

Final Report

ATTN: ASR Program Managers, Drs. Dorothy Koch
Climate and Environmental Sciences Division
Office of Biological and Environmental Research
Department of Energy
19901 Germantown Road
Germantown, MD20874

Title of Research Project: Continuous Evaluation of Fast Processes in Climate Models Using
ARM Measurements

Investigator: Zhijin Li, Researcher

Joint Institute for Regional Earth System Science and Engineering, UCLA
9258 Boelter Hall, Los Angeles, CA 90095
Phone: (310) 794-5273; Fax: (310)943-1656
Email: zhijinli@jifresse.ucla.edu

Contributors:

Feng Sha,

Institute for Regional Earth System Science and Engineering, UCLA

Yangang Liu, Wuying Lin, Tami Toto, and Andrew Vogelmann

Brookhaven National Laboratory

February 1, 2016

Contents

1	BACKGROUND AND OBJECTIVES	4
2	MAJOR ACHIEVEMENTS	6
2.1	An Improved MS-3DVAR Framework.....	6
2.2	The FASTER Data Assimilation System	6
2.3	A 3DVAR Aerosol Data Assimilation System	8
2.4	Multiscale Forcing.....	9
2.5	Large-scale Hydrometeor Forcing.....	11
2.6	Large-scale Aerosol Forcing	12
3	PUBLICATIONS AND PRESENTATIONS	14
4	REFERENCES	16

1 Background and Objectives

This five-year award supports the project “Continuous Evaluation of Fast Processes in Climate Models Using ARM Measurements (FASTER)”. The goal of this project is to produce accurate, consistent and comprehensive data sets for initializing both single column models (SCMs) and cloud resolving models (CRMs) using data assimilation. The data assimilation work focuses on the ARM SGP region. ARM measurements are assimilated along with other available satellite and radar data. Reanalyses are then generated for selected ARM IOPs, with a goal of producing reanalysis data sets for some selected period of time. This project also aims to deliver a comprehensive data assimilation system (FASTER-DA) to the FASTER teams to carry out data assimilation experiments for a variety of applications.

The FASTER-DA system is developed to have a capability of producing time-dependent three-dimensional fields of meteorological variables, aerosol concentrations and size distributions, hydrometeors, and land surface variables. Data assimilation was identified as one of four general measurement strategies at the inception of the ARM program. Stokes and Schwartz (1994) envisioned it as follows: “To test models on a variety of physical scales, it is necessary to develop methods that will allow the output of individual instruments, which measure different parameters, to be combined to infer the time-dependent three-dimensional field of meteorological variables.” The success of the ARM large scale forcing estimates is an outstanding testimony to the success of recent work toward this end (e.g., Zhang et al., 2001; Xie et al., 2004). Because of the progress in data assimilation methodologies in the past decade, the availability of high resolution satellite and radar measurements and advancements in computing capacity, we aim to use data assimilation to “infer the time-dependent three-dimensional fields of meteorological variables” and more.

This FASTER-DA system incorporates multiple features designed particularly for FASTER. It is implemented in the community Weather Research and Forecasting model (WRF) at a cloud resolving resolution approaching 1 km. Since such a CRM resolves a wide range of temporal and spatial scales, conventional data assimilation algorithms used in operational centers become ineffective. We then employ a multi-scale three-dimensional variational data assimilation scheme (MS-3DVAR) (Li et al., 2012a, b). This MS-3DVAR system is built on top of WRF/GSI. The Community Gridpoint Statistical Interpolation (GSI) system is an operational

data assimilation system at the National Centers for Environmental Prediction (NCEP) and has been implemented in the WRF model (WRF/GSI) (Developmental Testbed Center, 2012).

While FASTER-DA will keep abreast of the continuing advancements in data assimilation made by NCEP, it is also enhanced by the incorporation of a land surface three-dimensional variational data assimilation (3DVAR) scheme specifically for the ARM SGP region; and a comprehensive aerosol 3DVAR scheme. The components of the FASTER-DA system are summarized in Fig. 1.

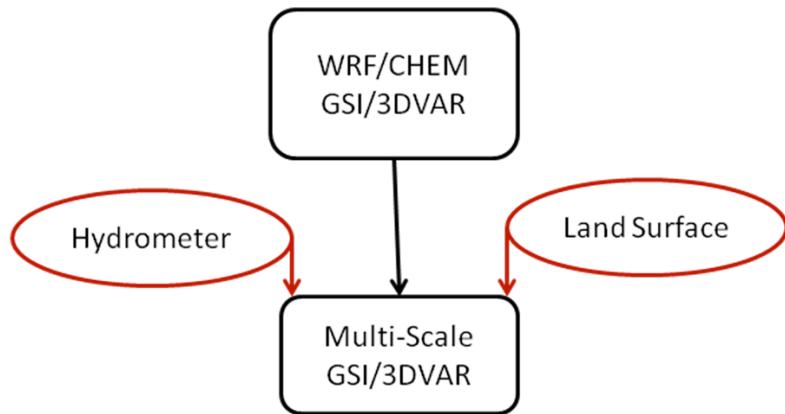


Figure 1: Components of the proposed FASTER-DA system: a multi-scale WRF/GSI with an enhanced capability for assimilating high resolution observations in CRMs; a comprehensive aerosol 3DVAR module; and a land surface 3DVAR scheme specifically formulated for the ARM SGP.

