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ABSTRACT

A new approach to parameterize physical processes with weather and climate models is presented, with a specific example for diabatic heating processes. Traditionally diabatic processes within these models are parameterized separately in terms of vertical (1-D) representations of short- and longwave radiative flux divergences, stable and convective clouds and precipitation, and turbulent flux divergence. However, we propose a methodology where satellite remote-sensed data are utilized to create a unified parameterization that incorporates the net effect of each of the physical processes. This is not only computationally efficient but also implicitly includes real world three-dimensional processes. Model results are proposed along with observational analysis and simulation experiments that can provide recommendations to the remote sensing community on the types of data most useful in creating a unified parameterization of diabatic heating.

Introduction

The traditional procedure to parameterize physics in weather and climate models at spatial scales that are too small to be explicitly resolved in the models, is to separately represent turbulence fluxes, shortwave radiative fluxes, longwave radiative fluxes, and convective and stratiform cloud-precipitation processes. The traditional parameterizations are typically 1-D column models that interact with the dynamical core of a given atmospheric model. These subgrid parameterizations are then used to diagnose the effect of these physical processes within the model. However, such a separation is not realistic as the parameterized processes are, in fact, three-dimensional and may interact with each other.

With respect to convective cloud parameterizations, a cumulus parameterization workshop (1) concluded that there are three major approaches to cumulus parameterization: traditional, statistical, and super-parameterization (or multi-scale modeling Framework, MMF). Most traditional column-based convective parameterization schemes in regional and global atmospheric models presently use a mass-flux (e.g., 2,3) or quasi-equilibrium approach (4). The statistical approach is a statistical parameterization based on the analysis of cloud resolving model output (1).

The super-parameterization approach uses data from many Cloud Resolving Model (CRM) simulations to diagnose the cloud system response to large-scale parameters. In MMF a full 2D CRM is embedded within each grid cell of a large-scale model (5). However, the MMF is presently very computationally expensive, and is, as yet, impractical for operational weather forecasting, ensemble simulations, or climate simulations.

There was also a consensus from the cumulus parameterization workshop (1) that a consistent, comprehensive cloud database (associated with clouds and cloud systems that developed in different geographic locations) should be generated from the ensemble of CRMs for use in the development and improvement of cumulus parameterization schemes. This cloud data is to be generated in close collaboration with parameterization developers. However, new and innovative ideas for the optimal way to use the CRM data sets are needed.

We propose a different approach in which satellite (and other available) observations are used to construct unified parameterizations, which includes the combined effect of each of the atmospheric physics processes, Since the observations are sampling reality, this assures that three-dimensional interactions are implicitly included.

To illustrate the methodology, we focus first on subgrid-scale diabatic effects. As given in Pielke (6), the conservation equation for potential temperature can be written as,

$$\partial \theta /\partial t = -u \partial \theta /\partial x - v \partial \theta /\partial y - w \partial \theta /\partial z + S_\theta \quad (1)$$

The source/sink term S_θ includes all of the diabatic physics, which, in a model, is decomposed into separate parameterizations and a resolvable term for phase changes of water.

The term θ is the potential temperature and is defined as

$$\theta = T_V (1000\text{mb}/p)^{R_d/C_p} \quad (2)$$

such that θ can be calculated from the virtual temperature, Tv, and pressure, p (mb). R_d and C_p are the gas constant for dry air and the specific heat of air at constant pressure. T_V is obtained from

$$T_V = T (1 + 0.61q)$$

where q is the specific humidity of the air.

Methodology

Our methodology is that instead of using separate physics to compute the terms that comprise S_θ, observed data are used to construct this term in the format of a transfer function (e.g., a "look-up-table"), as proposed by Matsui et al. (7) and Pielke et al. (8) for the individual parameterizations that comprise S_θ.

