Quantifying Sensor Web Capabilities Through Simulation: Recent Results

Michael Seablom and Stephen Talabac
NASA Goddard Space Flight Center, Greenbelt, MD

David Emmitt
Simpson Weather Associates
Charlottesville, VA

Joseph Ardizzone
Science Applications International Corporation
McLean, VA

***Abstract.* Progress toward the construction of a "sensor web simulator" (SWS) as applied to a future wind lidar mission is discussed along with preliminary results. The motivation for the simulator is to provide the community a tool that would quantify the scientific return of a meteorological application in which a numerical forecast model intelligently drives data collection. Because the design and implementation of such a complex observing system would be costly and would involve significant risk, end-to-end simulation is essential. We expect the SWS to provide information systems engineers and Earth scientists with the ability to define and model candidate designs and to quantitatively measure predictive forecast skill improvements. The SWS will serve as a necessary trade studies tool to: evaluate the impact of selecting different types and quantities of remote sensing and in situ sensors; characterize alternative platform vantage points and measurement modes; and to explore rules of interaction between sensors and with weather forecast/data assimilation components to reduce model error growth and forecast uncertainty. We will show results depicting forecast skill impact from an end-to-end simulation performed "by hand" in which key elements of the simulator were present, and make note of progress toward the construction of the simulator that will culminate in a live demonstration in late 2009.**

The development of atmospheric numerical models over the past four decades has helped to improve weather prediction by linking together the many atmospheric and oceanic observations through data assimilation and to apply appropriate constraints based upon the governing equations. Predictive skill of the state-of-the-art atmospheric models have slowly improved over this time. In the mid 1970's the operational models used by the European Centre for Medium Range Weather Forecasts (ECMWF), considered to be the world's best, had roughly 3-4 day skill of forecasting large-scale atmospheric features, while today the skill is approaching 9 days (statistics for US models are shown in Figure 1). Over this thirty year period there have been a number of evolutionary developments that have contributed to the observed improvement in skill: more numerous and better quality observations from satellites, improvements in the numerical techniques employed by the numerical models and the data analysis schemes, and improvements in the computational infrastructure (i.e., high performance computing, networking, and large-scale data stores).

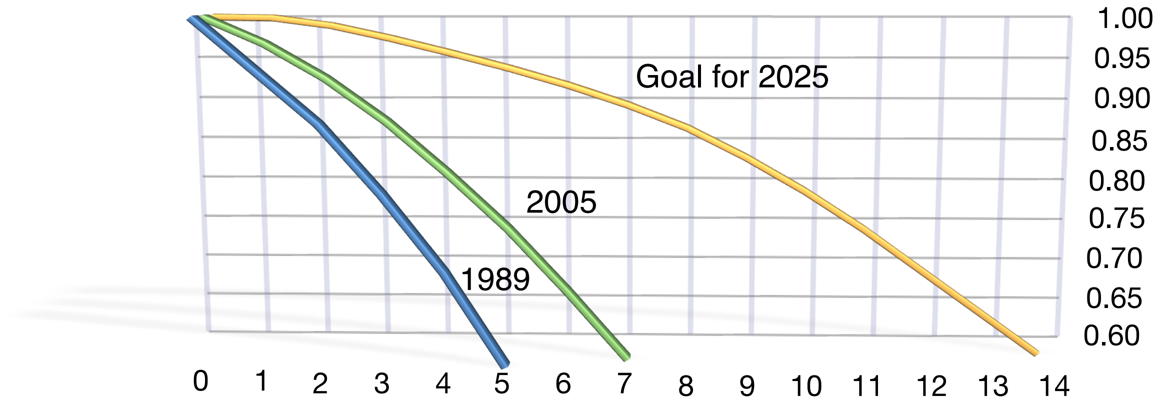

Figure 1. Anomaly correlation representing growth of predictive skill (in days, X axis) for 1989 (blue), 2005 (green), and the goal for 2025 (gold) for US operational models. When the correlation falls below 0.6 the forecast is deemed to have no skill.

Meanwhile, the development of complete Earth System models (i.e., atmosphere + ocean + chemistry + ...) has proceeded more slowly, with the individual components developed in essentially a stovepipe fashion by various research institutions. The recent emergence of the Earth System Modeling Framework (ESMF), a software infrastructure that provides common data structures, interfaces, and methods for the modeling community, has provided the first capability to easily couple major Earth System model components. Bringing the full suite of observations to bear on the numerical models remains elusive and is an area that must be addressed in order to make progress toward the stated strategic goals.