2 Major Achievements

During the implementation of five years, the proposed objectives were achieved and supplemented by additional achievements beyond the proposed objectives.

2.1 An Improved MS-3DVAR Framework

Systematic theoretical and numerical analyses were carried out to further improve and refine MS-3DVAR. In this MS-3DVAR, a decomposition of the cost function is derived for a set of distinct spatial scales. The decomposed cost function allows for the background error covariance to be estimated separately for the distinct spatial scales, and multi-decorrelation scales to be explicitly incorporated in the background error covariance. MS-3DVAR minimizes the partitioned cost functions sequentially from large to small scales. The multi-decorrelation length scale background error covariance enhances the spreading of sparse observations and prevents fine structures in high-resolution observations from being overly smoothed. The decomposition of the cost function also provides an avenue for mitigating the effects of scale aliasing and representativeness errors that inherently exist in a multi-scale system, thus further improving the effectiveness of the assimilation of high-resolution observations. The improved framework has been implemented to optimize FASTER-DA for improving the effectiveness of the assimilation ARM observations. The major results have been presented in Li et al. (2015, Mon. Wea. Rev), Li et al. (2015, J. Geophys., Res.), and Li et al. (2016).

2.2 The FASTER Data Assimilation System

A prototype FASTER-DA system based on the MS-3DVAR and WRF GSI was successfully implemented in triple domains nesting at the resolutions of 18 km, 6km, and 2km for the ARG SGP site (Li et al., 2015, J. Geophys., Res.). Along with conventional and satellite radiance data processed by NCEP, ARM Balloon-Borne Sounding (SONDE) profiles and surface meteorological observations were assimilated. The systems was delivered to FASTERs teams, is now available to the ARM community, and is supporting the LES ARM Symbiotic Simulation and Observation (LASSO) Workflow.

The FASTER-DA system showed a strong capacity of representing intensive convective systems. Here is an example. A mesoscale convective system moved into the ARM SGP region from the northwest around 21 UTC 13 June 2007 and intensified. Figure 2 presents a GOES infrared image and a NEXRAD reflectivity map around 03 UTC 14 June. Both the infrared image and the radar reflectivity map captured the mesoscale convective system.

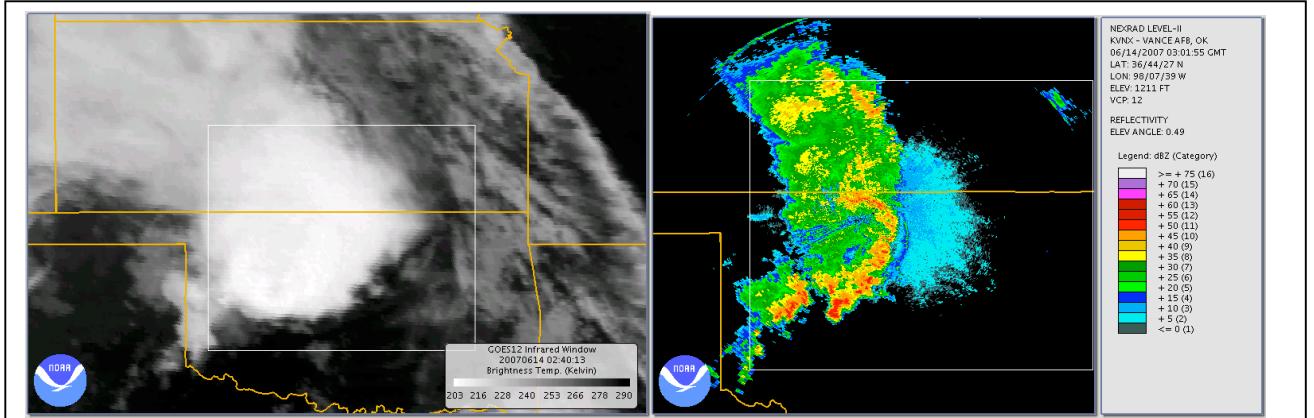


Figure 2: GOES infrared image and NEXRAD reflectivity map. The GOES image is a snapshot at 0240 UTC 14 June. The observed reflectivity map was taken at 0302 UTC 14 June with a radar elevation angle of 0.49 degrees.

Figure 3 displays the simulated maximum reflectivity, which can be directly compared with the observed reflectivity shown in Fig. 2. Without MS-DA, the model reflectivity is significantly weaker than the observed, and the MCS structure is loosely organized. In contrast, with the MS-DA, the strong convective echo is realistically reproduced in both its intensity and spatial structure. The MS-DA significantly improves the representation of the intensity and spatial structure of the mesoscale convective system.