The remote sensing community uses such an approach routinely in its algorithms to convert satellite radiances into variables, for example (e.g., see ref. 9). There is also a direct analogy to the approach several investigators have made in land surface modeling. Like the convective parameterization problem, the land surface parameterizations are fraught with highly complex interactions between vegetation, soil and moisture. Further, like in convective schemes most desired parameters are not directly measurable such as stomatal resistance, soil diffusivity and grid averaged heat capacity. Given this complexity some modelers have resorted to simpler models constrained by satellite observations to recover fluxes as a residual. In particular, McNider et al. (10), Jones et al. (11), Alapaty et al. (12) and others have proposed and used morning satellite surface tendencies to infer the moisture availability and evening tendencies to infer heat capacity (13). The triangle method of Gillies et al. (14) is another example where a look-up table approach is used to derive surface energy fluxes from satellite observed values of vegetation fraction and surface radiant temperature.

What we propose is to utilize this methodology to develop computationally fast parameterizations for use in models. We illustrate this method for the physics of diabatic heating, but it can be applied to any quantities that are parameterized within weather and climate models.

The procedure is as follows:

1. Satellite observations, at their sampling time, are used to obtain T (e.g., GOES), the horizontal winds (e.g., Windsat, GOES), and water vapor (GOES), liquid water (e.g., Cloudsat, TRMM) and ice (Cloudsat) for each of the footprints that are viewed by the satellite over a period of time. This data needs to be transferred to a gridpoint format.
2. The individual terms in Eq. (1) are directly computed for the sampling time period of the observations:

   i) $\partial \theta / \partial t$

   ii) $u \, \partial \theta / \partial x - v \, \partial \theta / \partial y$

   while $w \, \partial \theta / \partial z$ is diagnosed using the spatial gradient of the horizontal wind field (w is diagnosed from the conservation of mass and/or using quasi-geostrophic theory The horizontal wind field can be derived from the temperature field using thermal wind relation and clouds movement, when applicable).
3. The value of S_θ is then computed as a residual;

   $$S_\theta = u \, \partial \theta / \partial x + v \, \partial \theta / \partial y + w \, \partial \theta / \partial z + \partial \theta / \partial t.$$
4. The model resolved portion of S_θ can be subtracted out also;

   $$\langle S_\theta \rangle = S_\theta - L \, w \, \partial q_s / \partial z$$

   where $L \partial q_s / \partial z$ is the latent heat of model-resolved phase change when q is equal to q_s and $w > 0$ [q_s is the saturation specific humidity]. This calculation can be generalized to include phase changes of liquid and ice also, and w is the grid volume averaged vertical velocity. The quantity $\langle S_\theta \rangle$ is then the subgrid-scale diabatic contribution, provided the satellite observations are available

5. Using satellite measured values of temperature, the horizontal winds, and water vapor, cloud liquid water and ice, the individual terms in #3 and #4, and other needed information can be obtained and inserted into the transfer function, **T**,

   INPUT = $\sum$ (satellite input of $u \partial \theta / \partial x + v \partial \theta / \partial y$, $\partial \theta / \partial t$, $u \partial q / \partial x + v \partial q / \partial y$, $\partial q / \partial t$, time of year, latitude) $\rightarrow$ **T** $\rightarrow$ $\langle \mathbf{S_\theta} \rangle$

   The unified parameterization is **T**, which can be expressed as a look-up table, as a transfer function, or by use of artificial intelligence techniques, including neural networking or genetic algorithms.

Two necessary conditions for this approach to provide an accurate unified parameterization are 1) that the satellite observations are sufficiently accurate with the needed spatial and temporal resolution and 2) that the satellite observations encompass a broad and global range of meteorological conditions. One of the most promising future satellite sensors that suit the requirements of the present concept is GIFTS (The Geosynchronous Imaging Fourier Transform Spectrometer). This is a measurement concept which combines a number of advanced imaging technologies with the Fourier Transform Spectrometer (FTS). The GIFTS will improve the observation of all three basic atmospheric state variables (temperature, moisture, and wind velocity) allowing much higher spatial, vertical, and temporal resolutions than is now achievable with currently operational geostationary weather satellites. Figure 1 shows the simulated retrieval accuracies of GIFTS for temperature and humidity profiles and their comparison with current GOES retrievals (15). The displacement of the measured water vapor and cloud features from GIFTS measurements will be used as tracers of the transport of atmospheric water as well as other important constituents (e.g., CO_2 and O_3). A key advance over current geostationary wind measurement capabilities is that the water-vapor winds will be altitude-resolved throughout the troposphere. The GIFTS wind system uses the retrieved moisture fields on constant altitude surfaces to identify gradients for motion vector calculations. This novel approach eliminates the height assignment issue that is often the biggest source of error in the retrieval of atmospheric winds. Velden et al. (16) demonstrated that wind fields obtained by tracking the moisture gradients from an air-borne hyperspectral instrument matched the measurements of a Doppler Wind Lidar nicely with wind speed deviations limited to less than 3 m s^{-1}. In cloudy areas where wind fields could not be obtained as accurately from the satellite measurements the wind data could be supplemented from the standard weather analyses. The proof of concept presented in the next section can provide further information to the remote sensing community that is needed to obtain this information.

