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1. INTRODUCTION

The Local Analysis and Prediction System (LAPS) analyzes three-dimensional moisture and other state variables hourly (or more frequently) over a high-resolution relocatable domain. LAPS analyses have been routinely used to initialize local-scale, high-resolution models such as the Colorado State University's Regional Atmospheric Modeling System (RAMS) model and the National Center for Atmospheric Research's MM5 (mesoscale model, version 5) as a means to utilize local data in the forecast model. LAPS has been integrated into the Advanced Weather Information Processing System (AWIPS) as part of the National Weather Service (NWS) modernization. Research to expand LAPS capabilities is one avenue toward providing advanced technologies and new innovations to the operational forecaster.

This paper describes progress toward advancing the variational technique in the LAPS moisture analysis. To date, the variational step has been used only with GOES sounder radiances. Other moisture variables were analyzed separately and either merged with that variational result or with the background field prior to the variational step (Birkenheuer 2000, 1999). This change will enable the use of more data in the variational framework. The solution strategy allows different data sources to be represented by different terms in the minimized functional. The functional can automatically adjust to match the datasets present. More important, this approach accommodates nonlinear functionals.

1.1 Brief History of LAPS

During the 1980s, FSL conducted forecast exercises to test its workstation prototypes. Forecasters were burdened with the impossible task of reviewing all the incoming data made possible through new technologies, while producing timely forecasts. It became obvious that local data needed to be objectively analyzed in conjunction with nationally disseminated data. Conceived as a resolution to this challenge, LAPS was designed to analyze available local data in real time on affordable computer workstations and utilize the analyses to initialize local-scale forecast models. So far LAPS has been

interfaced with RAMS and MM5, but in principle it can function with any weather prediction model. Such models can address specific problems of a small forecast domain with greater detail than can be achieved with nationally disseminated model guidance (Snook et al. 1998). A more detailed review of LAPS is available in McGinley et al. (1991).

The LAPS system is routinely tested with new data sources and innovative improvements, using more "conventional" data, which typically are nationally disseminated. Advanced data include Doppler reflectivity and velocity fields, satellite observations including GOES infrared (IR) sounder data, wind profiler data, automated aircraft reports, and dual-channel ground-based radiometer data. New data sources included here are GOES-derived layer precipitable water data (GVAP), and Global Positioning System (GPS) data.

2. DATA SOURCES SPECIFIC TO THIS UPGRADE

2.1 GOES-Derived Layer Precipitable Water Data

GVAP data were obtained from the University of Wisconsin - Madison in real time on a daily basis (Menzel et al. 1998). The new variational scheme scales the appropriate parts of the LAPS moisture column to fit each of the three layers provided by GVAP data. The prior LAPS system only utilized total column GVAP water vapor data. The GVAP layers (defined as surface to 0.9 sigma, 0.9 to 0.7 sigma, and 0.7 to 0.3 sigma) are converted to a pressure coordinate system as part of the GVAP preanalysis. Also as part of this step, data are distributed on an analysis grid with a radial influence corresponding to the field of view. In this case, 30 km GVAP data have a nominal latency of 2 h at the current time.

2.2 Global Positioning System Vapor Delay Data

GPS data refer to derived total column water vapor (zenith) from GPS signal delay (Wolfe et al., 2000). These data are obtained in real time with a characteristic latency of 20 min. GPS data are immune from cloud effects, and therefore can be used where clouds are present. A horizontal influence of 12 km was applied to the GPS data. Similar to the GVAP data

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treatment, these data are distributed on an analysis grid.

2.3 Cloud Data

Gridded cloud data are obtained from the LAPS cloud analysis, which relies on satellite image data in addition to Doppler radar, ACARS, surface-based observations of sky conditions, and pilot reports. These data define clear fields of view for utilizing satellite radiance data and help identify regions that require saturation due to complete cloudiness. In partly cloudy regions, the scheme relates cloud fraction to RH and influences the variational result. The partial cloud enhancement starts at 0.6 cloud fraction assigning a 60% RH at that point, and ramps linearly to saturation at total cloud cover.

