Advances in Radiative Transfer Modeling in Support of Satellite Data Assimilation

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ABSTRACT

Development of fast and accurate radiative transfer models for clear atmospheric conditions has enabled direct assimilation of clear-sky radiances from satellites in numerical weather prediction models. In this article, fast radiative transfer schemes and their components critical for satellite data assimilation are summarized and discussed for their potential applications in operational global data assimilation systems. The major impediments to the fast radiative transfer schemes are highlighted and a call is made for broader community efforts to develop advanced radiative transfer components that can better handle the scattering from atmospheric constituents (e.g., aerosols, clouds, and precipitation) and surface materials (e.g., snow, sea ice, deserts).

1. Introduction

Satellite observations of the atmosphere, land, and oceans are now a major component of the environmental observing system, since they provide critically important information to better understand and forecast short-term as well as climatic changes in weather. Through data assimilation techniques, the satellite observations as well as other sources of atmospheric and oceanic data, sampled at different times, intervals, and locations can be combined into a unified and consistent description of the atmospheric state. Global objective analyses are produced from these diverse observations in combination with the a priori knowledge of the evolving atmospheric state as given by numerical weather prediction (NWP) models. By far, the greatest volume of data ingested into these numerical models is from satellite instruments, whose data have contributed to a dramatic improvement of forecast accuracy over the last 20 years.

Since the first meteorological satellite was launched in April 1960, much progress has been made in the utilization of satellite data in NWP models. This progress is a result of improved satellite instruments, increase in computer power, and improvements in numerical models and data assimilation techniques. From 1960 to 1995, the forecasts of the 36-h mean sea level pressure over North America went from having no skill at all (i.e., being no more useful than a forecast based on climatology), to being skillful 72% of the time. This dramatic improvement of forecast skill has been directly attributed to the launch, beginning in 1995, of an improved series of meteorological satellite instruments, called the Advanced Microwave Sounding Unit (AMSU), whose data are assimilated in the more sophisticated NWP models, which are run using more powerful computers (Uccellini et al. 2001).

Satellite measurements (radiances) are directly assimilated into the NWP model using a computationally efficient, optimum procedure, which minimizes the difference between the radiances and those computed based on the NWP output of the atmospheric state. In the absence of cloud absorption and atmospheric scattering from precipitation an accurately parameterized radiative transfer model was used to assimilate satellite measurements into global NWP models for clear atmospheric conditions (e.g., Eyre 1989; Garand et al. 2001). However, in order to utilize the full capabilities of AMSU and other advanced instruments, which includes all weather conditions, an accurate radiative transfer model is needed that incorporates cloud absorption and scattering from hydrometeors. Such a forward model has been developed to enable the computation of both the satellite radiances and their change with atmospheric variables (i.e., Jacobian) over a broad range of wavelengths from the microwave to the infrared (Weng et al. 2005).

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Direct assimilation of satellite cloudy radiances into NWP models is a difficult problem, requiring very accurate variational schemes. The problem has been pursued by some major centers. At the European Centre for Medium-Range Weather Forecasts (ECMWF), Moreau et al. (2004) developed a one-dimensional variational (1DVAR) system to assimilate the radiances at the microwave window channel frequencies that are more sensitive to cloud liquid water, water vapor, sea surface wind, and temperature. The 1DVAR retrievals of the vertically integrated cloud liquid water and water vapor are then assimilated into a four-dimensional variation (4DVAR) system. A similar process has been also developed for 1DVAR SSM/I retrieval at Meteorological Service of Canada (MSC; Deblonde et al. 2007). At National Oceanic and Atmospheric Administration (NOAA), Weng et al. (2007) also developed a Hybrid Variational Scheme (HVAR), which is a 1DVAR retrieval of temperature profiles from the AMSU instrument, and 4DVAR assimilation of retrieved temperature profiles. A similar algorithm has also been tested in the UK Met Office (English and Une 2006). During the 2005 hurricane season, the HVAR was applied to several storms, resulting in improved analyses of the hurricanes three-dimensional warm core temperature structure and accompanying wind fields within and around the rain bands. Both the lower-level wind speed and upper-level divergence were also enhanced, displaying a reasonable asymmetric structure.

