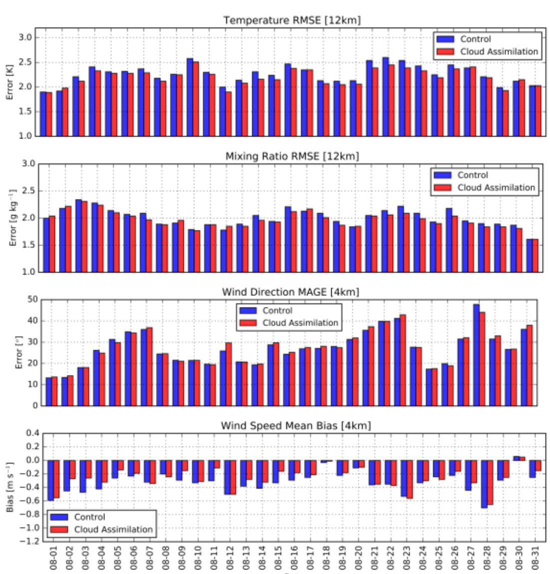

Figure 6. Surface statistics for August 2006. From top to bottom, 12-km temperature RMSE, 12-km mixing ratio RMSE, 4-km wind direction MAGE, and 4-km wind speed MB.

Figure 6 shows comparisons between the Control and Cloud Assimilation simulations for select grids of temperature, mixing ratio, wind direction and wind speed which are representative of the effect of the cloud assimilation on the surface statistics. Generally, the cloud assimilation reduces the error in temperature and mixing ratio while slightly increasing the error in the wind speed and direction. However, the difference in the wind statistics between the Control and Cloud Assimilation simulations becomes less as the model grid spacing is reduced.

The assimilation technique also reduced the error with respect to NCEP's stage IV precipitation product. Figure 7 shows the 4-km precipitation RMSE for the Control and Cloud Assimilation simulations for August 2006.

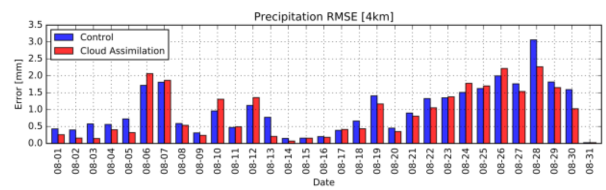

Figure 7. Precipitation RMSE for the 4-km domain for August 2006.

At the 4-km resolution, there is still some variability in the error reduction due to advection processes, but the majority of the time the error is reduced.

The final evaluation of the model results was with respect to USCRN pyranometer stations. For this, linear comparisons were made. Figure 8 shows the comparison of the model predicted to the observed shortwave downwelling radiation. The assimilation technique was found to improve the predicted shortwave radiation.

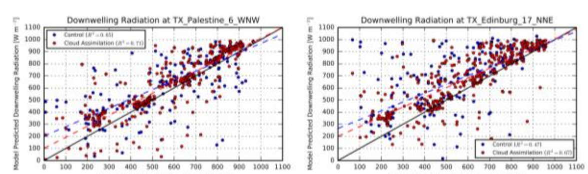

Figure 8. Model predicted (4-km) downwelling shortwave radiation vs observed at two different USCRN observations sites in Texas. Blue is the Control simulation and Red is the Cloud Assimilation simulation.

The coefficient of determination (R^2) was found to be greater for the Cloud Assimilation simulation, 0.71 compared to 0.65 and 0.67 compared to 0.47, at both locations. This indicates that the assimilation technique improves the ability of the model at predicting shortwave radiation due to improved cloud performance.

6. CONCLUSION

In this study, GOES satellite derived cloud albedo and cloud top temperature information was assimilated into the WRF model to improve the placement of clouds in space and time. An analytical technique for estimating vertical velocities necessary to produce or dissipate clouds based on the observations was developed. The results indicate that the cloud assimilation technique improves the model prediction clouds in space and time when compared to GOES cloud fields. The assimilation technique was tested for two different time periods, August 2006 and August 2013, and used slightly different configurations but the improvement was determined to be consistent. The average daily percent change in the AI for both the August 2006 and August 2013 simulations were found to be greater than 13%, 10%, and 5% for the 36-km, 12-km, and 4-km domains, respectively. At the same time, the cloud assimilation lead to a reduction in the precipitation error and improved the predicted downwelling shortwave radiation.

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