Operational use of so-called “targeted observations” could facilitate the evolution of predictive skill. Studies at NASA and NOAA have investigated techniques to identify critical regions of the atmosphere that are highly sensitive to analysis errors. Increased data sampling in these regions has, in some instances, resulted in better predictive skill (Toth, et. al, 2001). The ability to extrapolate this capability to a global scale and interact with the full suite of observational assets will ultimately determine the full potential of the technique.

Approach

Implementation of an operational national forecasting system that includes autonomous targeted observations would be costly and would involve risk. New technologies would need to be developed for integrating disparate hardware and software components that would collect observations, perform quality control, analyze data, perform numerical forecasts, identify where new observations are required, initiate planning and scheduling, and perform command and control for the end-to-end observing system. Aside from the engineering challenges, the mathematical complexities of data assimilation and the chaotic nature of the atmosphere ensure there are no guarantees that the suggested sensor web would be a panacea for improving predictive skill of weather forecasts.

The simulator is a critical first step in the development path of using intelligent targeting for operational data assimilation and forecasting. Many parameters will control the behavior of the simulated observing system (e.g., sensor measurement and instrument targeting parameters; attributes of the forward and return link communications architecture, etc.). Of particular significance, the simulator will permit the user to modify the values of these parameters thus enabling trades analyses to be performed. By creating and then exploring “What-if?” operations concepts and