Until now much of the impact of satellite data has been demonstrated through radiance assimilation of cloud-free atmospheres. In the next decade, many advanced microwave and infrared sensors will be deployed in space with higher spatial and spectral resolution so as to increase their sensitivity to aerosols, clouds, precipitation, and surface parameters beyond that of current instruments. To utilize the data from current sensors as well as the next generation of instruments, the forward-modeling capability needs to be enhanced to include the scattering and polarization resulting from these atmospheric and surface features. Only then will the assimilation of aerosol, clouds, and rain-affected radiances make a major impact on NWP forecasting, and add to our knowledge of clouds, air quality, and the hydrological cycle. Of course, to facilitate improved forecasting through direct radiance assimilation, concomitant improvements must also be made in the microphysical modeling of hydrometeors and the use of higher NWP grid resolutions to resolve convective-scale processes.

This paper will review several radiative transfer modeling components that are critically important to the improvements in direct satellite radiance assimilation under all weather conditions. These components are being developed through National Aeronautics and Space Administration (NASA)/NOAA/Department of Defense (DoD) Joint Center for Satellite Data Assimilation (JCSDA) Program and include the forward radiative transfer model and its Jacobian, fast gaseous absorption models, and surface emissivity and reflectivity models.

2. Current radiative transfer schemes used for satellite data assimilation

a. Discretization of radiative transfer model

Data assimilation of satellite data uses a variational analysis approach to combine the satellite measurements with an a priori initial guess based on the NWP model (Rodgers 2000). Specifically, assuming that the errors in the satellite observations, $\mathbf{I}^0$, and a priori information, $\mathbf{I}$, are unbiased, uncorrelated, and have Gaussian distributions, the best estimate of the atmospheric state, $\mathbf{x}$, minimizes the cost function:

$$J = \frac{1}{2}(\mathbf{x} - \mathbf{x}^b)^{\mathrm{T}}\mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}^b) + \frac{1}{2}[\mathbf{I}(\mathbf{x}) - \mathbf{I}^o]^{\mathrm{T}}(\mathbf{E} + \mathbf{F})^{-1}[\mathbf{I}(\mathbf{x}) - \mathbf{I}^0], \quad (1)$$

where the second term contains the coupling of satellite radiances with the state variables derived from NWP models. In addition to the observed radiance vector, $\mathbf{I}^0$, and simulated radiance vector, $\mathbf{I}$, for a set of channels (or frequencies), (1) also contains the error covariance matrix, $\mathbf{B}$, associated with the background state variable $\mathbf{x}^b$, and the error matrices associated with observations, $\mathbf{E}$ and forward models, $\mathbf{F}$.

Minimization of the cost function is obtained using an iterative process that computes the descent direction at state $\mathbf{x}$. The value of the cost-function gradient at each iteration is given by (Eyre 1989; Garand et al. 2001)

$$\nabla_x J = \mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}^b) + \mathbf{H}^{\mathrm{T}}(\mathbf{E} + \mathbf{F})^{-1}[\mathbf{I}(\mathbf{x}) - \mathbf{I}^0], \quad (2)$$

where $\mathbf{H}^{\mathrm{T}}$ is the adjoint operator of the Jacobian matrix, $\mathbf{H}$, which is the derivative of the radiance with respect to the input variables (e.g., $\partial\mathbf{I}/\partial\mathbf{x}$) as determined using a tangent-linear approximation of the radiative transfer model. The radiative transfer model also provides the relationship between the model state vector and observed radiances [i.e., $\mathbf{I}(\mathbf{x})$], by determining the radiance output to state vector inputs.