Proof of Concept

The proof of concept of this methodology is to use regional model simulations (e.g., using RAMS; 17), to construct **T** since each of the **INPUT** values can be obtained from the model fields and the value of $<\mathbf{S}_\theta>$ can be computed by summing each of the diabatic terms that are calculated in the model using the traditional 1-D, separate parameterizations.

The goal is to recreate $<\mathbf{S}_\theta>$ from the sum of the turbulent flux divergence, the shortwave radiative flux divergence, the longwave radiative flux divergence, the phase changes of water on the subgrid scale, and cumulus cloud flux divergence of θ. If we refer to this value of $<\mathbf{S}_\theta>$ as $<<\mathbf{S}_\theta>>$, and the transfer function calculated version as $<\mathbf{S}_\theta>$, then the methodology is successful if the diabatic heating calculated by the traditional way using separate parameterizations, $<<\mathbf{S}_\theta>>$, produces essentially the same result as using the transfer function approach, $<\mathbf{S}_\theta>$; i.e.,

$$<<\mathbf{S}_\theta>> \approx <\mathbf{S}_\theta>.$$

and the calculation of **$<S_\theta>$** is computationally much more rapid. After we prove the concept, **$<S_\theta>$** can then replace the separate, more computationally expensive individual calculations of the subgrid diabatic terms before. The transfer function, **T,** can replace the traditional approach of parameterization .

To demonstrate skill of the method when remotely sensed data is used to construct T, the proof of concept experiments will also include computation of source/sink term from simulated satellite data, denoted by $\left\langle S_\theta^* \right\rangle$. The simulated satellite data are computed from the model fields such as to have spatial and temporal resolution and error characteristics of the actual satellite data, including future sensors. Coarser spatial and temporal resolution of the simulated data relative to the model produce representativeness errors in $\left\langle S_\theta^* \right\rangle$. Amplitude errors assigned to the individual fields (i.e., temperature, humidity, wind) would reflect the data accuracy resulting from the measurement and retrieval errors. The quantity $\left\langle S_\theta^* \right\rangle$ is by definition stochastic because it contains information about the errors in the data. This property implies that an ensemble average of model simulations using $\left\langle S_\theta^* \right\rangle$ from a range within the error margins should be compared with the control model simulation. A small difference between the two model results would imply high skill of the method. This difference represents a global measure of the impact of the data errors. In the proof of concept experiments, the simulated data errors could be varied to determine desired resolution and accuracy in the data to result a satisfactory estimate of **$<S_\theta>$.**

The development of an efficient transfer function **T** relies on a high degree of spatial and temporal correlation among the meteorological fields. More specifically this allows pattern recognition techniques to reduce the dimensionality of input space. Empirical Orthogonal

Functions and Rotated Empirical Orthogonal functions have already proved successful in identifying physically meaningful patterns (18, 19, and many others) and can be used in this case as well. Neural networks and genetic algorithms also could be successful not only because of their robustness, but also because they can help determine the relationship between variables, when the explicit form of the relationship is not easily determined (20, 21). Fausett (20) also foresees as that computing resources will allow for faster computation and larger storage capabilities (both in memory, and physical disk space), such that neural networks become even more attractive in their ability to determine relationships for extremely large data sets. Besides the above mentioned approaches, artificial intelligence techniques used for pattern recognition purposes by other communities could be employed to build the transfer function **T**.

Finally once the transfer function is completed it not only serves as a proof of concept of the unified lookup table approach proposed here, but also can be used as part of RAMS or any other model for climate studies and numerical weather prediction with considerable computational advantage.