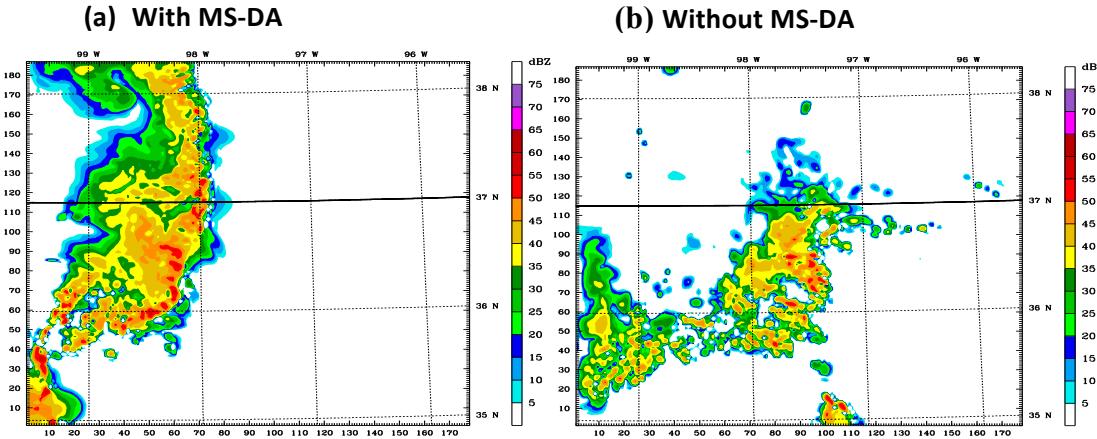


Figure 3: Model reflectivity at 0300 UTC, June 14, 2007. The model reflectivity, which is the maximum in the vertical column, with and without the assimilation of the ARM observations is presented in panels (a) and (b), respectively. The color scale indicates reflectivity in dBZ. See Li et al. (2015, J. Geophys. Res.).

2.3 A 3DVAR Aerosol Data Assimilation System

As the FASTER project advanced, it was recognized that aerosol analyses are required for initializing both SCMs and CRMs to improve the representation of cloud and aerosol interactions. We developed a unique and advanced aerosol data assimilation scheme (aerosol DA) (Li et al., 2013, *Atmos. Chems. Phys.*; Zang et al., 2015). Thus, FASTER-DA consists of MS-GSI for meteorological fields and aerosol DA. We note that the system is incorporates novel formulations to reduce the computational cost incurred by a large number of analysis variables, which is crucial for aerosol data assimilation for generating long-time aerosol reanalysis.

Using the developed aerosol data assimilation system, we have produced a one-month aerosol reanalysis product for the Routine AAF Clouds with Low Optical Water Depths (CLOUD) Optical Radiative Observations (RACORO) field campaign. The reanalysis product was produced by assimilating the surface PM2.5 from the EPA operational monitoring network and speciated measurements from the Interagency Monitoring of Protected Visual Environments (IMPROVE) monitoring network into WRF/Chem. The reanalysis product includes three-dimensional concentrations of eight species, at four discrete MOSAIC size bins at 0.038-0.1, 0.1-

1.0, 1.0-2.5 and 2.5-10 μm (Zaveri et al. 2008). Figure 4 presents a scatter plot of the PM2.5 concentrations from a control simulation without data assimilation and a data assimilation analysis, respectively, against the observations. The observations used are from an Oklahoma City station at 00, 06, 12 and 18 UTC. The PM2.5 in the control simulation without data assimilation is significantly underestimated. The observed mean concentration of PM2.5 is 3.9 μgm^{-3} , while that of the control simulation is 1.5 μm , with a bias of -1.4 μgm^{-3} . The correlation is 0.51 and the RMSE is 3.3 μgm^{-3} , compared with a standard deviation of 3.8 μgm^{-3} in the observed PM2.5. In the data assimilation analysis, the bias is greatly reduced to as small as -0.2 μgm^{-3} . The correlation between the analysis and observed PM2.5 is as high as 0.87, while the RMSE decreases to 0.9 μgm^{-3} . These results show that this 3DVAR scheme can effectively assimilate the PM2.5 observations.