For a plane-parallel atmosphere, the radiance vector is obtained from the differential form of the radiative transfer equation

$$\mu \frac{d\mathbf{I}(\tau, \mu, \phi)}{d\tau} = -\mathbf{I}(\tau, \mu, \phi) + \frac{\varpi}{4\pi} \int_0^{2\pi} \int_{-1}^{1} \mathbf{M}(\tau; \mu, \phi; \mu', \phi')\mathbf{I}(\tau, \mu', \phi')\, d\mu'\, d\phi' + \mathbf{S}(\tau, \mu, \phi; \mu_0, \phi_0), \tag{3}$$

where the integral term contains the contributions due to multiple scattering while the source term is given by

$$\mathbf{S} = (1 - \varpi)B[T(\tau)] \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \frac{\varpi F_0}{4\pi} \exp(-\tau/\mu_0) \begin{bmatrix} M_{11}(\mu, \phi; \mu_0, \phi_0) \\ M_{12}(\mu, \phi; \mu_0, \phi_0) \\ M_{13}(\mu, \phi; \mu_0, \phi_0) \\ M_{14}(\mu, \phi; \mu_0, \phi_0) \end{bmatrix}, \tag{4}$$

where $\mathbf{M}$ is the scattering phase matrix; $\mathbf{I} = [I, Q, U, V]^{\mathrm{T}}$ is the Stokes vector; $B(T)$ is the Planck function at temperature T; F_0 is the solar spectral constant; μ_0 and ϕ_0 are the cosines of the zenith angle and the azimuthal angle of the sun, respectively; μ and ϕ are the cosines of zenith angle and the azimuthal angle in the scattering direction, respectively; ϖ is the single-scattering albedo; and τ is the optical thickness. The second term in (4) is generally omitted at microwave and infrared frequencies but is occasionally used for applications such as sun glint effects on the microwave measurements.

For scattering media, numerical radiative transfer solutions require that the integral term in (3) be expressed as a finite series so that the radiance field is represented as a number of discrete streams from different directions, that is, zenith angles. Depending on the observation angle and accuracy requirement, the number of streams can be as little as two (Bauer et al. 2005). Furthermore, the azimuthal dependence of the Stokes vector is expanded in a series of Fourier harmonics whose amplitudes are a function of zenith angle (or streams). The amplitude for each zenith angle (or stream) can then be simplified as

$$\mu_i \frac{d}{d\tau} \begin{bmatrix} \mathbf{I}_m(\tau, \mu_i) \\ -\mathbf{I}_m(\tau, \mu_{-i}) \end{bmatrix} = \begin{bmatrix} \mathbf{I}_m(\tau, \mu_i) \\ \mathbf{I}_m(\tau, \mu_{-i}) \end{bmatrix} - \varpi \sum_{j=1}^{N} \begin{bmatrix} \mathbf{M}_m(\mu_i, \mu_j) & \mathbf{M}_m(\mu_i, \mu_{-j}) \\ \mathbf{M}_m(\mu_{-i}, \mu_j) & \mathbf{M}_m(\mu_{-i}, \mu_{-j}) \end{bmatrix} \begin{bmatrix} \mathbf{I}_m(\tau, \mu_j) \\ \mathbf{I}_m(\tau, \mu_{-j}) \end{bmatrix} w_j - \begin{bmatrix} \mathbf{S}_m(\tau, \mu_i, \mu_0) \\ \mathbf{S}_m(\tau, \mu_{-i}, \mu_0) \end{bmatrix}, \tag{5}$$

where μ_i and w_i are the Gaussian quadrature points and weights, respectively. Note that $\mu_{-I} = -\mu_i$ and $w_{-I} = w_i$. Because of the characteristics of the phase matrix, the radiance components for the sinusoidal and cosinusoidal azimuthal modes can be decoupled, recombined, and solved independently (Weng 1992; Schulz et al. 1999; Weng and Liu 2003).

