Next Generation
Geostationary Satellites

The next generation GOES will begin with GOES-R, which is currently scheduled to launch in the year 2015. GOES-R will be equipped with the Advanced Baseline Imager (ABI), an imager that has significantly improved spectral, spatial and temporal resolution relative to the current GOES I-M series satellites. These improvements will greatly enhance our ability to make mesoscale weather, climate, oceanographic and environmental observations.

Because of the long lead-time required to design, build, and test new and complex satellite equipment, preparations for GOES-R applications are well underway. The approach for these “Risk Reduction” activities is to use data from existing operational and experimental satellites to create subsets of observations that resemble those we will eventually receive from GOES-R. These simulated GOES-R datasets will then be used for the development of algorithms for new satellite products or for the improvement of existing products, particularly for atmospheric and surface-related phenomena, using the additional GOES-R resolution capabilities that will be available.

The major objective of our specific data assimilation research is to prepare algorithms to maximize the use of information from future GOES-R observations, especially in the area of operational severe weather forecasts.

Challenges of Data Assimilation

Data Assimilation is the technique of blending data from very different sources in order to produce a new data set which is most consistent with the atmospheric state. Advanced data assimilation methods, which extract information about the true atmospheric state from observations and combine it with the information from a forecast model, have proven to be powerful tools in improving weather forecasts. New observations from GOES-R will pose new challenges to the data assimilation methods. A major issue that needs to be addressed is to estimate if, and how much, the GOES-R observations are expected to improve our knowledge about the true atmospheric state. In order to address this challenge, one needs to quantify (1) what is the amount of information provided by the currently available meteorological observations (e.g., conventional surface and upper-air observations) and (2) how much new information will be brought by the GOES-R data. Our goal is to prepare methodologies capable of answering these questions before the GOES-R observations are available.

The answers to the questions posed above are not trivial, since the same observations could bring more or less information, depending on where and when the observations are taken, and on how accurate the forecast is for that place and that location. In other words, the information from observations is dependent on the number and quality of the observations and on the forecast uncertainty. Unlike the data assimilation methods currently used in operational weather centers (in the U.S. and worldwide), the next generation ensemble-based data assimilation methods are demonstrating a qualitatively new capability to address the above challenges. Of special importance is the new capability to estimate and use realistic forecast uncertainty, which depends on the atmospheric conditions. This forecast uncertainty is typically defined in terms of a covariance matrix measuring forecast errors, the so-called “flow-dependent” forecast error covariance. At CIRA, we are developing and exploring ensemble-based data assimilation methods for applications to the future GOES-R observations and to other current and
upcoming satellite missions (e.g., CloudSat, Global Precipitation Mission-GPM and Orbiting Carbon Observatory-OCO).

**Ensemble Data Assimilation**

Ensemble-based data assimilation methods employ ensembles of forecast model runs to estimate flow-dependent forecast uncertainty. Using flow-dependent forecast error covariance is essential for extracting maximum information from each observation because in the areas of high forecast uncertainty (where ensemble members differ among each other the most), the information given by the observations is more important. The opposite is true in the areas where the forecast uncertainty is low (i.e., all ensemble members are similar).

Under the GOES-R research project and various other research projects at CIRA, we are employing and further developing an ensemble-based data assimilation method, referred to as the Maximum Likelihood Ensemble Filter (MLEF). For the GOES-R application, we are focusing on the MLEF capability to extract maximum information from the future GOES-R observations. This is accomplished by evaluating information measures of assimilated observations. Information measure called *Degrees of Freedom for Signal* (DFS) is often used in meteorological applications. The DFS is a number, defined for a selected set of observa-

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**Fig. 1a-c.** Surface pressure forecast difference (hPa) between the experiments with and without data assimilation. In the experiment with data assimilation a 6-hour forecast after data assimilation is used. In the experiment without data assimilation a longer-term forecast is used, initialized at the beginning of the data assimilation experiment (first data assimilation cycle). Both experiments used the same boundary conditions. The triangle denotes the best position of Hurricane Katrina estimated by the NOAA/National Hurricane Center report. The panels cover last 24 hours before the landfall: (a) 28 Aug 2005 at 0000 UTC, which corresponds to 8th data assimilation cycle, (b) 28 Aug 2005 at 1200 UTC, which corresponds to 10th data assimilation cycle, and (c) 29 Aug 2005 at 0000 UTC, which corresponds to 12th data assimilation cycle. Negative values (blue and purple colors) indicate lower pressure, while positive values (yellow and red colors) indicate higher pressure in the experiment with data assimilation. Note that the data assimilation is moving the cyclone towards the observed location, since the triangle is located in the blue (lower pressure) area.
DATA ASSIMILATION