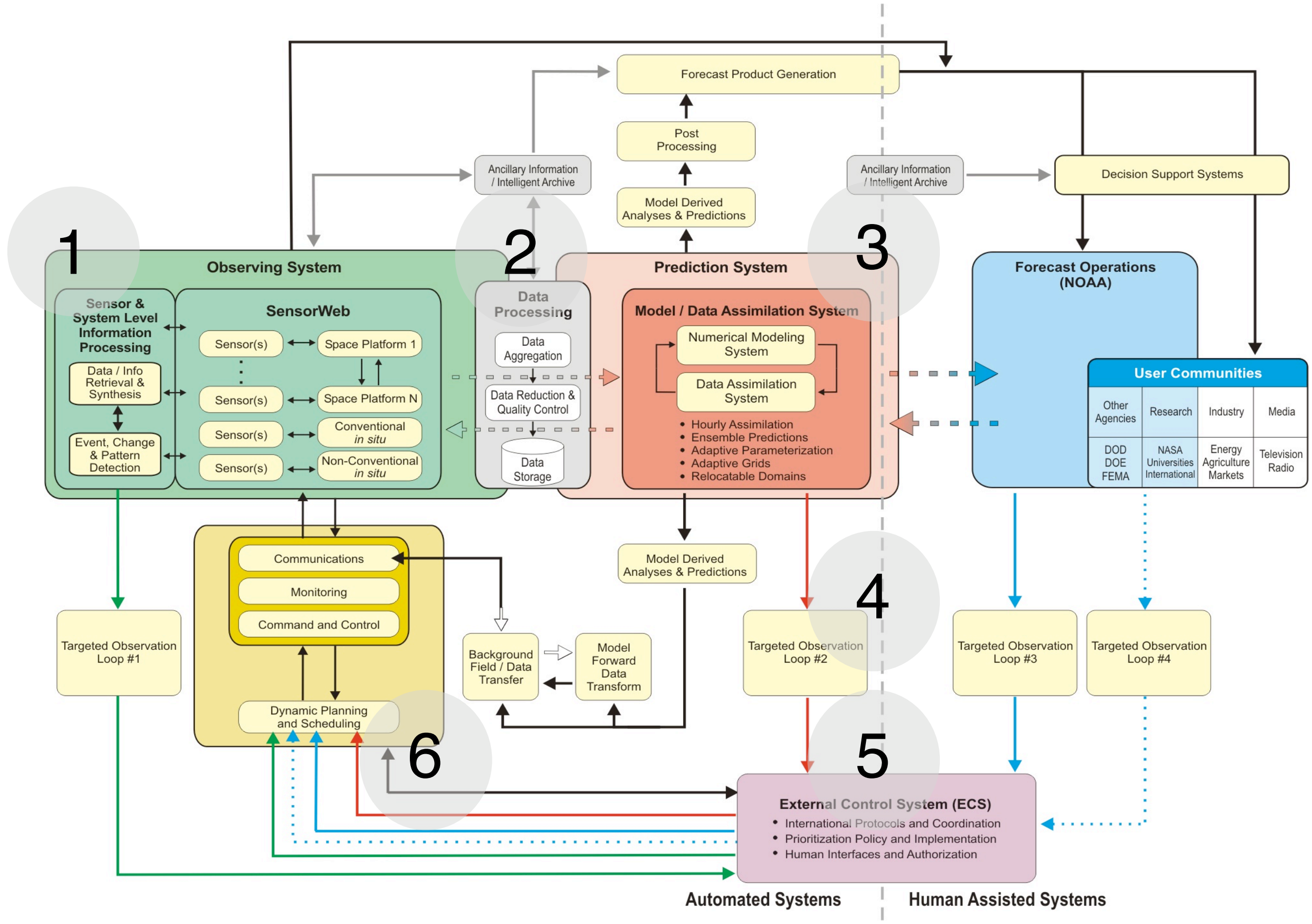

Figure 2. "Science layer" - main architecture for the sensor web simulator.

scenarios, the SWS will become a valuable decision support tool that can be used to quantitatively assess the value of alternative intelligent targeting schemes toward predictive skill improvement, and permit the user to weigh any science benefits against the concomitant observing system's overall complexity and cost. Our approach to an operational model-driven sensor web is depicted in Figure 2, and is based upon Steiner, et. al (2002). Major functionality of the simulator is captured in its key components:

1. **Observing System**: provides data to the simulation environment, either through the use of historical case studies or, in the case of a simulation of a future instrument, Observing System Simulation Experiments (OSSEs) are performed by this component to generate realistic, synthetic measurement data.
2. **Data Processing**: performs data selection and quality control.
3. **Prediction System**: performs the major roles of data assimilation and numerical prediction.
4. **Targeted Observing**: provides the specific requests for observations to be made over a specific location and time. Requests can be made directly from the observing system (in the case of a feature of interest being observed), from the assimilation system (in the case of identification of a set of observations specifically to reduce model error), or from human intervention (in the case of a scientist

performing a field experiment and needing some control over the assets).

5. **External Control System**: matches the capabilities of the assets with targeting requests and produces an optimized targeting request for the Command and Control component. For example, if the data assimilation system requests more observations of the jet stream and simultaneously a scientist requests higher fidelity measurements of a severe weather outbreak over Kansas, the External Control will attempt to satisfy both requests based upon its knowledge of the future positions of satellites, best opportunities for cloud-free measurements, etc.
6. **Command and Control**: performs the scheduling and issues the necessary commands to modify the normal behavior of an asset (e.g., switch to high data-rate collection).

A more detailed description of the sensor web concept and the components of the simulator are discussed in Seablom, et. al (2007).

Wind Lidar Use Case

To help guide the design of the SWS, a "zeroth-order" simulation was set up and executed that tested the use of model-directed observations. The experiment used synthetic observations based upon the proposed Global Wind Observing Sounder (GWOS) lidar mission (Kakar, et. al, 2007). Most of the major elements of the simulator were engaged, the exceptions being the command and control component and the simulator architecture or workflow control. The components were run manually and sequentially, and the lessons learned would provide input for the final architectural design. This process has already provided valuable information regarding the end-to-end data flow requirements.

In order to obtain complete vector wind components GWOS must sample an air parcel from at least two different perspectives. The instrument is comprised of multiple coherent and direct detection lidars that have the ability to operate through four telescopes. Two of the telescopes are oriented nominally ±45° in both azimuth and elevation pointing in front of the spacecraft, with the other two similarly oriented pointing aft. The combination of the fore and aft line-of-sight shots produce an estimated vector wind for multiple vertical levels. As currently designed the instrument can perform approximately 300 million shots in its lifetime with a pulse rate of 5Hz and 100Hz for the coherent and direct detection laser subsystems respectively.

Using sensor web concepts we investigated a modification to the GWOS operations that would (1) minimize the required number of lidar shots without compromising information of the atmospheric state, and (2) target data collection for specific regions of the atmosphere that would potentially have the greatest impact on forecast skill. For (1) GWOS would be provided the first guess wind field from a global forecast model. Observed line-of-sight winds from the GWOS "fore shot" would be compared with the predicted winds from the model and valid at the time of the observation. If the winds were considered to be in adequate agreement the aft shot would not be performed. If such agreement were ubiquitous there could be a substantial reduction in the lidar's duty cycle and potentially extending the life of the instrument. For (2) we would use estimates of the model's forecast error to direct GWOS to target those regions of the atmosphere estimated to be in a state of low predictability, and/or target sensible weather features of interest. We assume to capture the maximum number of targets would require slewing of the spacecraft.