Equation (5) can be solved using standard routines such as the multilayer discrete ordinate method (Weng 1992; Schulz et al. 1999), the Doubling-adding method (Evans and Stephens 1991), and the matrix operator method (Liu and Ruprecht 1996). For spherical and randomly oriented nonspherical scatters the scattered radiation is azimuthal independent so that the integration of the phase matrix over azimuth angle can be determined analytically (Liu and Weng 2002). Also, the first two Stokes components, I and Q, are decoupled from the U and V components, and the solutions can be expressed in terms of the atmospheric and surface optical parameters for fast computation. Furthermore, for these particular scattering particles, the difference between the radiance (i.e., brightness temperature) for the two-stream and multistream model is typically less than 2 K at various microwave frequencies so that concise analytic solutions can be obtained (Liu and Weng, 2002). However, a more general class of scatterers must be considered to characterize the polarization from clouds at infrared and microwave wavelengths. To obtain solution for this case, a delta-four stream scheme was developed that reduces the phase function to four expansion terms (Liou et al. 2005).

Other fast schemes used to solve the radiative transfer Eq. (3) include the successive order of interaction (Greenwald et al. 2005). This method takes advantage of the truncated doubling method for a single layer and the successive order of interaction for vertical integration. The truncation used in the doubling procedure is a good approximation for infrared and microwave frequencies, where errors in the brightness temperature are generally less than 0.1 K when using 16 streams. This error is significantly less than that derived with the delta-Eddington model (Bauer et al. 2005) while the computational speeds between the two models are very similar. Another approach is the discrete ordinate tangent-linear radiative transfer solution (Voronovich and Gasiewski 2004), which uses symmetric matrices to make the solution numerically stable and simpler to calculate. Lastly, a doubling-adding method (DA) is one of the most accurate tools for obtaining detailed multiple-scattering calculations and has served as a reference for comparison of the other radiative transfer solutions. However, the method has never been used operationally because of the tremendous demand on computational resources. Liu and Weng (2006) derived an analytical expression to replace the more complicated thermal source terms in the DA method, which is now referred as the advanced doubling-adding (ADA) method. The ADA is about 61 times faster and has the same accuracy as the DA method. Computation codes of ADA have been translated into the tangent-linear and adjoint codes for determining the linear operators contained in the cost function used for satellite data assimilation [see (2)].

Each of the above models is valid at different wavelengths, and has different accuracies and computational speed. Intercomparisons such as that done by Smith et al. (2002) provide vital information on the optimal selection of the radiative transfer and Jacobian model to be used in satellite data assimilation. The advantages of each model may ultimately be combined in a more refined version by taking advantage of their speed and accuracy relative to benchmark solutions.

One of critical issues affecting the speed of radiative transfer calculations for precipitating atmospheres is the determination of the scattering coefficients and phase-matrix parameters for different types of hydrometeor distributions. Operational NWP assimilation permit only a fraction of a millisecond time for complete calculation of the radiance and its Jacobian. However, the term-by-term Mie calculations of the scattering coefficients and phase-matrix parameters are not only too computationally intensive for operational use but often involve redundant calculations for similar hydrometeor profiles. One way to overcome this problem is to produce lookup tables for the parameters that cover the range of hydrometeor types, size distributions, and temperature conditions, and also fit within a small prescribed memory space.

To facilitate fast forward radiative transfer simulations required for the data assimilation under completely or partially cloudy conditions, it is critical to build advanced radiative transfer models that can account efficiently and accurately for both the absorption of atmospheric gases and the multiple scattering of atmospheric particles (cloud droplets, ice crystals, and aerosol particles). The radiative transfer models now start including a treatment of completely or partially cloud-filled fields of view and can be applicable for (a) aerosol layers both above or below cloud layers, (b) multiple cloud layers (e.g., an ice- cloud layer over a water-cloud layer) in a vertical column, and (c) a single-layered cloud containing a mixture of both ice- and water-phase particles, or the so-called mixed-phase clouds.