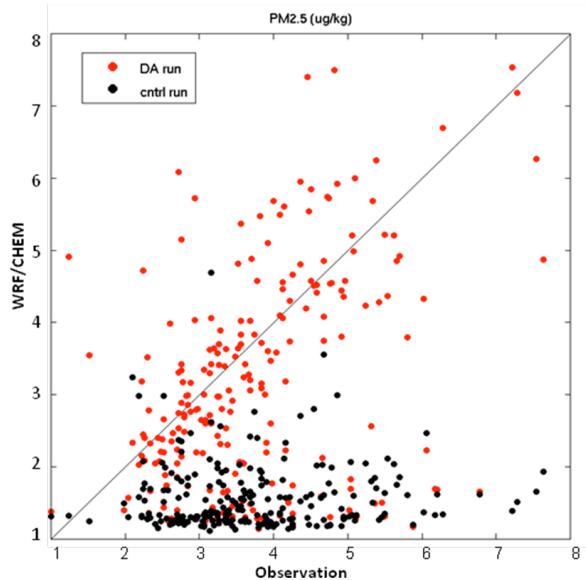


Figure 4: Scatter plot of the PM2.5 mass concentrations against observations in the analysis with (red) and without (black) data assimilation. The observations are assimilated. These 00, 06, 12 and 18 UTC observations from an Oklahoma City stations during the period from 00 UTC, 1 June to 18 UTC, 30 June, 2009, are used.

2.4 Multiscale Forcing

Physics parameterization is known sensitive to spatial resolutions used in climate models. As the climate model resolution becomes increasingly higher, the grid spacing represented by a

SCM is required to reduce accordingly. From the forgone MS-3DVAR analysis using a cloud resolving WRF, large scale forcing was derived for a hierarchy of grid sizes (Feng et al., 2015).

The magnitude of the derived forcing fields varies significantly with the grid spacing, and it generally increases as the grid size is reduced. More importantly, vertical velocities and moisture and temperature divergences often change their signs for different grid sizes (Fig. 5). These sign changes can dictate the formation of clouds and precipitation in SCMs. The derived multiscale forcing thus offers the forcing for SCMs for different grid sizes, and furnishes ensemble SCM simulations SCMs.

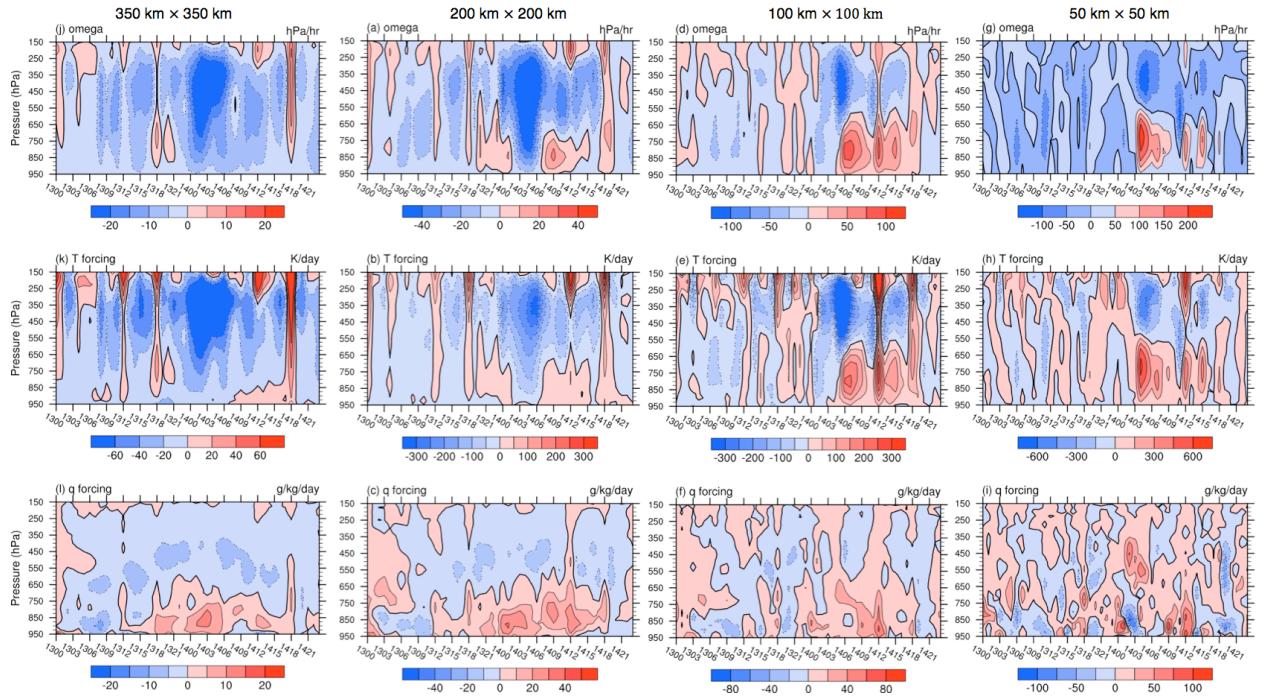


Figure 5. Large-scale forcing fields derived for different grid sizes, including the entire innermost model domain ($\sim 350 \text{ km} \times 350 \text{ km}$), $200 \text{ km} \times 200 \text{ km}$, $100 \text{ km} \times 100 \text{ km}$, and $50 \text{ km} \times 50 \text{ km}$. The magnitudes of all the forcing fields increase dramatically as the domain sizes were reduced. In spite of different magnitudes, the pattern of each forcing filed is consistent well except those from $50 \text{ km} \times 50 \text{ km}$ domain, more scattering features appear as the domain size reduce from $350 \text{ km} \times 350 \text{ km}$ down to $100 \text{ km} \times 100 \text{ km}$. Upper panel is vertical p-velocity (in hPa/hr), middle is T forcing (in K/day), and lower is q forcing (in g/kg/day).