Application to Models Using Remotely Sensed Data and Virtual Cloud Library

The demonstration that a unified parameterization can be achieved using the model as the test bed, indicates that the procedure will work when remotely sensed data is used to construct **T.** The next step in the assessment is to collect available satellite data to determine if sufficient information is available in satellite measurements and they are accurate enough to derive $\langle \mathbf{S}_\theta \rangle$. In addition, with new satellites planned (geostationary satellites in particular), the development of this approach to model parameterization could assist satellite developers in decisions with respect to what instrumentation to place on them.

Although the ultimate goal is to use the observations for constructing unified LUTs, it requires more than several years to launch the next-generation of geostationary satellites. Thus, we propose to use a virtual cloud library (VCL) as an initial step. VCL is being constructed by the NASA's MMF (22). Whereas VCL is a model-generated dataset, it has the comprehensive dataset required for constructing the unified LUT. Those massive datasets can be efficiently hardwired through the unified LUT or neural network approach as proposed by Matsui et al. (7) and Pielke et al. (8).

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References

1. Tao W-K, Starr D, Hou A, Newman P, Sud Y (2003) *Bull. Amer. Meteor. Soc.,* **84**, 1055-1062.
2. Kain JS (2004) *J. Appl. Meteor*., **43,** 170-180.
3. Grell GA (1993) *Mon. Wea. Rev*., **121**, 764-787.
4. Arakawa A, Schubert WH (1974) *J. Atmos. Sci*. **31**, 674-701.

5. Randall DA, Khairoutdinov M, Arakawa A, Grabowski W (2003) *Bull. Amer. Meteor. Soc.,* **84,** 1547-1564.

6. Pielke Sr RA (2002) *Mesoscale meteorological modeling*. 2nd Edition, Academic Press, San Diego, CA, 676 pp.

7. Matsui T, Leoncini G, Pielke Sr RA, Nair US (2004) Atmospheric Science Paper No. 747, Colorado State University, Fort Collins, CO 80523, 32 pp.

8. Pielke Sr RA, Matsui T, Leoncini G, Nobis T, Nair U, Lu E, Eastman J, Kumar S, Peters-Lidard C, Tian Y, Walko R (2006) *National Wea. Digest*, in press.

9. Kidder S, Vonder Haar TH (1995) *Satellite meteorology: An introduction*. Academic Press, 466 pp.

10. McNider RT, Song AJ, Casey DM, Wetzel PJ, Crosson WL, Rabin RM (1994) *Mon. Wea. Rev.,* **122,** 2784-2803.

11. Jones AS, Guch IC, Vonder Haar TH (1998) *Mon. Wea. Rev*., **126**, 634–645.

12. Alapaty K, Seaman N, Niyogi D, Hanna A, (2001) *J. Appl. Meteor*., **40**, 2068-2082.

13. McNider RT, Lapenta WM, Biazar AP, Jedlovec GJ, Suggs RJ, Pleim J (2005) *J. Appl. Meteor*., **44**, 1346-1360

14. Gillies RR, Carlson TN, Cui J, Kustas WP, Humes KS (1997) *Int. J. Remote Sens.,* **18**, 3145-3166.

15. Li J, Sun F, Seemann S, Weisz E, Huang AH-L (2004) *20th AMS International Conference on Interactive Information and Processing Systems (IIPS) for Meteorology, Oceanography, and Hydrology,* Seattle, WA, 11-15 January, Paper P2.32