For an ice-phase cloud, a comprehensive database of the single-scattering properties of ice particles with various geometries has been developed (Yang et al. 2005). For a liquid-phase cloud, the droplets are simulated using a modified gamma size distribution with an effective radius as a function of rain rate for precipitating clouds. For nonprecipitating clouds, cloud optical properties are computed from cloud water content and effective radius (Liu and Weng 2006). The dielectric constant of water is computed from a microwave model (Ulaby et al. 1986) and an infrared and visible model (Irvine and Pollack 1968. To quantify the effect of aerosols in the data assimilation system, a radiative transfer model including aerosol is requested. In the current NOAA air quality forecast and satellite data assimilation system, aerosol distributions and types are taken from Goddard Chemistry Aerosol Radiation and Transport (GOCART) model that simulates major tropospheric aerosol components of dust, sulfate, black carbon (BC), organic carbon (OC), and sea-salt aerosols. The organic carbon and black carbon are further distinguished with hydrophobic and hydrophilic. Under a hydrophilic situation, the aerosol effective size swells with ambient water vapor. The sea-salt aerosol is also divided into a small mode (SSAM) and a coarse mode (SSCM). The effective aerosol size for SSAM, SSCM, and sulfate depends on ambient relative humidity. The size of dust aerosol is independent from relative humidity and its range is divided into 5 size bins in GOCART model where the first size bin corresponds to 4 sub size bins with fixed volume concentrations in percentage. There are 8 aerosol types in total: dust, dry OC, wet OC, dry BC, wet BC, SSAM, SSCM, and sulfate. The output of the GOCART model is the concentrations for up to 5 aerosol types of the 8 aerosol types. A lookup table is necessary to store the precalculated aerosol optical parameters such as dry mass extinction coefficient, single-scattering albedo, and asymmetry factor. In the aerosol lookup table, a lognormal size distribution is characterized through a median radius and its geometric standard deviation parameters (Chin et al. 2002). The refractive indices of these chemical components are based on studies by Hess et al. (1998). Lorenz–Mie code is used to compute mass extinction coefficient, single-scattering albedo, asymmetry factor, and phase expansion coefficients.

b. Fast gas absorption models

Under clear atmospheric conditions, radiative transfer modeling uses atmospheric absorption coefficients as the key input. The absorption varies with the atmospheric conditions in a complicated way and is often computed through the line-by-line (LBL) spectral models. Although LBL models are accurate, they take considerable time to calculate transmittances for just a few atmospheres. To provide accurate transmittances in a timely fashion, fast optical transmittance (OPTRAN) models have been developed for specific instrument channels. The current fast models used in the U.S. operational data assimilation are based on an approach developed by McMillin and Fleming (1976), but there have been incremental changes made by a number of groups since then. With the coming of hyperspectral instruments, the requirements placed on the fast models are changing, and this modification process is continuing. Radiative transfer process should take into account the instrument filter response functions because each new instrument flown on a new spacecraft has its own specifications. Appropriate changes are made to the LBL models to regenerate the new coefficients for the transmittances of new instruments.

Recently, a fast and optimal spectral sampling (OSS) absorption model was developed for improved accuracy across the entire spectrum (Moncet et al. 2004). The OSS is a new approach that allows for rapid calculations of radiance for any class of multispectral, hyperspectral, or ultraspectral sensors at any spectral resolution and any wavelength by selecting and appropriately weighting the monochromatic radiances contributed from gaseous absorption and particle scattering over the sensor bandwidth. This allows the calculation to be performed at a small number of spectral points while retaining the advantages of a monochromatic calculation such as that needed for the exact treatment of multiple scattering and/or polarization. The OSS method is well suited for remote sensing applications that require extremely fast and accurate radiative transfer calculations: atmospheric compensation, spectral and spatial feature extraction, multisensor data fusion, subpixel spectral analysis, qualitative and quantitative spectral analysis, sensor design, and data assimilation. The OSS is currently used as part of the National Polar-Orbiting Operational Environmental Satellite System (NPOESS) environmental parameter retrieval algorithms. With the OSS method, the channel radiance is calculated from