In the derivation of large scale forcing, the impact of sub-grid size processes has long been a concern but remains not systematically analyzed. Because of its cloud resolving spatial

resolution, the MS-3DVAR analysis can be used to characterize the sub-grid size processes and its impact on the derived large scale forcing. The sub-grid scale process induced components become increasingly significant, and it turns out that the horizontal large scale convergence often becomes comparable with those from the large scale fields when the grid size goes to be smaller than 200 km. Its impact on SCMs must be taken into account. The vertical convergence induced by the sub-grid processes is partially or fully parameterized in climate models. The inclusion of the sub-grid process component may need to be parameterization.

2.5 Large-scale Hydrometeor Forcing

The forgone MS-3DVAR analysis has been used to derive the hydrometeor forcing for SCMs (Feng et al., 2016). Hydrometeor species from WRF output include cloud water, rain water, cloud ice, snow, and graupel. Currently, we use CAM5 as a testing platform of which microphysics only predict cloud ice and cloud water. Hence, the large-scale forcing of cloud ice and cloud water are computed as the average over the model innermost domain to represent the hydrometeor forcing. The analysis domain is centered at the Central Facility and covers objective variational analysis domain. Although the divergence of hydrometeors is typically smaller than the divergence of water vapor, its impact is significant when cloud and precipitation system are active in the model domain, particularly at upper levels. By comparing SCM simulations between the cases with and without the divergence of hydrometeors included, it is shown that the forcing can significantly affect cloud water contents in SCMs (Fig. 6).