Results of Tests

We emphasize that at this stage of the project the purpose of the stated experiments is to help design the simulator, and is not meant to draw definitive conclusions regarding the configurations (1) and (2). In the third year of the project we intend to conduct a more formal observing system simulation experiment (OSSE) under the direction of a senior scientist and under the review of the NASA Global Modeling and Assimilation Office (GMAO).

Through our partnership with Simpson Weather Associates, Inc., we acquired a sufficiently large sample of simulated lidar data. This comprised an approximate 50-day sample of u- and v-wind components from a simulated conical-scanning lidar, and was properly sub-sampled to simulate the exact look angles that would be available from

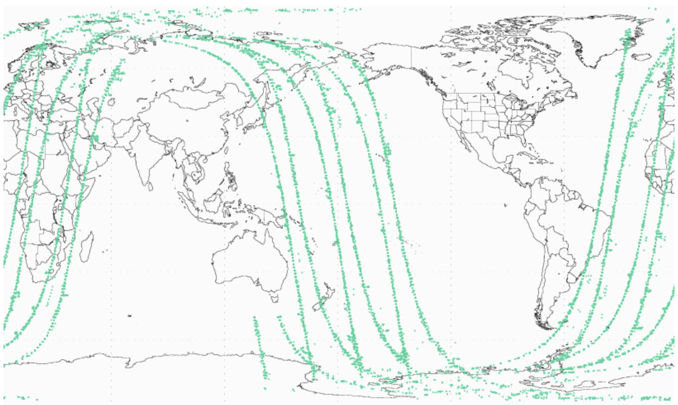

Figure 3. Sample configuration of simulated lidar data.

GWOS (Figure 3). For data analysis, which made use of NOAA's Gridpoint Statistical Interpolation (GSI), the lidar's observation errors were defined to be identical to those used for rawinsondes. For (1) we set up a control case which used no lidar data, a case in which lidar data were used only where there was "significant" disagreement with the forecast winds, and a case in which all lidar data were used. Because the current version of the GSI does not support assimilation of line-of-sight winds our experiment made use of only vector wind components. For operations this would be undesirable but for the purpose of (1), i.e., design of the overall architecture, we believe the assumption is acceptable. The model's first guess u- and v-wind components were therefore compared to the simulated lidar u- and v-wind components. Where the differences were within a pre-defined value (ε) data were withheld from the assimilation process, in essence "turning off" the aft shot. Changing the values of ε would allow mission designers to weigh the benefit of reducing the lidar's duty cycle against the overall impact to the science (i.e., predictive skill or another quantifiable metric).

A 20-day period was selected for executing the three configurations. Five day forecasts were launched from each of the 00Z assimilation periods.

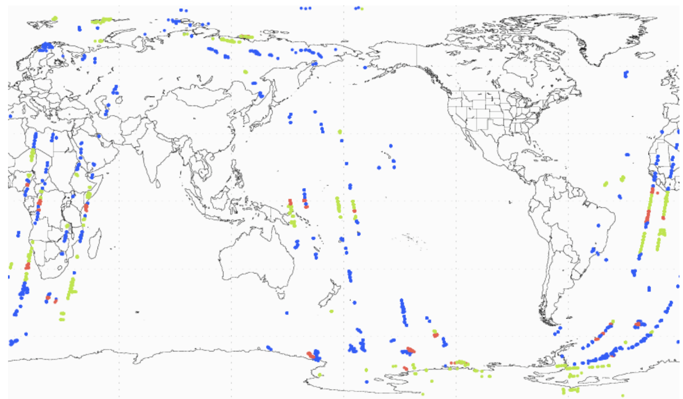

Figure 4. Lidar data following removal of observations based upon $\varepsilon \leq 1$ ms^{-1}. Data shown is for the assimilation period 12 September 1999, 12UTC. Blue points indicate a coherent shot, green are direct, and red are both.