$$\bar{\mathbf{I}} = \int_{\Delta\nu} \phi(\nu)\mathbf{I}(\nu)\,d\nu \cong \sum_{i=1}^{N} w_i \mathbf{I}(\nu_i); \quad \nu_i \in \Delta\nu, \qquad (6)$$

where N is the total number of nodes within a channel spectrum domain with i being the ith node; ϕ is the spectral response function; ν_i is the wavenumber node and w_i is the weight determined by fitting the "exact" calculations (from LBL model) for globally representative set of atmospheres (training set). At the selected nodes, the lookup tables of absorption coefficients for relevant species are stored. Maximum brightness temperature errors between the LBL and OSS using the lookup table calculations are less than 0.05 K in the infrared and are about 0.01 K at microwave wavelengths (Moncet et al. 2004).

In the NWP community, there are many fast gaseous absorption models developed for satellite data assimilation. A complete survey and the performance accuracy of these models are reviewed by Garand et al. (2001). It is shown that for specific instruments like the Atmospheric Infrared Spectrometer (AIRS), a Stand Alone Radiative Transfer model (SARTA) developed by University Maryland at Baltimore County (UMBC; Strow et al. 2003) performs the best. This was obtained by comparing SARTA with all other fast models that were not specifically fitted to the AIRS instrument. Unfortunately, the original version of SARTA does not have tangent-linear and adjoint models.

The transmittance at microwave frequencies near 60 GHz is also highly affected by the Zeeman effects, which split the oxygen spectral lines near 60 GHz into a number of finely spaced lines. The intensity of the split lines, and their separation, depends on the earth's magnetic field strength and its orientation with respect to the satellite instrument's viewing direction and its received polarization. For fast computation of the absorption coefficients including the Zeeman effects, a LBL model (Rosenkranz 1995) is parameterized using various predictors including the earth magnetic field magnitude (B), polarization (left and right circularly), temperature, and angle between magnetic field and propagation direction of electromagnetic (EM) wave. This parameterization has resulted in an excellent simulation of the brightness temperatures from the Defense Meteorology Satellite Program (DMSP) Special Sensor Microwave Imager and Sounder (SSMIS; Han 2006).

c. Surface emissivity modeling

For window channels as well as lower sounding channels, the measurements respond to the radiation emanating from the earth's surface. As such, the radiance and Jacobian computations require accurate knowledge of the surface emissivity and reflectivity. Without accurate surface models, the measurements from these channels are often greatly different than the a priori estimate, so that the radiances cannot be assimilated into NWP models. Therefore, in addition to the radiative transfer model of the atmosphere, a surface model must be developed to properly include the variability of emissivity and reflectivity.

Shortly after the launch of the first AMSU instrument in 1998, an ocean emissivity model was developed at NOAA/National Environmental Satellite, Data, and Information Service (NESDIS) for radiance assimilation. This model calculated the emissivity by linear combining of the contributions from calm and rough water. The calm water emissivity was calculated using the Fresnel equations with the dielectric constant for seawater as input (Klein and Swift 1977), while the emissivity for wind-driven seas was calculated using the empirical model initially developed by Stogryn (1972), which includes the foam coverage and its relationship to wind speed, viewing angle, and microwave frequency (Hollinger 1971; Wilheit 1979). A sea surface emissivity model developed by the Met Office, United Kingdom (English and Takashima 1998), was also tested in the operational environment. This model was initially developed based on geometrical optics, where the large-scale ocean waves are modeled using tilting surface facets whose scattering coefficients are proportional to the number of surface facets with a sloping angle satisfying the specular reflection condition. The slope distribution of the large-scale roughness was computed from an ocean surface spectrum (Cox and Munk 1954). It is found that the first version of the UK fast emissivity model (FASTEM-1) produced better results in simulating the AMSU data at higher frequencies, whereas the NEDSIS emissivity model performs better at frequencies less than 37 GHz.