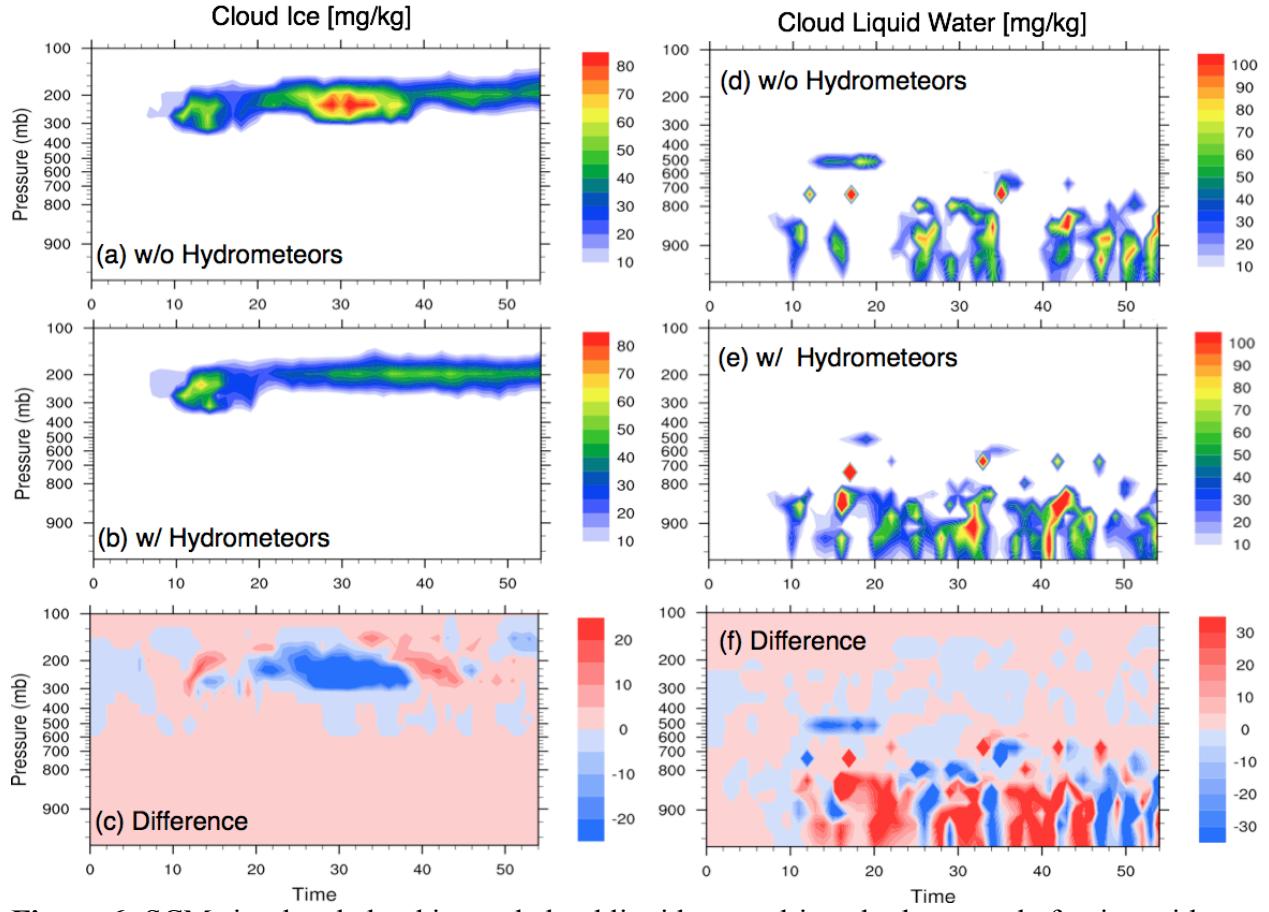


Figure 6: SCM simulated cloud ice and cloud liquid water driven by large-scale forcing with hydrometeors and without hydrometeors and their difference. Simulation starts at 18 UTC June 12 and ends at 00 UTC June 14, 2007.

2.6 Large-scale Aerosol Forcing

Investigation of aerosol-related issues such as evaluation of model-simulated aerosol indirect effects against ARM observations often requires multiscale data set; however, measurements alone often cannot satisfy all the requirements. The developed aerosol 3DVAR system represents one of most comprehensive and sophisticated aerosol data assimilations scheme. By assimilating observations arranging from total mass concentrations of PM2.5 and PM10 to a variety of speciated concentrations, it estimates multi-species concentrations simultaneously and estimates not only mass concentrations but also number concentrations. The generated reanalysis offers three-dimensional aerosol fields that can be utilized to initialize from cloud resolving to single column models, which is essential for comparing model-predicted variables against field measurements.

As cloud and aerosol interactions are developed, the large scale aerosol forcing is needed for SCMS. We have derived large scale aerosol forcing. Figure 7 presents an example of time evolution of the forcing that derived from the WRF/Chem aerosol data assimilation analysis. Within a period of 100 hours, the aerosol large scale forcing undergoes dramatic variation. Such variations strongly invite the investigation on the impact of the aerosol large scale forcing in SCMs.

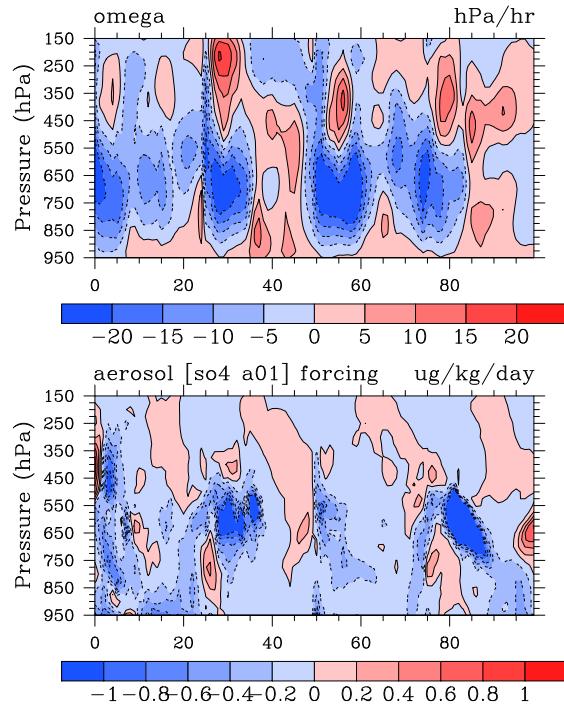


Figure 7: Time evolution of the large-scale vertical velocity ($\bar{\omega}$: hPa/h) and aerosol forcing ($\bar{\mu}$ g/kg/day). Time period: 00 UTC 06 May ~ 00 UTC 10 May 2009.