In the first stage of this research, we applied the MLEF to quantify the information content of conventional observations. In the second stage, which is currently underway, we will examine and further develop this methodology in application to satellite observations with similar characteristics as the future GOES-R observations. We expect that the second stage should result in a well-tested data assimilation algorithm capable of extracting maximum information from the GOES-R observations, before these observations become available.

We have recently applied the MLEF to improve forecast simulations of Hurricane Katrina by assimilating conventional surface and upper-air observations into the Weather Research and Forecasting (WRF) model. In the experiments presented, the model spatial resolution is 30 km with 28 vertical levels (totaling 75x70x28 grid points) and we employ 32 ensemble members. Observations are assimilated every 6 hours, during 12 consecutive data assimilation cycles. Fig. 1a-c shows an example of the impact of data assimilation on improving the forecast of Hurricane Katrina. Most significant improvements are obtained by placing the cyclone center to the more correct location, as indicated in the figure by the dipole (positive-negative) pattern in the pressure difference field, while the improvements in the cyclone intensity were smaller. These improvements are quite substantial considering that only a relatively small number of observations are assimilated. For illustration, we also include a visible satellite image of Hurricane Katrina (Fig. 2), valid approximately at the same time as the surface pressure difference field given in Fig. 1b.

Does More High Quality Data Mean More Information?

We expect that the GOES-R observations will be of excellent quality and will have high spectral, spatial and temporal resolution. Can we automatically assume that more high quality data will result in improved data assimilation and forecast results? Classical data assimilation methods, which do not employ flow-dependent (but prescribed) forecast error covariance, would yield “yes” as an answer. This answer, even though desirable, may not be correct. Modern data assimilation methods, such as ensemble-based methods, could provide a different answer because of the use of the flow-dependent forecast error covariance.

We have calculated the DFS for the same case of Hurricane Katrina, given in Fig. 1a-c. The DFS results are shown in Fig. 3. The model integration domain was divided into 9 equally sized areas (sub-domains) and the DFS are calculated for each sub-domain. The sizes of the sub-domains are selected by taking into account the spatial scale of the tropical cyclone. One can immediately notice that the highest amount of information is provided by the observations from the central sub-domain (pink color indicates that the DFS is equal or larger than 14). This is exactly the sub-domain where the cyclone center is located. Note that the number of observations (the number of crosses) is not the highest in this sub-domain, thus the forecast uncertainty played a dominant role in defining the information content. Note also
that there are more observations in the three sub-domains located in the northern part of the model domain, but these observations carry less information because the values of the DFS are smaller (colored in orange and green). These results demonstrate the ability of the MLEF to correctly take into account the characteristics of the atmospheric flow when extracting information from the available observations, thus maximizing the benefits of the assimilated observations.

Additional information can be found at http://www.cira.colostate.edu/projects/ensemble/

**What is Next?**

The experimental results with conventional upper-air and surface observations were quite encouraging. The next step of our research is to test the same methodology in application to satellite observations. We have already selected an interesting severe weather case (a very strong extratropical cyclone named Kyrill that occurred over Europe during 18-19 January 2007) and started collecting satellite data from the Meteosat Second Generation (MSG) satellite that resemble those we will receive from the future GOES-R instrument. In this case, the WRF model will be run in finer resolution (15 km/49 levels), thus the data assimilation experiment will be computationally more demanding. It will be interesting to examine if the data assimilation algorithm will be able to correctly extract information from the satellite observations, while taking into account the flow-dependent forecast uncertainty.

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**Fig. 3.** The DFS calculated in data assimilation cycle 10 (valid at 12 UTC 28 Aug 2005), shown, in shading, for each of the 9 sub-domains covering the model domain. Also shown are the locations of the assimilated observations (crosses) and the location of the tropical cyclone, as defined by the isolines of the magnitude of the horizontal wind (in ms⁻¹), obtained by the analysis at the model level corresponding to a height of 700 m.