In the targeting configuration we defined ε=1.0ms^{-1}, thus removing any lidar data in which the "observed" wind was within 1ms^{-1} of the model's first guess value. The net effect of this is depicted in Figure 4. For this sample period nearly 80% of the data met the criterion and were prevented from being included in the data assimilation cycle. In operations this would translate to a duty cycle reduction of about 30% (the minimum duty cycle would be 50% with the fore shots taken continuously). To test whether the duty cycle reduction had any negative impact on the forecast skill we employed the commonly-applied anomaly

$$\frac{\Sigma(F-C)(O-C)}{(\ \Sigma(F-C)^2\ )^{1/2}\ (\ \Sigma(O-C)^2\ )^{1/2}} \qquad \text{(Eq. 1)}$$

correlation (eq. 1), where *F* is the 500 hPa forecast, *C* is the climatological value, and *O* is the observed value. Applying the anomaly correlation for (1)

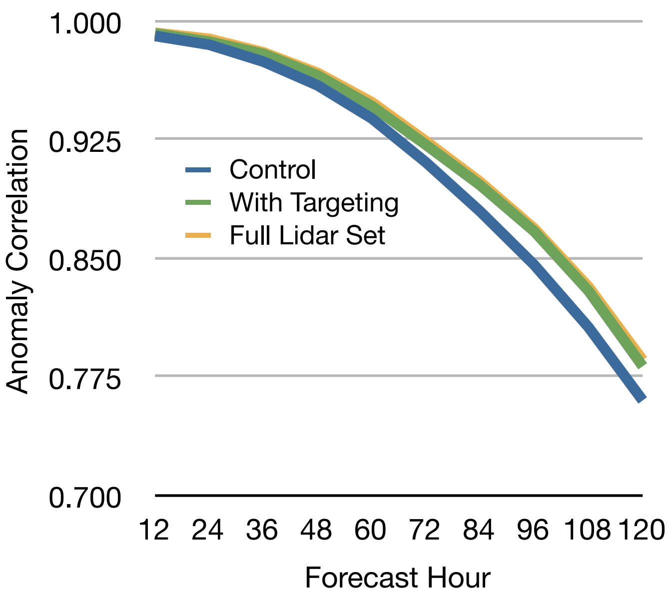

Figure 5. Lidar data following removal of observations based upon ε ≤ 1 ms^{-1}. Data shown is for the assimilation period 12 September 1999, 12UTC, Northern Hemisphere only.

produced the results shown in figure 5.

Not surprisingly, the full lidar set has the highest correlation while the control set (no lidar data) has the worst. When the targeted data were deleted from the assimilation the Northern Hemisphere results indicate little degradation; for the Southern Hemisphere (not shown) the results are more ambiguous.

For (2) we conducted a set of experiments to examine the impact of slewing GWOS for adaptive targeting. This included identifying so-called "sensitive regions" in the atmosphere (regions where the forecast is highly responsive to analysis errors) and autonomous detection of features of interest (e.g., tropical cyclones and jet streaks). To calculate the sensitive regions of the atmosphere adjoint techniques have proven to be successful (Leutbecher and Doerenbecher, 2003). Our work plan includes the eventual incorporation of the adjoint technique that is now under development by GMAO scientists. Acknowledging the time constraints for the test case, we employed a less sophisticated method that calculated the difference between two 500hPa[1] height forecast fields at 12-hour and a 36-hour verification times. If the atmosphere was in a perfectly predictable state the difference between the two forecasts should be zero. Figure 6 depicts the results of this effort, with the 500hPa field from the 12hr forecast in the black contours and "large" difference between the two forecasts in color shading. The latter would be used to make targeted observations with the lidar by slewing the spacecraft into an off-nadir mode for the purpose of capturing as many of the sensitive regions as possible.

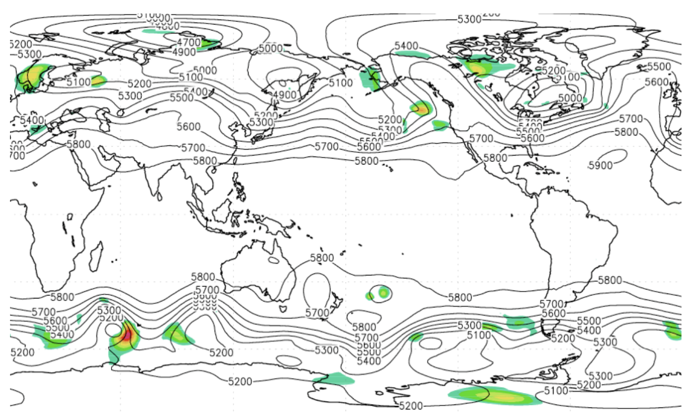

Figure 6. Differences between two forecasts launched 72 hours apart and valid at the same forecast hour ("large" values are shaded). The 500hPa height field is also displayed (contours) for one of the forecasts.