3 Publications and Presentations

Publications

1. Li, Z., Z. Zang, Q. B. Li, Y. Chao, D. Chen, Z. Ye, Y. Liu, and K. N. Liou, 2013: A Three-Dimensional Variational Data Assimilation System for Multiple Aerosol Species with WRF/Chem and an Application to PM2.5 Prediction, *Atmos. Chems. Phys.*, 13, 4265–4278, doi:10.5194/acp-13-4265-2013.
2. Li, Z., S. Feng, Y. Liu, W. Lin, M. Zhang, T. Toto, A. Vogelmann, and S. Endo, 2014: Development of Fine Resolution Analysis and Expanded Properties of Large-Scale Forcing. Part I: Methodology and Evaluations, *J. Geophys. Res.*, doi:10.1002/2014JD022245.
3. Feng, S., Z. Li, Y. Liu, W. Lin, M. Zhang, A. Vogelmann, T. Toto, and S. Endo, 2014: Developmen of Fine Resolution Analysis and Expanded Properties of Large-Scale Forcing. Part II, Scale-Awareness and Application to Single Column Models, *J. Geophys. Res.*, doi: 10.1002/2014JD022254.
4. Lin, W., Y. Liu, A. M. Vogelmann, A. Fridlind, S. Endo, H. Song, S. Feng T. Toto, Z. Li, and M. Zhang, 2014: RACORO Continental Boundary Layer Cloud Investigations. Part III: Separation of Parameterization Biases in Single-Column Model CAM5 Simulations of Shallow Cumulus. *J. Geophys. Res.*, doi:10.1022/2014JD022524.
5. Vogelmann, A. M., A. Fridlind, Lin, T. Toto, S. Endo, W. Lin, J Wang, S. Feng, Y. Zhang, D. Turner, Y. Liu, Z. Li, S. Xie, A. S. Aberman, M. Zhang, and M. Khairoutdinov, 2015: RACORO Continental Boundary Layer Cloud Investigations. Part I: Case Study Development and Ensemble Large-Scale Forcings. *J. Geophys. Res.*, doi:10.1022/2014JD022713.
6. Zang, Z., Z. Hao, X. Pan, Z. Li, D. Chen, L. Zhang, and Q. Li, 2015: Background error statistics for aerosol variables from WRF/Chem Predictions in Southern California, *Asia-Pacific Journal of Atmospheric Sciences*, 51, 2, 123-135, doi: 10.1007/s13143-015-0063-8.
7. Li, Z., J.C. McWilliams, K. Ide, and J.D. Fararra, 2015: A Multi-Scale Data Assimilation Scheme: Formulation and Illustration. *Monthly Weather Review*, 143, 3804-3822.
8. Li, Z., X. Chen, W. I. Gustafson and A. Vogelmann, 2016: Multiscale Data Assimilation and Spectral Properties for Atmospheric and Oceanic Fine Resolution Models, *Applied Mathematics and Computation*, submitted
9. Feng, S., Z. Li, Y. Liu, W. Lin, M. Zhang, A. Vogelmann, T. Toto, and S. Endo, 2016: Development of Fine Resolution Analysis and Expanded Properties of Large-Scale Forcing. Part III, Hydrometeor Forcing and Single Column Model Experiments, *J. Geophys. Res.*, to be submitted.

Presentations

1. Li, Z., and Z. Ye, 2010: A Multi-Scale Three-Dimensional Variational Data Assimilation System and Its Application to Cloud Resolving Models, A23A-0028, presented at 2010 Fall Meeting, AGU, San Francisco, Calif., 13-17 Dec.
2. Zang, Z., Z. Li, Q. Li, D. Chen, Y. Chao, and K.-N., Liou, 2010: A Multi-Scale Three-Dimensional Data Assimilation Scheme for Improving Regional Particulate Matter

Prediction, A31A-0030, presented at 2010 Fall Meeting, AGU, San Francisco, Calif., 13-17 Dec.

3. Li, Z., and Z. Ye, 2011: Improved Simulations of Clouds and Precipitation Using Data Assimilation. FASTER Breakout, 2011 ASR Science Team Meeting, San Antonio, Texas, March 28, 2011.
4. Li, Z., and Z. Ye, 2011: Untangling Uncertainties of Cloud and Precipitation Processes in a Cloud Resolving Model Using Data Assimilation. A13D-0343, 2011 Fall Meeting, AGU, San Francisco, Calif., 3-7 Dec. 2012.
5. Zang, Z., Z. Li, Q. Li, D. Chen, Y. Chao, and K.-N., Liou, 2011: Prediction of PM2.5 Using A Multi-Scale Three-Dimensional Variational Data Assimilation System with WRF/Chem during CalNex 2010, A23B-0153, 2011 Fall Meeting, AGU, San Francisco, Calif., 3-7 Dec., 2011.
6. Li, Z., Z. Ye, Y. Liu, and W. Lin, 2011: Improved Cloud and Precipitation Modeling In a Cloud Resolving Model Using Data Assimilation. Climate and Earth System Modeling PI meeting, Washington DC, September, 19-22, 2011.
7. Li, Z., Z. Ye, Y. Liu, W. Lin, T. Toto, and A. Vogelmann, 2012: Building a Multiscale Aerosol Data Assimilation System for the FASTER Project. 2012 ASR Science Team Meeting, Arlington, Virginia, March 12, 2012.
8. Li, Z., Y. Liu, W. Lin, and S. Feng, 2013: Development of a Multi-Scale Data Assimilation System for Model-Observation Integration and Climate Model Evaluation. 2013 AGU Fall Meeting, 11 December, San Francisco, invited talk.
9. Feng, S., Z. Li, Y. Liu, W., Lin, A. Vogelmann, 2013: Extended Large-Scale Forcing Derived from the Multiscale Data Assimilation System and Its Application to Single-Column Models
10. Feng, S., Li, Z., Z. Ye, Y. Liu, W. Lin, T. Toto, and A. Vogelmann 2012: Improved Hydrometeor Simulations Using Cloud Resolving WRF and Multi-Scale Data Assimilation and Applications to Climate Model Evaluation. A23D-0248, 2012 Fall Meeting, AGU, San Francisco, Calif., 3-7 Dec. 2012.
11. Lin, W., H. Song, Y. Liu, S. Endo, Z. Ye, and Z. Li, 2012: Analysis of High-Resolution Cloud Simulations Using Dynamical Downscaling and Data Assimilation, 2012 ASR Science Team Meeting, Arlington, Virginia, March 12, 2012.
12. Feng, S., Li, Z., Y. Liu, W. Lin, T. Toto, and A. Vogelmann 2013: Improved Hydrometeor Simulations Using Cloud Resolving WRF and Multi-Scale Data Assimilation and Applications to Climate Model Evaluation. 2013 ASR Science Team Meeting, Potomac, Maryland, March 18-21, 2013.
13. Li, Z., S. Feng, Y. Liu, W. Lin, T. Toto, and A. Vogelmann, 2013: Aerosol Reanalysis Using a Multi-scale Aerosol Data Assimilation System. 2013 ASR Science Team Meeting, Potomac, Maryland, March 18-21, 2013.
14. Liu, Y., Fridlind, A., Endo, S., Li, Z., Vogelmann, A., Toto, T., Song, H., Lin, W., Del Genio, A., Donner, L., and Hogan, R., 2013: Development of Integrative LES-CRM-SCM-NWP Evaluation Framework and Demonstration with RACORO Cases. 2013 ASR Science Team Meeting, Potomac, Maryland, March 18-21, 2013.
15. McGraw, R., Liu, Y., and Li, Z., 2013: Sparse Particle Models for Data Analysis and Assimilation. 2013 ASR Science Team Meeting, Potomac, Maryland, March 18-21, 2013.