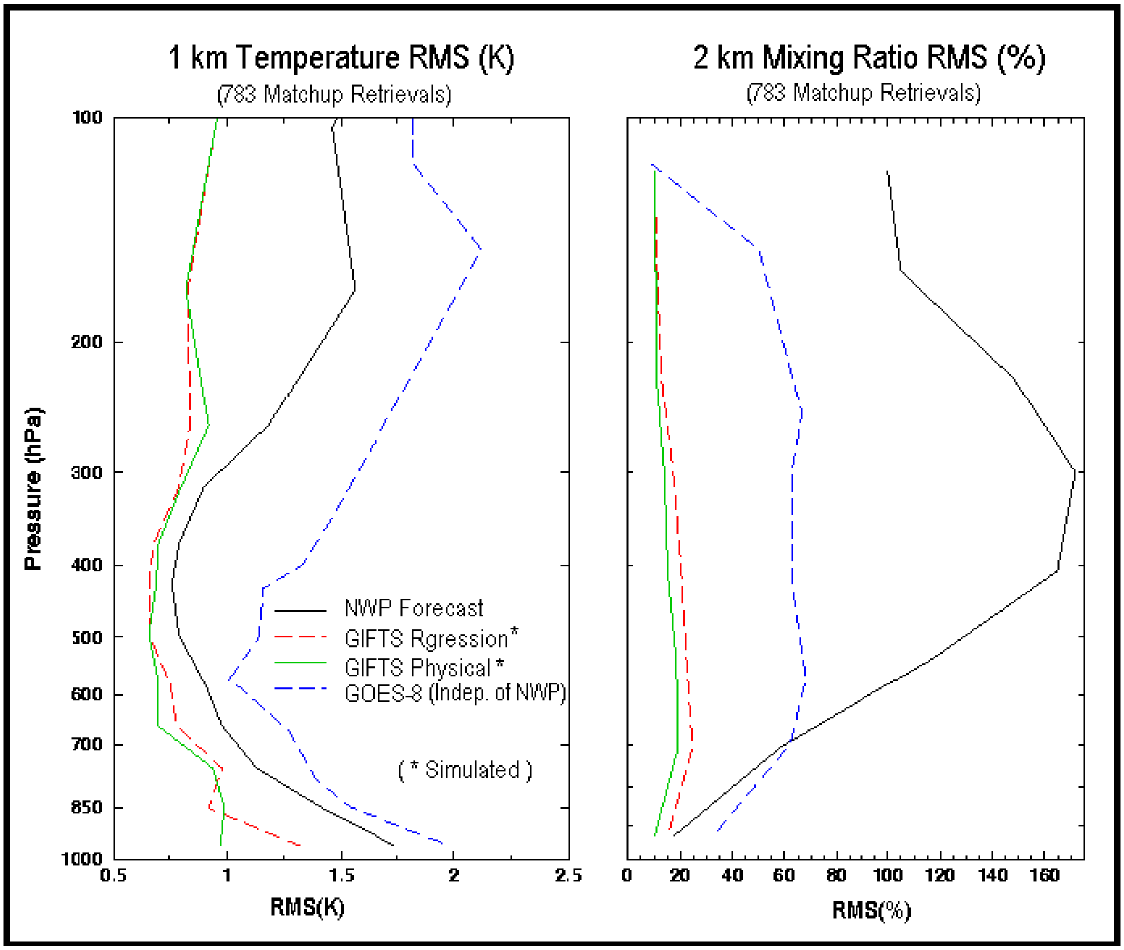
16. Velden CS, Dengel G, Dengel R, Huang AH-L, Stettner D, Revercomb H, Knuteson R (2004) *20th AMS International Conference on Interactive Information and Processing*

Systems (IIPS) for Meteorology, Oceanography, and Hydrology, Seattle, WA, 11-15 January, Paper P2.32.

17. Cotton WR, Pielke Sr RA, Walko RL, Liston GE, Tremback C, Jiang H, McAnelly RL, Harrington JY, Nicholls ME, Carrio GG, McFadden JP (2003) *Meteor. Atmos. Phys*., **82**, 5-29.
18. Castro CL, Pielke Sr RA, Adegoke J, Schubert SD, Pegion PJ (2006) *J. Climate*, in press.
19. Reynolds RW, Smith TM (1994) *J. Climate*, **7**, 929-948.
20. Fausett LV (1994) *Fundamentals of neural networks: architectures, algorithms and applications*, Prentice-Hall, Inc., Englewood Cliffs, NJ, 461 pp.
21. Martello S, Toth P (1990) *Knapsack Problems – Algorithms and Computer Implementations*. Wiley Interscience Series in Discrete Mathematics and Optimization, 296 pp.
22. Tao W-K, Chern J, Atlas R, Randall D, Lin X, Khairoutdinov M, Hou A, Peters-Lidard C, Simpson J (2006) *Mon. Wea. Rev*., submitted.

LIST OF FIGURES

Figure 1: Simulated accuracies of temperature and humidity profiles by GIFTS and their comparison with the accuracy of GOES-8 retrievals and NWP forecasts (15).



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