3. LAPS MOISTURE ANALYSIS

The specific humidity (SH) module is one of 17 LAPS algorithms that span everything from data preparation and quality control (QC) to actual analysis. In addition to state variables, LAPS also produces highly specific analyses of special interest, such as aircraft icing threat and relative humidity with respect to both mixed and liquid phases. The SH module is one of the last analyses run, prior to the new mass balance scheme. It incorporates many fields that have already been processed such as clouds and surface moisture.

3.1 Background Setup

Like most analysis systems, LAPS requires a starting field, which it later modifies by adding information from other datasets. This background, or first-guess field for the test discussed here, is FSL's Mesoscale Analysis and Prediction System (MAPS) analysis. Updated each hour, MAPS is the development model of the operational Rapid Update Cycle (RUC-2) at the National Centers for Environmental Prediction (NCEP). The background model moisture data are interpolated to the denser LAPS grid and reconciled with the LAPS temperature analysis to avoid supersaturation.

Additionally, LAPS can also use a previous short-range forecast (i.e., MM5 1-h forecast initialized with LAPS) and uses this as the background for the next analysis in the cycle. This four-dimensional data assimilation (4DDA) scheme is currently being tested using an hourly update cycle.

3.2 Boundary Layer Moisture

Since the surface analysis uses hourly observations, its representation of surface moisture is possibly the most up-to-date moisture field attainable using conventional data sources, and is key to tracking moisture changes in the boundary layer. The boundary layer moisture module mixes surface humidity into the

calculated boundary layer by adjusting the moisture in the low levels of the 3-D grid.

3.3 GVAP and GPS Pre-analysis

The GVAP and GPS fields are individually preanalyzed prior to the variational step. This is done to specify data at all grid points and assure they have a spatial influence related to instrument characteristics. The preanalysis consists of a simple nearest gridpoint assignment of the observation, and a smoothed interpolated field between observation locations. In addition to the three GVAP fields (one for each sigma layer) and the one GPS field, each field has a corresponding weighting function. The spatial weight controls the horizontal influence of the data field at grid points surrounding those that represent the observation. This includes the spatial influence of observations and other error factors (i.e., limb effects for microwave data, a possible future consideration). In addition, data latency (temporal considerations) can be set up to modify data source influence in the variational step in this same function.

3.4 The Expanded Variational Adjustment

The variational adjustment using GOES radiances (Birkenheuer 1999) is being expanded to include GVAP layer precipitable water (over the column water previously analyzed), GPS total column water, and cloud information in one step. The cloud information is made available from the LAPS cloud analysis (Albers et al. 1996). In this newly revised variational approach, cloud fraction is included in the moisture solution.

3.5 Cloud Saturation

As a safeguard to assure consistency, a final check is made to the field to make sure that moisture is saturated in 100% cloudy areas with respect to the applicable water phase. With the variational step now including cloud influence, this adjustment is invoked less often.

3.6 Quality Control

The final step in the SH algorithm is quality control. Each moisture value is compared to the LAPS analyzed temperature, and if supersaturated, it is reported and reduced to saturation. Typically, supersaturation rarely occurs.

4. VARIATIONAL FORMALISM

The mathematical formalism of the variational procedure is presented in equation 1. The advantage of this approach is that it offers a robust method for operational application and can accommodate nonlinear terms.

$$\begin{aligned}
J = & S_{SAT} \sum_{k=1}^7 \frac{GT(g_i)[R(t, cq, o_3)_i - R_i^o]^2}{E_{SAT}^2 L_{SAT}} + \sum_{i=1}^N \frac{(1-c_i)^2}{E_{BACK}^2} \\
& + S_{GPS} \frac{(\sum_{i=1}^N c_i q_i - Q^{GPS})^2}{E_{GPS}^2 L_{GPS}} \\
& + S_{GVAP} \sum_{j=1}^3 \frac{G(g)(\sum_{i=1}^N P_{ji}(c_i q_i) + Q_j^{GVAP})^2}{E_{GVAP_j}^2 L_{GVAP}} + S_{CLD} \sum_{i=1}^N \frac{g_i [c_i q_i - q_s(t_i)]^2}{E_{CLD}^2 L_{CLD}}
\end{aligned} \tag{1}$$