4 References

Ackerman, T. P., and G. M. Stokes, 2003: The Atmospheric Radiation Measurement Program, *Physics Today*, 56, 38-44.

Developmental Testbed Center, 2012: *Gridpoint Statistical Interpolation (GSI) User's Guide for Version 3.0*, Available at <http://www.dtcenter.org/com-GSI/users/docs/index.php>.

Fast, J. D., Gustafson, Jr., W. I., Easter, R. C., Zaveri, R. A., Barnard, J. C., Chapman, E. G., and Grell, G. A., 2006: Evolution of ozone, particulates, and aerosol direct forcing in an urban area using a new fully-coupled meteorology, chemistry, and aerosol model, *J. Geophys. Res.*, 111, doi:10.1029/2005JD006721.

Li, Z., Y. Chao, J.C. McWilliams, K. Ide, and J.D. Farrara, 2012a: A multi-scale three-dimensional variational data assimilation scheme for coastal oceans. *Quart. J. Roy. Meteorol. Soc.*, accepted.

Li, Z., Y. Chao, J.C. McWilliams, K. Ide, and J.D. Farrara, 2012b: Experiments with a Multi-Scale Data Assimilation Scheme. *Tellus A*, under revision.

Li, Z., Z. Zang, Q. Li, D. Chen, Y. Chao, Z. Ye, Y. Liu, and K.-N. Liou, 2012c: A Three-Dimensional Variational Data Assimilation System for Multiple Aerosol Species with WRF/Chem and an Application to PM2.5 Prediction, *Atmos. Chems. Phy. Discussion*, accepted.

Lorenc A. C. and P. Payne, 2007: 4D-Var and the butterfly effect: Statistical four-dimensional data assimilation for a wide range of scales, *Quart. J. Roy. Meteor. Soc.* 133, 607-614.

Stokes, G.M., and S.E. Schwartz, 1994: The Atmospheric Radiation Measurement (ARM) Program: Programmatic background and design of the cloud and Radiation Testbed. *Bull. Amer. Meteor. Soc.*, 75, 1201-1221.

Wu, W.-S., R. J. Purser, and D. F. Parrish, 2002: Three-Dimensional Variational Analysis with Spatially Inhomogeneous Covariances. *Mon. Wea. Rev.*, 130, 2905-291.

Zaveri, R. A., Easter, R. C., Fast, J. D., and Peters, L. K., 2008: Model for simulating aerosol interactions and chemistry (MOSAIC), *J. Geophys. Res.*, 113, D13204, doi:10.1029/2007JD008782.

Xie S., R. T. Cederwall, M. Zhang, 2004: Developing long-term single-column model/cloud system-resolving model forcing data using numerical weather prediction products constrained by surface and top of the atmosphere observations, *J. Geophys. Res.*, 109, D01104, doi:10.1029/2003JD004045.

Zhang, M. H., J. L. Lin, R. T. Cederwall, J. J. Yio, and S. C. Xie, 2001: Objective analysis of ARM IOP Data: Method and sensitivity, *Mon. Wea. Rev.*, 129, 295–311.