To demonstrate the functionality of the External Control component we also included a set of rule-based targets. These targets are based upon sensible weather and are depicted in Table 1. The targets were prioritized in the order of the following subcategories:

[1] The height of the 500 hectopascal pressure layer, roughly half the weight of the atmosphere, usually 5-6km above sea level.

1. Feature is over land
2. Feature is over the coastline
3. Feature is over ocean but is approaching land
4. Feature is over ocean and is moving away from land
5. Feature is over ocean and is far from land (> 1000km)

Feature - Description	Threshold	Ranking
Tropical Cyclones	All discernable	1
Extratropical Cyclones	< 980 hPa	2
Thermal Advection Centers	> 0.25 K/hr at 850 hPa	3
Jet Centers	> 50m/s above 500 hPa; > 35 m/s below 500 hPa	4
Deepening Centers	> 0.5 hPa/hr	5

Table 1. Autonomous feature detection ranking.

To emulate the effects of slewing we generated additional synthetic lidar data that were positioned ±150km off the nadir viewing angle of the instrument. The results of applying targeting and slewing are shown in Figure 7, which indicates the results if right and left slewing were performed. For this experiment approximately 33% additional data were captured over the targeted features.

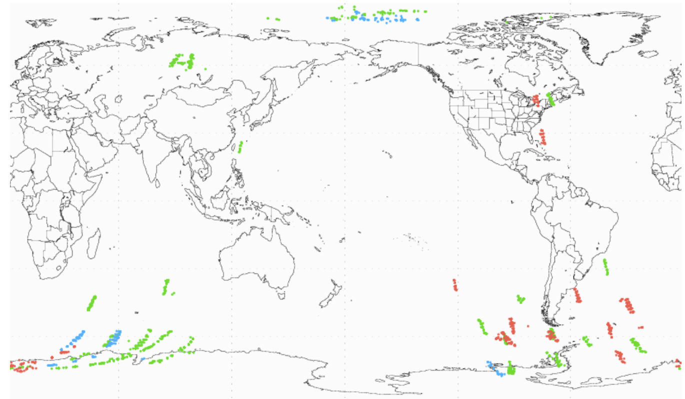

Figure 7. The features of interest that would be captured (for one instance of the assimilation period) with with right and left (red and blue) slewing of the spacecraft.

Summary of Experiments

The investigations described here are intended to provide examples of how the simulator would be used to explore mission formulation, alternatives and, eventually, to support on-orbit mission operations. The lessons learned from the manual execution of the major elements will be used during the second year of the project to guide the final design and for constructing the final prototype. Although the results of these experiments have not been scientifically validated, they demonstrate that the types of "what if" scenarios likely to be performed by investigators making use of the simulator have a significant impact on predictive skill of the forecast model.

References

Kakar, R., Neeck, S., Bajpayee, J., Shaw, H., Gentry, B., Kavaya, M., Sing, U., "Overview of An Advanced Earth Science Mission Concept Study for a Global Wind Observing Sounder"; Study slides, January 2007.

Leutbecher, M., and A. Doerenbecher, 2003: Towards consistent approaches of observation targeting and data assimilation using adjoint techniques. Geophysical Research Abstracts, Vol. 5, 06185, European Geophysical Society.

Seablom, M., Talabac, S., Higgins, G., and Womack, B., 2007: The Applicability of a Sensor Web Simulator to Evaluate a Future Lidar Mission. Preprints for the 2007 NASA Science

Technology Conference, June, 2007, NASA Earth Science Technology Office.

Steiner, M., Atlas, R., Clausen, M., Kalb, M., McConaughy, G., Muller, R., Neeck, S., Seablom, M., 2002: "Advanced Weather Prediction Technologies: NASA's Contribution to the Operational Agencies", Technical Report, NASA Earth Science Technology Office.

Toth, Z., I. Szunyogh, C. Bishop, S. Majumdar, R. Morss,, and S. Lord, 2001: On the use of targeted observations in operational numerical weather prediction. Preprints for the Fifth Symposium on Integrated Observing Systems, January, 15–19, 2001, Albaquerque, NM, AMS, 72–79.

Acknowledgements

This work was funded under a 2006 NASA ESTO AIST award. The authors are grateful to Mr. Joe Terry for setting up and executing the experiments used in this report.