Microwave emissivity models were also developed to help improve the radiance assimilation over land (Weng et al. 2001). Prior to this model development, constant emissivity values were used for unfrozen land, snow cover, and sea ice in the NOAA global data assimilation system. Modeling the emissivity for such heterogeneous surfaces is a daunting task. In the case of snow it requires an understanding of radiative transfer theory for dense media (Weng et al. 2001). For example, a more physically based emissivity model was developed for snow, which includes the volumetric scattering from ice crystals based on strong fluctuation theory. In the case of vegetation-covered land, geometrical optics was used to calculate the leaf reflectivity and transmissivity since the leaf size is typically larger than the microwave wavelength while surface roughness is approximated using small perturbation theory. However, it soon became evident that these emissivity models were deficient in representing the true surface features retrieved from the AMSU instrument (Weng et al. 2001) as well as the aircraft microwave measurements obtained during the NASA Cold Land Processes (CLP) experiments (Stankov et al. 2004). Furthermore, in cold climate regimes such as Greenland, the internal characteristics of snow are very complex, exhibiting both stratification and metamorphosis. As such, very large differences exist between the satellite measurements and modeled emissivity.

Modeling the land emissivity at infrared wavelengths is even less advanced, compared to that at the microwave frequencies. Much of this stems from the fact that, compared to microwave frequencies, the infrared emissivity is generally higher and less variable over most land surfaces. However, over deserts, minerals such as quartz have emissivities near unity while the emissivity of limestone is near 0.6 for wavelengths between 7 and 9 μm. Instead of relying on emissivity models, a lookup table of IR emissivity derived from satellite and ground-based retrievals (Knuteson et al. 2006) is proposed for uses in satellite data assimilation systems. In the current NOAA global operational data assimilation system, the emissivity spectra are specified as function of surface types.

3. Major impediments

Direct assimilation of satellite radiances under clouds and precipitation requires detailed information on the profiles of cloud microphysical variables as background information and the error characteristics of the error covariance matrix as shown in (1) and (2). Currently, operational forecast models and cloud prognostic schemes run slightly different physical packages. In principle, this prediction scheme can resolve cloud condensates only when the model resolution is increased to less than a few kilometers. At courser resolutions, the forecast model has to rely on a cumulus parameterization scheme (Arakawa and Schubert 1974; Moorthi and Suarez 1999) to determine the clouds and precipitation associated with convective motion. In addition to the cumulus parameterization, NWP models also employ a stratiform cloud water parameterization scheme (e.g., Sundqvist 1978).

To understand the quality of the model-predicted cloud condensates, more observational datasets to characterize the errors of the forecasted cloud water–ice content need to be developed. Retrievals from satellite passive sensors may be used for assessments of model errors in the column-integrated water (Weng et al. 1997). However, errors in the profiles of cloud condensates predicted by forecasting models may be better characterized when the data from aircraft in situ measurements or satellite active sensors such as CloudSat (Stephens et al. 2002) are available. Also, the satellite-derived cloud water is subject to substantial retrieval errors.

Further difficulties and limitations arise from the fact that scattering by clouds and precipitation is a function of particle size, which is not currently predicted in NWP models. This problem is acute when the size parameter (ratio of particle size to wavelength) is large. Determination of mean particle size from satellite visible/near infrared (VIS/NIR) or development of diagnostic and/or prognostic schemes in NWP models for mean particle size is crucial for the use of cloudy radiances in NWP models. Alternatively, an ad hoc relationship between cloud particle size and ambient temperature and ice water content (Heymsfield and Platt 1984) can be also tested for radiative transfer in ice-phase clouds.

At the infrared wavelength ranging from 3 to 15 μm, aerosols may have considerable effect on radiance calculations. It is known that most models developed for chemistry aerosol radiation and transport take into account the major tropospheric aerosol components, including sulfate, dust, black carbon, organic carbon, and sea-salt aerosols. Each of these aerosols requires more demanding computational power for determining their optical parameters. In addition, knowledge of their concentrations, particle size, and shape is very limited from any ground-based measurements, although they are critical parameters in radiative transfer calculations.