Each term in (1) is modified by the variable S , which is a switch (with the exception of the background term which is always on). Thereby, the terms can be used or ignored depending on whether or not data are available or if clouds are present. Furthermore, a user can easily add terms for new datasets by simply creating a new term. The variables are as follows:

- C_i the coefficient vector applied to q to adjust the moisture field. Ideally this would have the same dimensions as q has levels, but may be reduced depending on computer horsepower. Adjustment of this parameter is in essence the variational fit to the solution, i.e., $c_i q$ becomes the adjusted q field. The adjustment coefficient is a scalar with a lower limit of 0 (never negative). A value of 1 indicates no change to the background. Because of this, the system will only work with a quantity such as temperature or humidity that uses absolute units. For example, using this approach to analyze temperature in degrees F will fail.
- q the specific humidity profile at one LAPS grid point
- R the forward-modeled radiance or radiance observation with the superscript o .
- i index for the LAPS vertical (vector dimension of q), with a current maximum of 40 (accommodating the climatological stratospheric layers needed for the forward radiance model).
- k the index indicating the satellite sounder or imager channel used.
- Q^{GPS} the total precipitable water measurement from GPS.
- E the error function (squared quantity) that describes the observation or background error, subscripted by observation type.
- L spatial weighting term subscripted by observation type. This weights the smoothed (preanalyzed) field value by its proximity to the observation and reflects the horizontal influences of the measurement. Each data source has an associated gridded field of spatial-weighting terms characterizing its proximity to the observation and its spatial representation.
- P the function to convert from pressure to sigma coordinates

- Q^{GVAP} the GOES vapor total precipitable water layer data. The layers are defined in sigma coordinates and vary grid point to grid point.
- j the index of the GVAP layer, with a current maximum of 3 (1 is lowest, 3 is highest).
- Cld cloud function designating cloudy regions in the vertical, with dimensions of q .
- J the functional to be minimized.
- t is the temperature profile (LAPS) at the same location as q .
- S logical switch for the observation type to be present or not. Each term in the functional can be easily included or excluded depending on the presence of the data source. Also new data sources can be added by including new terms.
- $q_s(t)$ saturated q as a function of temperature.
- g cloud fraction indicator as a function of level.
- G a function of g such that it indicates cloud in the column. For radiance measurements, this has the advantage of disabling IR terms including GVAP. Finally, the GPS term would be unaffected by clouds in principle since the data source can deliver data in cloudy areas. However, the analysis needs to probably give more credence to the cloud field, since it is vital the cloud field complements the moisture field. G can be a linear function of cloud such that it might serve to help define partly cloudy regions by allowing a smooth gradient from total through partly cloudy to clear air.
- GT is a similar function to G , but it may be nonlinear and can match the satellite radiometer's field of view.

5. SOLUTION METHODOLOGY

The minimization of (1) is accomplished using the same methods as the prior moisture analysis. The Powell method (Brent 1973) employs a multidirectional search to seek out a solution. Typically, two to five calls of the algorithm are required to find a solution. Each call to the numeric method involves approximately 25 calls to the functional. Although more efficient methods are available, this technique has worked reliably to date. Model adjoints are not required for this technique.

6. EXAMPLE

The very deep and premature monsoon flow over the regional observation cooperative (ROC) domain in early July 2001 provided a very good signal for moisture study. Figures 1 and 2 contrast the old and new analysis schemes. Both figures depict a cross section of relative humidity from west to east through Boulder, Colorado.

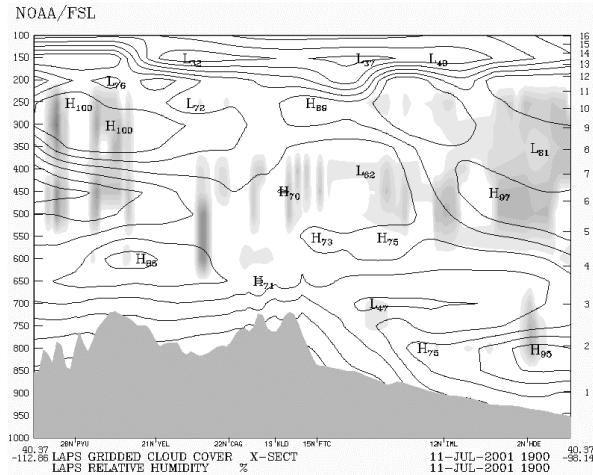


Fig. 1. Cross section through 40° N latitude showing relative humidity and cloud fraction through the ROC domain.

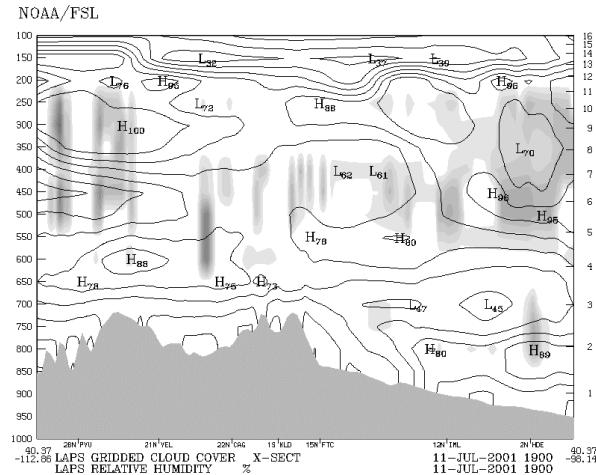


Fig. 2. Same as Fig. 1 except using the newer variational analysis.

For the most part, the two analyses are very similar with the newer scheme possibly showing more detail. The cloud field is the same in both sets and is depicted by shaded features. The lighter shades indicate low cloud fraction while black would show 100% cloud. It is apparent that very low cloud fractions existed; therefore, clouds had minor impact on the RH adjustment. Even so, the analysis shows higher RH values in partly cloudy areas. A quantitative evaluation of the scheme is currently being performed.

7. SUMMARY

The new functional solution is now being tested with broader focus on the run times and feasibility of real-time operation. These aspects of the algorithm look promising, even for AWIPS-type resources. Error functions are currently approximated and will require refinement.

When running the system in 4DDA mode, it quickly becomes apparent that model and analysis moisture components must be compatible. For example, the model may base RH computations on the liquid phase for all temperatures while the analysis may use ice as a reference below some threshold temperature. Such discrepancies can lead to artificial "generation" of water or chronic drying of the atmosphere as these discrepancies are compounded in the 4DDA cycle. The new variational scheme has demonstrated a resistance to this effect during ongoing 4DDA tests.

8. REFERENCES

Albers, S., J. McGinley, D. Birkenheuer, and J. Smart 1996: The Local Analysis and Prediction System (LAPS): Analyses of clouds, precipitation, and temperature. *Wea. Forecasting*, **11**, 273-287.

Birkenheuer, D., 2000: Progress in applying GOES-derived data in local data assimilation, *10th Conf. on Satellite Meteorology and Oceanography*, Amer. Meteor. Soc., Long Beach, CA, 70-73.

_____, 1999: The effect of using digital satellite imagery in the LAPS Moisture Analysis. *Wea. Forecasting*, **14**, 782-788.

Brent, R.P., 1973: *Algorithms for minimization without derivatives*. Prentice-Hall, Chapter 7.

McGinley, J. A., S. Albers, and P. Stamus, 1991: Validation of a composite convective index as defined by a real-time local analysis system. *Wea. Forecasting*, **6**, 337-356.

Menzel, W. P., F. C. Holt, T. J. Schmit, R. M. Aune, A. J. Schreiner, G. S. Wade, and D. G. Gray, 1998: Application of GOES-8/9 Soundings to weather forecasting and nowcasting. *Bull. Amer. Meteor. Soc.*, **79**, 2059-2077.

Snook J. S., P. A. Stamus, J. Edwards, Z. Christidis, and J. A. McGinley, 1998: Local-domain mesoscale analysis and forecast model support for the 1996 Summer Olympic Games. *Wea. Forecasting*, **13**, 138-150.

Wolfe, Daniel E., Seth I. Gutman, 2000: Developing an operational, surface-based GPS water vapor observing system for NOAA: Network design and results. *J. Atmos. Oceanic Technol.*, **17**, 426-440.