For fast gas absorption models, more trace gases such as carbon dioxide, monoxide and methane should also be considered, because forecast models are making more use of satellite measurements that are sensitive to these constituents. Presently, transmittance models only include a number of "fixed" gases and variable gases such as water vapor and ozone. Assimilating the satellite measurements into forecasting models and predicting their distributions require the transmittance models that include variations in minor gases. As the gas absorption models and other radiative transfer components become more accurate, the variations in retrieved temperature due to changes in minor gases become significant when they are ignored.

Quantitative assessments of errors arising from various radiative transfer modules are very important components because the errors are typically used to define the observational error covariance matrices in satellite data assimilation systems. Without knowledge of errors of simulated radiances relative to observations, the information from new satellite measurements cannot be probably extracted during the data assimilation process. Most recently, various fast gas absorption models have been quantified for their errors relative to the LBL computations (Saunders et al. 2007). A comparison of radiative transfer models for simulating radiances with AIRS has been also undertaken. Results from 14 LBL and fast parameterized infrared models agree to within 0.02 K for forward computations when compared to a reference LBL model averaged over a subset of profiles and regions, and the mean differences increase to 0.2 K when compared with AIRS observations. For the Jacobians, the gradients of radiance to the state parameters from all models have some profiles/channels that do not fit the reference well (Saunders et al. 2007).

The performance of forward models under scattering cloudy and precipitating atmospheres can vary substantially from case to case. At visible wavelengths, errors are strongly dependent on our knowledge on particle shapes and orientation, and spatial inhomogeneity. In infrared and microwave wavelengths, the errors can range from a few tenth to tens of kelvins. In aerosol-scattering conditions, for example, simulated High Resolution Infrared Sounder (HIRS) radiances can be biased by 2–3 K at its window channels (Liu et al. 2007).

Over land where surface emissivity varies, the errors are strongly dependent on our knowledge in surface emissivity and atmospheric conditions. Taking microwave water vapor sounding channels as an example, the contributions to the brightness temperature from surface emission and reflected downwelling radiation can be significantly large over polar regions where atmospheres are typically dry and become semitransparent. In the absence of scattering, an error of emissivity of a few percent can result in an error in brightness temperatures of a few kelvins at 183.3 $\pm$ 3 and 183.3 $\pm$ 7 GHz, respectively, (note that these channels are nominal sounding channels for most of atmospheric conditions; Weng and Yan 2003).

4. Future work

For the radiative transfer component, the highest priority items are as follows:

1) Continue refining the rapid gas absorption model for current and future sensors, including the absorption coefficients for hyperspectral instruments such as AIRS, Infrared Atmospheric Sounding Interferometer (IASI), Cross-track Infrared Sounder (CrIS), and the corresponding Jacobian codes. Developed models should be in line with the current data assimilation interface at the Joint Center for Satellite

Data Assimilation (JCSDA) community radiative transfer model.

2) Update rapid atmospheric gaseous absorption coefficients as instrumental parameters, spectral knowledge, or requirements change. For infrared sounding instruments that experience changes in the spectral response shape and central wavelength, fast models are needed to rerun the LBL forward-model calculation with the improved instrumental response functions and new fast model coefficients.
3) Develop and improve radiative transfer schemes to include scattering from aerosol, clouds, and precipitation. One of the key components is to speed up the computation with a lookup table of optical parameters using particle size, dielectric constant, and mixing ratio as inputs.
4) Develop infrared emissivity models for land surfaces. Surfaces containing quartz, limestone, and other mineral compositions result in large variability in the infrared emissivity at wavelengths from 3 to 4 and 6 to 9 μm, and should be treated using mixing formulas having variable composition.
5) Improved microwave dense media theory is needed to simulate the emissivity for snow and sea ice. Dense media scattering should also be developed to include vertical stratification and solved through a comprehensive algorithm that is applicable to a broad range of wavelengths. The inputs to the snow and sea ice emissivity models should be closely linked to the output parameters from NWP boundary layer models.

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